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Students' study activities before and after exam deadlines as predictors of performance in STEM courses: A multi-source data analysis

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ABSTRACT

Many college students struggle with regulating the time and effort they invest in classes. We used digital trace data from a learning management system to examine students' behavioral engagement and associations with course performance in four chemistry courses ($N = 1596$). Results from Study 1a show that behavioral engagement declined across the course, except for high spikes in exam weeks. Students with higher regularity and continued engagement after midterm exams obtained higher course grades, whereas steep increases in study activities shortly before exams did not predict performance. Using a selective subsample of students ($n = 51$, with 510 observations over time) who identified chemistry as a challenging course, Study 1b explores whether intentions to regulate learning behaviors with goal-directed control strategies lead to changes in behavioral engagement. Intentions to use control strategies lead to short-term changes in behavioral engagement, but students did not implement planned adjustments to their study behaviors in the long run.

Educational relevance statement: This study shows that consistent behavioral engagement in a learning management system over the course of a semester and early increases in learning activities before critical course exams predicted students' academic success in chemistry college courses. Students showed increased behavioral engagement immediately before course exams, but such short-term increases did not lead to better course performance. Instead, regular course engagement, as indicated by click activity in a learning management system, was significantly related to students' end-of-term course performance. Findings from a small and selective subsample of students who perceived the course as particularly challenging (study 1b) further suggest that students' intentions to change their behavioral engagement for the following exam(s) predicted only short-term changes in observed engagement in the learning management system. Thus, these students might benefit from further support to effectively regulate their learning behaviors. Studies 1a and 1b suggest that digital trace data from the course's learning management system can be informative in identifying struggling students, particularly using trace data from weeks around exams.

As students transition from high school to college, they gain autonomy and relative independence in how they structure their learning and coursework. However, this increased freedom comes with its own set of challenges to self-regulate. Self-regulated learning (SRL) involves the regulation of cognition, meta-cognition, motivation, and behaviors central to college students' learning and success (Broadbent & Poon, 2015; Pintrich, 2004; Zimmerman, 1990). Behavioral regulation and engagement, including effective time management, effort regulation, and the ability to adjust study activities depending on situational course demands (Pintrich, 2004; Wolters & Brady, 2021), are key components

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of students' academic success in college (Kitsantas et al., 2008; Theobald, 2021; Wolters & Brady, 2021). However, the regulation of time and effort presents a significant challenge for many students, especially for students who are traditionally underrepresented in higher education (Ifenthaler et al., 2022; Park et al., 2018). Prior research suggests that first-generation students, socioeconomically disadvantaged students, and students from historically underrepresented minorities (URM) face greater challenges with regulating their learning (Nguyen et al., 2020; Rodriguez et al., 2021; Xu & Jaggars, 2014).

The primary focus of SRL research is typically on effective learning behaviors directed toward goal pursuit, while motivational theories, such as the motivational theory of lifespan development (MTD: Heckhausen et al., 2010; Heckhausen & Schulz, 1995), further emphasize that goals and behaviors need to be adapted to individual resources and situational constraints to allow individuals to stay committed to attainable goals. When self-set goals are overambitious, they need to be adjusted to a student's capacity to avoid the wasteful investment of effort (Heckhausen et al., 2010). Even though it constitutes an essential SRL component, students' ability to *adjust* their academic goals and study behaviors to situational course demands in real-life educational contexts remains understudied. Understanding how students modify their behavior to meet situational demands and goals is crucial for designing targeted support for struggling students.

In the present study, we focus on students' behavioral engagement and regulation in online courses and use longitudinal multi-source data from four introductory gateway chemistry courses at a US university to examine (a) how students change their study activities when approaching and shortly after important exam deadlines, (b) interindividual differences in study activities by demographic background characteristics, and (c) whether intraindividual changes in study activities predicted students' end-of-term performance (Study 1a; $N_{Students} = 1596$). Furthermore, with a small and selective subsample of students who identified their course as particularly difficult and important, we were able to explore whether self-reported goal-engaging and goal-adjustment control strategies are predictive of intraindividual changes in study activities (Study 1b; $N_{Students} = 51$).

1.1. Theoretical background

Student engagement and SRL are central psychological constructs and frameworks explaining links between contextual and personal characteristics with academic outcomes (Fredricks et al., 2004; Pintrich, 2004; Wolters & Taylor, 2012). In the present study, we are referring to the education-specific concept of school engagement by Fredricks et al. (2004) and the SRL framework by Pintrich et al. (1991); Pintrich (2004) as well as more general motivational concepts of goal engagement and goal adjustment (Heckhausen et al., 2010, 2019).

Fredricks et al. conceptualize behavioral, emotional, and cognitive engagement as three central components of student engagement. *Behavioral engagement* can include a) attendance and personal conduct in courses, b) involvement in learning and academic tasks, such as effort, persistence, and task completion, and c) involvement in broader school activities, such as sports clubs. SRL frameworks, such as the model by Pintrich et al. (1991); Pintrich (2004), overlap in several central components with Fredricks et al.'s conceptualization of engagement. Pintrich describes different areas of regulation that are essential for successful learning processes, including the regulation of behavior, cognition, motivation, and the learning context. *Regulation of behavior* includes the regulation of effort, time management, and persistence and thus, has a large overlap with Fredricks et al.'s concept of behavioral engagement. A central distinction of the SRL framework compared to engagement is the conceptualization of learning as a cyclical process including a planning phase, a performance phase, and an evaluation phase. In each of these phases, regulation is needed to adjust goals, study strategies, and effort to the current course demands and learning progress.

In the present study, we examine behavioral engagement as involvement and persistence in learning activities and academic tasks in a learning management system of university courses (Fredricks et al., 2004). We further focus on students' regulation of behavioral engagement as conceptualized in SRL frameworks (Pintrich, 2004) and motivational theory of lifespan development framework (goal-engagement and adjustment; Heckhausen et al., 2010), as we examine changes in students' behavioral engagement over time and in relation to relevant course exams.

1.2. Regularity in study activities across a course

Digital trace data from LMS – e.g., students' use of lecture videos, reading materials, and online self-assessment quizzes – are an increasingly used data source to investigate interindividual differences in students' learning behaviors and to identify (mal)adaptive study strategies in higher education (Arizmendi et al., 2022; Du et al., 2023). When students use LMS, their study activities are logged in digital traces, providing opportunities to investigate aspects of students' behavioral engagement, including time management and effort regulation in realistic course environments (Arizmendi et al., 2022; Baker et al., 2020; Fredricks, 2011).

Aligning with the theoretical assumptions regarding the significance of regular study activities for learning success (Fredricks et al., 2004; Pintrich & Zusho, 2007), empirical studies have demonstrated that students with more consistent engagement in learning activities via LMS achieve better grades and have a lower risk of course failure. For instance, You (2016) found that undergraduate students in South Korea who engaged in more regular and longer study sessions in the LMS achieved higher final grades. Jovanovic et al. (2019) examined LMS data from three engineering courses with a flipped classroom design at an Australian university, revealing that students who regularly accessed course resources (e.g., content videos) before lectures throughout a 13-week course achieved better final grades. Similarly, Hong et al. (2020) analyzed LMS data from undergraduate students enrolled in biology courses at a US university, finding that students who consistently used exercises and self-assessment quizzes obtained higher grades. In contrast, irregular click activities and declines in LMS engagement over a semester are linked to lower end-of-term course grades (Jovanovic et al., 2019) and a heightened risk of course failure (Nguyen et al., 2020; Park et al., 2017).

1.3. Study activities *before* exam deadlines and performance

Several studies have examined students' time management and study behaviors preceding relevant course deadlines and exams. Li et al. (2020) investigated study behaviors of undergraduates enrolled in a 10-week online chemistry course. The authors evaluated the proportion of assigned study units completed by students in an LMS (a) before the given deadline versus (b) on the due date, along with the time gap between students' submissions and the deadline. Students with better end-of-term performance completed more assignments ahead of each deadline and had longer time intervals between their submissions and the due dates. Furthermore, Li et al. (2020) observed that students who demonstrated sensitivity to deadlines—indicated by increased time spent working on course modules before relevant deadlines—achieved higher course grades. Notably, the steeper the increase in study time before a deadline, the smaller its positive effect on later performance. Thus, the extent of growth in students' study time *and* the point at which their study time increases significantly relates to their course performance. Similar results were reported by Rodriguez et al. (2021) for students' use of lecture videos before or after assigned due dates and by Park et al. (2018) and Sabnis et al. (2022) for the submission of required assignments relative to the due date. Students who engage in early exam preparations and access and submit assignments well before the deadlines achieve better course grades than their peers who prepare for and submit assignments shortly before the due dates.

1.4. Inter- and intraindividual differences in study activities

There is consistent evidence indicating that interindividual differences in study activities are associated with both retention rates and performance (Cicchinelli et al., 2018; Hong et al., 2020; Huang et al., 2022). Furthermore, research has revealed trends indicating interindividual differences in study behaviors among students by demographic backgrounds (Sabnis et al., 2022; Yu et al., 2020). Female students tend to display higher levels of study activities and more adaptive study patterns in LMS than male students (Nguyen et al., 2020; Sabnis et al., 2022). First-generation college students and students from ethnically underrepresented minorities are more likely to show procrastinating behavior, lower study activities overall, and to have more substantial declines in study activities during the semester (Nguyen et al., 2020; Rodriguez et al., 2021; Sabnis et al., 2022). Why these differences occur is not yet well understood. Lack of familiarity with effective study strategies and competing obligations such as employment or family obligations have been discussed as possible underlying causes. Less research combined digital trace data on students' engagement with survey data to examine interindividual differences based on personal characteristics. Theobald et al. (2018), for example, showed that university students with higher levels of conscientiousness distributed their learning more evenly across the semester which led to higher subsequent course grades. Findings regarding students' motivation and behavioral engagement are mixed with some studies reporting no associations between course-specific self-efficacy and intrinsic value with behavioral engagement with course materials (Cicchinelli et al., 2018; Huang et al., 2022), while others found that students with mastery goal orientation showed more metacognitive activities on a course LMS than students with higher perceived cost values (Hong et al., 2020). Self-reported SRL skills, particularly when measured at the end of a course, showed positive associations with behavioral engagement measures, such as the number of clicks and effort regulation in courses (Cicchinelli et al., 2018; Li et al., 2020).

While most studies focus on interindividual differences in overall study activities throughout courses, a growing body of literature takes advantage of the longitudinal nature of digital trace data to examine intraindividual changes in study activities. For instance, are short and steep increases in study activities and slow and steady increases before an exam similarly related to exam performance? Such studies have attempted to capture intraindividual changes by detecting critical change points in student click behaviors (Park et al., 2017), measuring the regularity of study activities (Baker et al., 2020; Li et al., 2020), and describing the longitudinal trend and changes in study activities (Li et al., 2020; Yu et al., 2018). Few studies have modeled these intraindividual changes in relation to critical course events. This is an important gap in the literature because regulation processes encompass a series of events wherein students constantly make decisions and take actions based on internal and external factors, such as their goals and available resources (Rovers et al., 2019; Winne & Perry, 2008).

A central challenge with digital trace data is that learning activities need to be contextualized to obtain meaningful indicators for the regulation of study time and effort (Du et al., 2023; Gašević et al., 2016). We combine multiple data sources from highly structured chemistry courses to investigate how students' behavioral engagement changes before and after critical course exams and possible implications for students' end-of-term performance. Furthermore, we examine interindividual differences in study patterns by students' demographic backgrounds to investigate whether some groups of students were at particular risk of showing maladaptive patterns of behavioral engagement (see study 1A).

1.5. Adjusting learning behavior and goals

A central aspect of time and effort regulation is that students intentionally adjust their learning activities to situational course demands to facilitate goal pursuit (Zimmerman, 2002). The motivational theory of lifespan development (MTD) further proposes that not only students' learning behaviors but also their individual goals need to be adapted to situational opportunities and constraints (Heckhausen et al., 2010). In educational settings, goals need to be adjusted to a given student's capacity to avoid wasting time and effort. Individual goal engagement would be reflected in *selective primary and secondary control strategies* that maximize behavioral investment (e.g., put effort and time into goal pursuit) and motivational focus (e.g., avoid distractions) on a chosen goal. These control strategies encompass goal-engaging actions and behaviors that help students sharpen their focus and facilitate goal attainment. Empirical research using self-report data indicates that employing *selective control strategies* is associated with adaptive motivational orientations and better performance outcomes (Daniels et al., 2014; Hall et al., 2006; Hamm et al., 2013). Goal adjustments are also needed when self-set goals are overambitious or unattainable (e.g., adjusting grade aspirations in challenging courses or using self-serving attributions; Heckhausen et al., 2010, 2019). These *compensatory control strategies* help students cope with setbacks while maintaining self-confidence (Bermeitinger et al., 2018; Hall et al., 2006; Tomasik & Salmela-Aro, 2012). Thus, goal-engaging and goal-adjustment control strategies serve important functions for learners.

To date, empirical studies rely on self-report data to assess the use of different control strategies. The present study expands upon prior evidence by analyzing intraindividual changes in students' study behaviors—assessed via digital trace data—before and after important exams (*Study 1a*) and combining self-report data on control strategies with digital trace data (*Study 1b*). This is the first study to explore whether self-reported intentions to employ different control strategies are related to changes in students' (online) learning activities in real-life academic contexts.

2. Present study

The study has two overarching goals. First, we examined students' study activities to identify successful patterns of behavioral engagement that predict students' end-of-term performance in gateway chemistry courses. In *Study 1a*, we combined digital trace data, course-syllabus data, and college records data on students' backgrounds and performance from the UCI-MUST project (Arum et al., 2021) to investigate the relations between inter- and intraindividual differences in students' behavioral engagement with the course LMS and end-of-term performance. Unlike prior studies that focused on specific time frames before submission deadlines or exams, we examined the entire academic term and investigated associations between intraindividual changes in study activities before and after course exams with end-of-term performance.

In *Study 1b*, we explored whether students' intentions to adopt goal-engaging or goal-adjustment control strategies in the course predicted changes in subsequent digital traces of behavioral engagement. Course-specific survey data was collected only for students' most important and most challenging courses because students are most likely to strive to regulate their study behaviors in such courses. Thus, *Study 1b* focused on a relatively small and selective subsample of 51 students who identified the targeted chemistry courses as personally important and challenging.

2.1. Research Questions in Study 1a

RQ1a: How does students' behavioral engagement in an LMS vary over the ten weeks of an academic term?

We examined interindividual differences and intraindividual variations in students' behavioral engagement before, during, and after relevant course exams. Based on existing literature, we expected significant changes in students' click activities across the academic quarter, with increased activities shortly before relevant course exams (Ifenthaler et al., 2022; Park et al., 2018). Analyses of post-exam changes were exploratory.

RQ2a: To what extent are different patterns of behavioral engagement associated with end-of-term course performance?

We expected that students who maintained a more consistent level of behavioral engagement throughout the academic term would achieve better end-of-term grades (Nguyen et al., 2020; Park et al., 2017). Furthermore, we hypothesized that students who increased their click activity well before course exams would outperform their peers who only increased their study activities shortly before exams (Li et al., 2020; Park et al., 2018; Zhang et al., 2011). Notably, we explored the associations between click activities *during* and *after* exam weeks and anticipated that continued click activities following exams would be associated with better end-of-term grades.

RQ3a: To what extent do behavioral engagement and end-of-term performance differ by students' demographic background?

We examined interindividual differences in the amount and intra-individual changes of study activities by demographic variables as well as associations between study activities and course performance to examine whether some student groups were at particular risk of showing unfavorable patterns of behavioral engagement. Based on prior empirical findings, we expected self-identified female students to show more click activities in their LMS, while first-generation college students and URM students would show fewer click activities in their LMS.

2.2. Research Questions in Study 1b

In *Study 1b*, we combined self-report data with LMS data to examine whether intentions to adopt selective goal-engaging or goal-adjustment control strategies were associated with changes in students' click activity in the course. For this purpose, we used data from a small subsample of students, who identified the course as particularly challenging and important for them.

RQ1b: To what extent are intentions to adjust learning behaviors (goal-engaging control strategies) and intentions to adjust goals (goal-adjustment control strategies) associated with behavioral engagement in the course?

We expected that students who endorsed goal-engaging control strategies (i.e., increasing time and effort, avoiding distractions) would exhibit increased study activities when preparing for their final exam (Daniels et al., 2014; Hall et al., 2006). In contrast, we hypothesized that students who endorsed goal adjustment control strategies (i.e., adjusting grade aspirations) would not show increased study activities when preparing for their final exams.

3. Methods

3.1. Sample and procedure

We used data from the UCI-MUST project (Arum et al., 2021), an ongoing longitudinal multi-cohort study of undergraduates' experiences and success at a large, diverse public university in California. Data collection started in the fall of 2019 with the ethical approval of the university's institutional review board (#HS: 2018-4646). College record data and digital trace data from the campus-wide LMS Canvas were collected from all freshman and junior students (2019/20 – ongoing; project sample A). The project IRB approved the access of administrative data and digital trace data of these students for research purposes. Additional survey data on undergraduates' course-specific activities and motivations were collected from a subsample of students who were recruited for this purpose and consented to participation (project sample B). All students in their freshman and junior years were invited to participate in the UCI-MUST project via email at the beginning of the academic year. Students received course credit and monetary incentives for participating in weekly surveys across one academic year. At the beginning of each academic term, these students identified two courses that they perceived as their most difficult and most important courses, and they answered course-specific questions about their regulation strategies.

We used data from a subsample of the larger project sample (see Fig. 1), including data from the fall 2020 term when instruction took place online in response to the COVID-19 pandemic. We used multi-source data from four chemistry gateway courses in the freshman year. We focused on this set of courses because information about course structures was available from the syllabi and the courses were designed with instructional and assessment activities embedded within the LMS. All four courses had a similar, highly structured design, which is typical for chemistry courses in the US. Each week, students were assigned to view pre-recorded lecture videos, complete assignments, and practice quizzes, and they had access to files, such as lecture notes and reading materials, on the LMS. Each course had two midterms and one final exam. The digital trace data captures students' use of all provided learning materials, assignments, and exams. Additional homework assignments were provided in a different online platform and thus, homework completion is not captured in the digital trace data.

3.1.1. Study 1a sample

In *Study 1a,* we used sample 1a ($N_{Students} = 1596$), which consisted of all undergraduate students who enrolled in the four chemistry lectures (65 % self-identified female students, 56 % first-generation college students, 25 % URM students; see Table 1). The demographic composition in these courses corresponds to the diverse undergraduate population at the study site.

3.1.2. Study 1b sample

In *Study 1b,* we used sample 1b ($N_{Students} = 51$), which consisted of a subsample of students in study sample 1a, who consented to participate in the survey study of the (UCI-MUST) project and selected these chemistry courses as their most difficult or most important course. In sample 1b, 80 % self-identified as female, 58 % were first-generation college students, and 31 % belonged to a URM in college (see Table 1). These students completed weekly surveys with course-specific questions across the academic term. In surveys in the week after the midterm exam, students reported their planned use of *goal-engaging control strategies* and *goal-adjustment control strategies* when preparing for the next course exam. Sample 1b is small, but well-suited for our research objectives because students self-selected the investigated chemistry courses as highly relevant and challenging for them. Therefore, we expect that these students would be particularly committed to the course and that behavioral engagement would be central to their learning success. It is important to note that sample 1b is not a representative subsample of all students enrolled in the course (sample 1a).

3.2. Measures

3.2.1. Digital trace data (Study 1a and 1b)

We used digital trace data from the LMS Canvas from the chemistry courses in fall 2020.

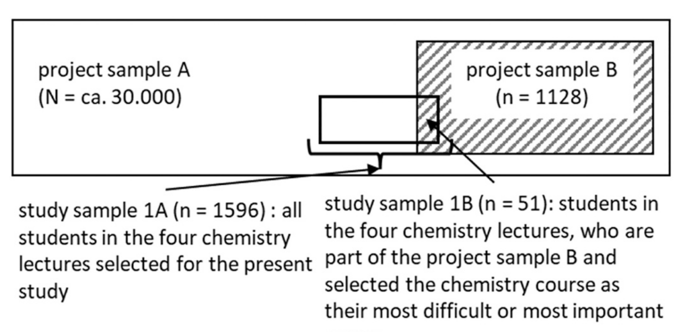

Fig. 1. Overview about the UCI-MUST project sample in the academic year 2020–21 and the study sample.

Table 1
Sample characteristics of sample 1a and sample 1b.

	Sample 1a	Sample 1b
N	1596	51
female (%)	65	80
first-gen. (%)	56	58
urm (%)	25	31
hs gpa, *M (SD)*	4.02 (0.21)	4.02 (0.20)
final grade, *M (SD)*	7.82 (2.69)	7.33 (3.18)
nr. of clicks on each day of week 1 *M (SD)*	25.40 (14.62)	24.16 (12.06)

Note. first-gen = first generation college student status. urm= historically underrepresented minority status. hs gpa = high school GPA min = 0, max = 5; final grade = letter grade converted into numeric values *min*(F) = 0, *max*(A+) = 12.

3.2.1.1. Behavioral engagement. We used the overall number of click activities each student had per day in their Canvas course space as a quantitative measure of behavioral engagement. This measure includes any activities students can perform in the system, such as viewing course materials and lecture videos, posting in forums, quizzes, and exams. First, we created a sum score of all click activities of each student per day. Second, we aggregated daily click activities on a weekly level per student. If a student had no click activity in a week, the student was assigned a zero for this week. We used weekly click activities in our final analyses because this time structure is most appropriate for the course's design; each week, students had new lectures, assignments, or exams. Third, we centered students' weekly click activities at the course means, because courses slightly differed in the mean activity level of the students (within-course centering, Enders & Tofighi, 2007). The within-course-centered variable measured a student's relative click activity compared to the course peers.

3.2.1.2. Exam weeks. Three courses had midterms in weeks 3 and 7. One course had midterms in weeks 4 and 8. All courses had the final exam in week 10. We created binary indicators to specify the weeks before course exams (*pre_exam*: 1 = week before exam; 0 = other weeks), the weeks of exams (*exam*: 1 = week with exam; 0 = no exam), and the weeks after midterm exams (*post_midterm*: 1 = week after midterm exam; 0 = other weeks). We created a continuous variable indicating the number of weeks in the academic term (*f20week*: min = 1, max = 10). We created one additional binary indicator for the week before the final exam (*pre_final*: 1 = week before final exam; 0 = other weeks), which was retained only in *Study 1b*.

3.2.2. College record data (Study 1a and 1b)

3.2.2.1. Final grade. We retrieved information on students' final course grades from college record data. Students received letter grades (A+ to F), which were transformed into a numeric variable (A+ = 12 to F = 0). We centered the variable of students' final grades at the course mean to remove between-course variance in grading.

3.2.2.2. High school GPA. We used high school GPA on a weighted 5.0 scale that accounted for the difficulty of high school courses (e.g., when advanced placement (AP) courses were taken) as an indicator of prior performance. We retrieved information on students' high school GPAs from college record data.

3.2.2.3. Demographic variables. We collected information on students' self-identified gender (1 = female, 0 = male), first-generation college student status (0 = continuing-generation student, 1 = first-generation student), and whether students belonged to a URM in college (0 = not URM, 1 = URM). Students were identified as URM if they declared their ethnicity as Hispanic, Black, Pacific-Islander, or American Indian/Alaskan Native in the admission process.

3.2.3. Self-reported data (Study 1b)

3.2.3.1. Control strategies. Students in sample 1b ($n = 51$) answered five questions about their intended use of control strategies after their first midterm exam in their chemistry course. Items were developed by the research team based on the control strategies literature in the MTD (Heckhausen et al., 2010; Heckhausen & Schulz, 1995). ***Selective goal-engaging control strategies*** were measured with three items: "Thinking about the next exam in your course [course name], how likely is it that you will 1) …increase your time and effort invested in this course? 2) … try harder to do well in assignments and exams? … 3) try to stay away from anything that could distract you from your coursework?" Items were combined into one measure with good reliability (Cronbach's Alpha: α = 0.82). *Goal-adjustment control strategies* were measured with two items: "Thinking about the next exam in your course [course name], how likely is it that you will 1) … adjust your grade aspirations for this course? 2) … become more realistic in your aspirations for this course?" The measure had good reliability (Spearman-Brown coefficient: $r = 0.90$).

4. Study 1a

4.1. Study 1a. Statistical analysis

We used longitudinal multilevel analysis with random intercepts and random slopes in Mplus Version 8.6 (Muthen & Muthen, 1998) to address our research questions in *Study 1a* and *Study 1b*. Data had a hierarchical structure with weekly measures of click activity per student (level 1) nested within students (level 2: $N_{Students} = 1596$), who were nested within courses (level 3: $N_{Courses} = 4$). We used twolevel models and controlled for nested data within courses by controlling for standard errors on level 3 with the Mplus option "type = complex twolevel random". This multilevel random modeling approach allowed us to investigate variation in click activity across the ten weeks of the fall term on an intraindividual level (time-variant predictors on level 1, random slopes on level 2; see Hamaker and Muthén (2020); Singer and Willett (2009)). This model examines how variation in click activity (random slopes) was related to student characteristics (level 2 predictors of random slopes), and how click activity predicted students' final course grades (random slopes as predictors for level 2 outcome).

For RQ1a, we specified a baseline model to examine intraindividual variation in click activities across the ten weeks of the fall 2020 term. We used data from $N_S = 1596$ students from $N_C = 4$ courses. On level 1, we used four time-variant predictors of students' weekly click activities: the number of the week in the quarter (week) and three binary indicators of weeks before an exam (pre_exam), exam weeks (exam), and weeks after the midterm exams (post_midterm). On level 2, we obtained the mean click activity on the student level in the quarter and the mean slopes for click activity in specific weeks of the term. To identify the baseline model that best fitted our data, we specified five models with stepwise inclusion of time-variant predictors (see Table 2).

In Model 5a, we used all four time-variant predictors to model intraindividual variation in students' behavioral engagement across the fall term. Models 4a and 5a had similar model fits regarding the fit indicators Akaike's Information Criterion (AIC) and Adjusted Bayesian Information Criterion (Adjusted BIC). We decided to use Model 5a as the baseline for subsequent analyses because of a slightly better AIC fit indicator and because this was the most comprehensive model considering variation in study activities in relevant time frames before, during, and after exam weeks (see Fig. 2).

To investigate how students' behavioral engagement predicted final course grades (RQ2a), we added time-invariant variables on level 2 in Model 7a (see Supplemental Material A for the Mplus code). We added demographic variables and students' high school GPAs as predictors of students' behavioral engagement across the quarter. We added students'

Table 2
Study 1a. Baseline models 1–5 to estimate intraindividual variation in click activities across the fall 2020 term in sample 1a.

			Model 1a		Model 2a		Model 3a		Model 4a		Model 5a	
			Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
Level 2	mean intercept	action cnt	0.19	(0.89)	**−0.63**	**(0.31)**	**−0.79**	**(0.37)**	−0.23	(0.22)	0.09	(0.31)
	mean slopes	week (linear)	−0.04	(0.17)	**−0.94**	**(0.24)**	**−0.96**	**(0.22)**	**−0.88**	**(0.24)**	**−0.83**	**(0.24)**
		pre exam					0.63	(0.36)			**−0.94**	**(0.22)**
		exam			**19.18**	**(3.53)**	**19.50**	**(3.39)**	**18.39**	**(3.64)**	**17.74**	**(3.61)**
		post midterm							**−2.76**	**(0.97)**	**−3.36**	**(1.00)**
		AIC	134,335		127,492		127,490		127,371		127,363	
		BIC	134,381		127,561		127,582		127,463		127,478	
		Adjusted BIC	134,362		127,533		127,544		127,425		127,430	

Note. Sample 1a ($N_S = 1596$; $N_C = 4$). Intercept week was week 1 of the quarter. AIC = Akaike's Information Criterion. BIC = Bayesian Information Criterion. Model 5 was selected for subsequent analysis in the study. Standard deviations of mean slopes in Model 5a: Week (linear) $SD = 0.81$; pre exam $SD = 0.48$; exam $SD = 10.42$; post midterm $SD = 0.89$. Bold font $p < .05$.

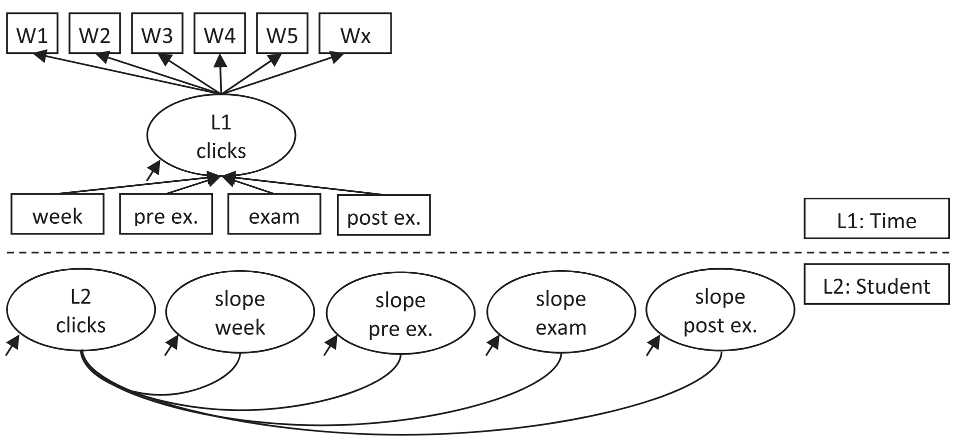

Fig. 2. Study 1a. Conceptual model of Model 5a (baseline model). *Note.* W1 – Wx = week 1 to 10, within-course centered mean daily click activity per student aggregated on a weekly level. Time-variant predictors: week = nr. of week in term; pre ex. = week before an exam; exam = week of an exam; post ex. = week after a midterm exam.

final grades as an outcome variable on level 2 to investigate how behavioral engagement and change in engagement at particular time points in the quarter predicted end-of-term performance (see Fig. 3).

4.2. Study 1a. Results

Fig. 4 shows box plots of students' click activity on each day aggregated on a weekly level and of final grades per course. Click counts had a similar range in all four courses, with medians of 15 to 19 clicks per day across the seven days of the week (i.e., medians of 105–133 clicks per week). Grade distributions were similar across all courses with medians ranging from 9 (corresponding to letter grade B+ in course 1) to 8 (corresponding to letter grade B in courses 2–4). Table 3 shows correlation coefficients of student characteristics, achievement measures, and overall click activities in the fall 2020 term. Click activities showed small but statistically significant positive correlations with female gender, first-generation college student status, high school GPA, and end-of-term course grade ($r = 0.07$ to $r = 0.19$).

4.2.1. Variation in behavioral engagement across the fall 2020 quarter (RQ1a)

Fig. 5 shows the within-course-centered average click activity for each day of the week across the fall 2020 quarter. On average, students' click activity increased during exam weeks (courses 1–3: weeks 3, 7, 10; course 4: weeks 4, 8, 10) and dropped in weeks after the midterm exams. Furthermore, the graph shows a slight gradual decline in students' click activities across the quarter, except for the exam weeks.

The baseline Model 5a in Table 2 supports these descriptive findings. Students had a mean slope of $b = -0.83$, $SE = 0.24$, $p = .001$ per week, that is, students' average click activity declined significantly across the ten weeks of the fall term. Due to this general decline, students had fewer clicks in weeks before exams than during the first week of the semester (i.e., intercept; $b = -0.94$, $SE = 0.22$, $p < .001$). Students' click activities spiked significantly during exam weeks, with an average of 17.74 more clicks on each day of the week compared to the first week in the term ($b = 17.74$, $SE = 3.61$, $p < .001$), and dropped significantly after midterm exams ($b = -3.36$, $SE = 1.00$, $p = .001$).

4.2.2. Variation in behavioral engagement and course performance (RQ2a and RQ3a)

First, we examined associations between students' background characteristics and grades, regardless of students' behavioral engagement (see Model 6a in Table 4). First-generation college students ($b = -0.37$, $SE = 0.17$, $p = .03$) and URM students ($b = -1.47$, $SE = 0.21$, $p < .001$) received lower end-of-term grades compared to their peers. High school GPA was positively associated with the end-of-term grade in the examined courses ($b = 3.58$, $SE = 0.27$, $p < .001$).

An additional set of analyses examined associations between students' background characteristics, behavioral engagement, and end-of-term course grades. Results in Table 5 show that female students ($b = 1.70$, $SE = 0.43$, $p < .001$), first-generation college students ($b = 1.86$, $SE = 0.53$, $p < .001$), and students with higher high school GPAs ($b = 2.81$, $SE = 0.70$, $p < .010$) had more click activities during the first course week ($\text{intercept}_{\text{week}}$). Students of all demographic groups had similar spikes in their click activities during exam weeks and declines in click activities during the remaining weeks of the quarter with a few exceptions. First-generation college students had steeper declines in their click activities across the entire term ($b = -0.17$, $SE = 0.06$, $p =$

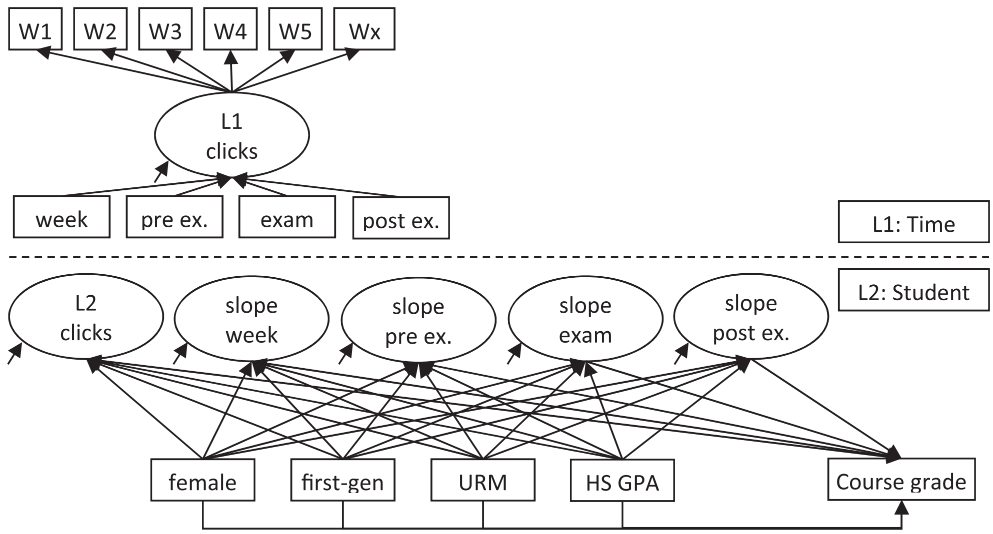

Fig. 3. Study 1a. Conceptual model of Model 7a. *Note.* W1 – W… = week 1 to 10, within-course centered mean daily click activity per student aggregated on a weekly level. Time-variant predictors: week = nr. of week in term; pre ex. = week before an exam; exam = week of an exam; post ex. = week after a midterm exam. Time-invariant predictors: female = female gender; first-gen = first-generation college student; URM = historically underrepresented minority student; HS GPA = high school GPA. For better visualization of the model, correlations of latent L2 variables are not displayed in the figure.

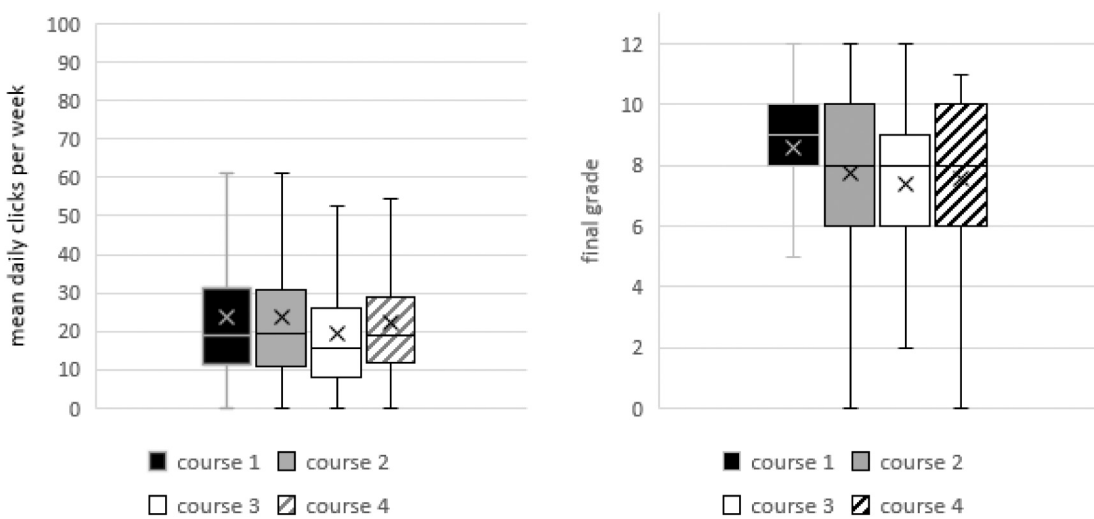

Fig. 4. Study 1a. Click activity and final grades in courses 1–4. *Note.* Click activity: Course 1: $M = 22.13$, $SD = 18.24$, $Median = 19$; course 2: $M = 23.47$, $SD = 18.3$, $Median = 19.33$; course 3: $M = 19.25$, $SD = 15.37$, $Median = 15.71$; course 4: $M = 22.13$, $SD = 15.06$, $Median = 19$. Final grade: 0 = F to 13 = A+. Course 1: $M = 8.5$, $SD = 2.38$, $Median = 9$; course 2: $M = 7.76$, $SD = 2.75$, $Median = 8$; course 3: $M = 7.3$ $SD = 2.73$, $Median = 8$; course 4: $M = 7.55$, $SD = 2.74$, $Median = 8$.

Table 3
Study 1a. Correlation matrix, sample 1a.

		1	2	3	4	5	6
1	female	–	0.03	0.04	**0.11**	**0.09**	−0.03
2	first-generation		–	**0.23**	0.03	**0.07**	**−0.12**
3	urm			–	0.01	−0.01	**−0.25**
4	hs gpa				–	**0.07**	**0.27**
5	click activities					–	**0.19**
6	final grade						–

Note. Sample 1a ($N = 1596$). first-generation = first generation college student status. urm = historically underrepresented minority status. hs gpa = high school GPA. Click activities – overall click activities in fall 2020. Click activities and final grades are within-course centered.
Bold font $p < .05$.

.01), students with URM status had lower increases in click activities during exam weeks ($b = -2.34$, $SE = 0.97$, $p = .02$), and steeper decreases in weeks after midterm exams ($b = -1.11$, $SE = 0.54$, $p = .04$).

Results regarding behavioral engagement and end-of-term grades revealed several notable findings. Students with more click activity in week 1 ($b = 0.26$, $SE = 0.05$, $p < .01$) and students who had continuously higher click activity across the quarter ($b = 1.88$, $SE = 0.34$, $p < .01$) earned significantly better grades. Hence, compared to a student with a mean slope across weeks ($M = -0.83$, $SD = 0.81$, see Table 2, Model 5a), which is roughly equivalent to two active days less in week 10 than in week 1, a student with a 1 SD more positive slope (nearly no decrease in behavioral engagement over time), will receive a 1.88 points higher end-

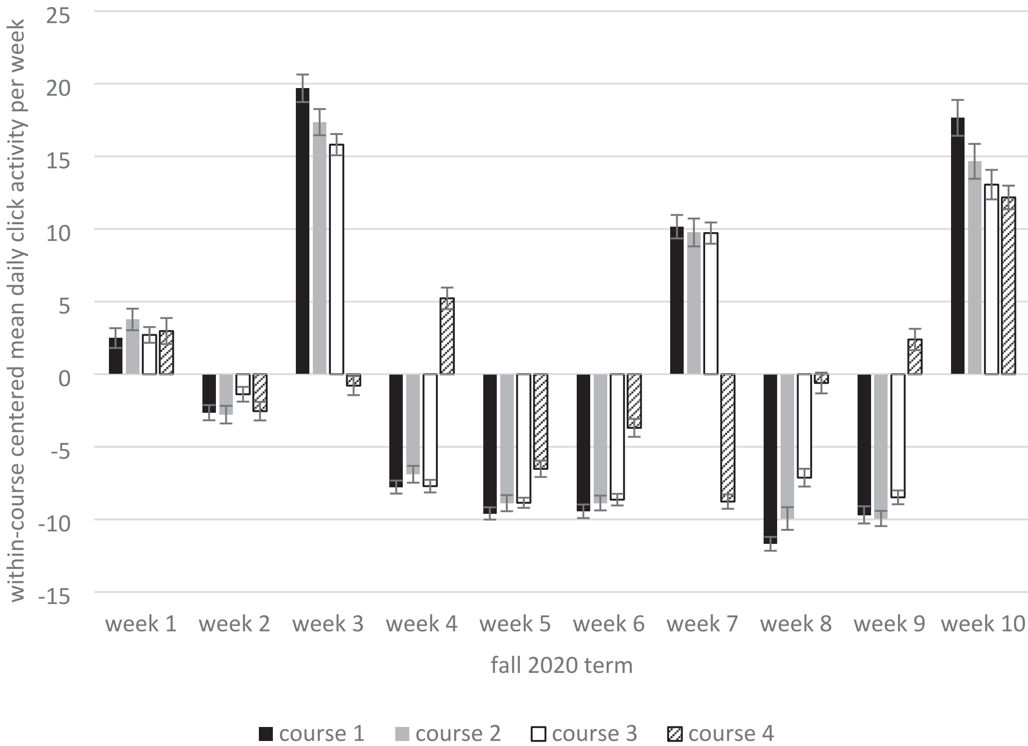

Fig. 5. Study 1a. Within-course centered click activity across the fall 2020 term in courses 1–4.

Table 4
Study 1a. Regression model to predict final course grade by students background characteristics.

Model 6a			
		Estimate	(SE)
level 2	Intercept	0.68	(0.22)
	female	−0.29	(0.16)
	first-generation	**−0.37**	**(0.17)**
	urm	**−1.47**	**(0.21)**
	hs gpa	**3.58**	**(0.27)**
	AIC	13,039	
	BIC	13,192	
	Adjusted BIC	13,129	

Note. Sample 1a ($N = 1956$). First-generation = first generation college student status (0 = no, 1 = yes). urm = historically underrepresented minority status (0 = no, 1 = yes). hs gpa = high school GPA (5.0 scale), final course grades have a metric of 0 = F to 12 = A+. Bold font $p < .05$.

of-term grade, corresponding to a change from a letter grade B to an A-.[1]

Results further showed that students who had higher click activities in weeks before an exam obtained better end-of-term grades in their course ($b = 2.09$, $SE = 0.38$, $p = .04$). Hence, students with a one-standard-deviation more positive slope of clicks compared to their peers in the week before the midterm exams ($M = -0.94$, $SD = 0.48$; see Table 2, Model 5a) achieved a 2.09 points better end-of-term grade. The steep increases in click activity during the exam weeks, instead, did not explain variance in the final grade, when click activity across the other weeks of the quarter was controlled. Notably, students who had lower drops in their click activities in the weeks after midterm exams obtained better end-of-term grades. Students with a one-standard-deviation more positive slope of clicks in the week after midterm exams ($M = -3.36$, $SD = 0.89$; see Table 2, Model 5a) achieved a 1.45 points better end-of-term grade. These findings suggest that continuously high behavioral engagement across all weeks of the quarter was most relevant for students' performance. In contrast, high peaks in behavioral engagement during the exam weeks were not related to better performance.

Controlling for interindividual differences in students' behavioral engagement, URM student status, and high school GPA were no longer predictive of students' end-of-term grades. However, first-generation college students received significantly lower grades after controlling for their click activity. Thus, first-generation college students with similar click activity throughout the quarter as their continuing-generation-college peers obtained an average of 1.16 points lower end-of-term grades. Fig. 6 shows that students with better final grades had higher behavioral engagement in all weeks of the term.

4.3. Study 1a – Discussion

Our objective was to investigate intra- and interindividual variation in students' behavioral engagement with the LMS of four introductory chemistry courses, and their effectiveness in promoting course performance outcomes. Two interesting findings emerged regarding RQ1a: All students experienced a spike in behavioral engagement during exam weeks, indicating their heightened sensitivity to critical exam dates in the course. Information from the course syllabi shows that provided course materials (e.g., lecture videos, materials, assignments) did not substantially differ between exam weeks and other weeks in the quarter. Hence, a steep increase in behavioral engagement cannot be explained by more available or assigned course materials in the exam weeks. This result aligns with previous studies that have observed substantial increases in study activities shortly before exams across various educational contexts (Ifenthaler et al., 2022; Li et al., 2020; Zhang et al.,

[1] The mean slope per week of $b = -0.83$ refers to about 7.5 clicks less in each week of the 10 weeks of the course. On average, students had 178 clicks in the first week of the quarter (25.4 clicks on each day of the week). A student with a mean slope across weeks would have about 124 clicks in week 10 of the course, roughly equivalent to two active days less, than in week 1. A student with a 1 SD more positive slope (mean slope $M = -0.83 + 1SD = 0.81$) would have a slope of -0.02 change across the weeks and hence, would have nearly no decrease in behavioral engagement over time, which was associated with a better course grade.

Table 5
Study 1a. Multilevel model with random intercepts and random slopes on associations of student characteristics, click activities across the fall term, and end-of-term grade.

Model 7a		click activity week 1		slope week		slope pre exam		slope exam		slope post midt.		final grade	
		Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
level 2	Intercept	−2.19	(0.77)	−0.77	(0.24)	−0.35	(0.42)	18.71	(3.10)	−3.40	(0.56)	8.50	(1.83)
	female	**1.70**	**(0.44)**	0.01	(0.06)	−0.31	(0.56)	−0.79	(1.48)	0.11	(0.65)	−0.26	(1.54)
	first-generation	**1.86**	**(0.53)**	**−0.17**	**(0.06)**	−0.10	(0.17)	0.34	(0.56)	0.57	(0.37)	**−1.16**	**(0.51)**
	urm	0.43	(0.73)	0.08	(0.17)	−1.03	(0.66)	**−2.34**	**(0.97)**	**−1.11**	**(0.54)**	2.02	(1.07)
	hs gpa	**2.81**	**(0.70)**	−0.23	(0.16)	1.80	(1.90)	0.55	(1.18)	0.40	(1.74)	−1.05	(5.18)
	click activity week 1											**0.26**	**(0.05)**
	slope week (linear)											**1.88**	**(0.34)**
	slope pre exam											**2.09**	**(0.38)**
	slope exam											−0.01	(0.03)
	slope post midterm											**1.45**	**(0.52)**
	AIC	140,283											
	BIC	140,743											
	Adjusted BIC	140,553											

Note. Sample 1a (N_S = 1596; N_K = 4). Intercept week was week 1 of the quarter. First-generation = first generation college student status. urm = historically underrepresented minority status. hs gpa = high school GPA (5.0 scale). Final grades have a metric of 0 = F to 12 = A+. AIC = Akaike's Information Criterion. BIC = Bayesian Information Criterion. Model 5 was selected for subsequent analysis in the study. Bold font $p < .05$.

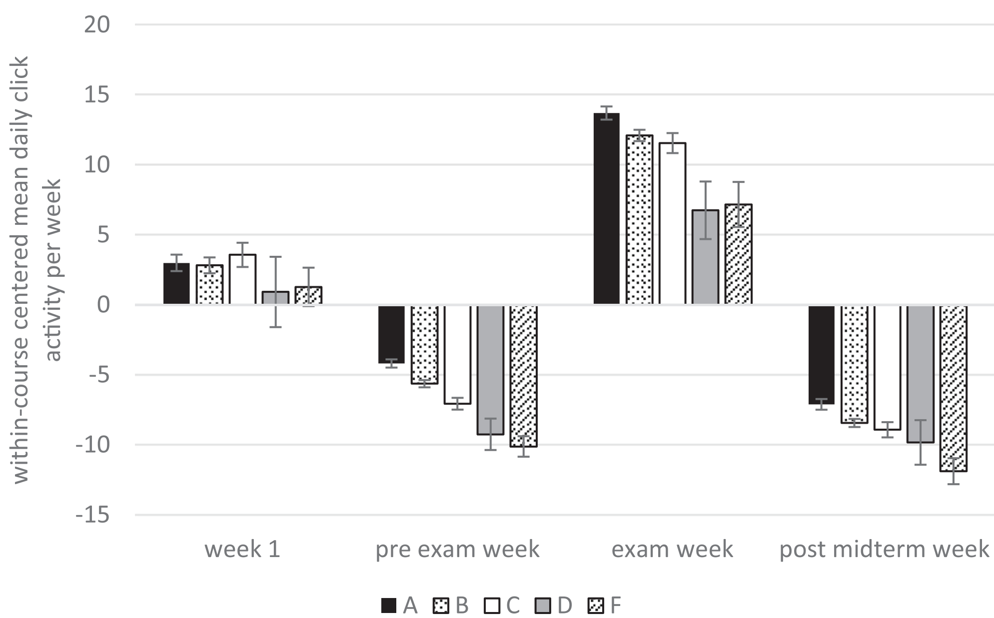

Fig. 6. Within-course centered click activity plotted by final letter grade in courses 1-4. *Note.* A – F = final letter grades in the four courses.

2011). Secondly, there was an overall decline in students' click activities over the academic quarter. This decline may reflect decreasing behavioral engagement during the term, as reported in other studies (e.g., Nguyen et al., 2020). Furthermore, higher education research has shown declines in students' motivation across the first college quarters (Benden & Lauermann, 2022; Corpus et al., 2020), which could be reflected in decreasing behavioral engagement in the LMS. On the other hand, students may become increasingly efficient in interacting with the LMS over time.

Findings regarding RQ2a demonstrated that students who maintained a more consistent pattern of behavioral engagement throughout the quarter achieved better end-of-term grades. While strong increases in behavioral engagement during exam weeks did not predict students' performance, higher behavioral engagement in the weeks before and after the exam weeks were associated with better performance. One standard deviation steeper increase in click activities in the week *preceding* the exams correlated with a performance difference of two grade points (e.g. the difference between a B and an A-). Instead, higher increases in click activities compared to peers *during* exam weeks were not related to performance. These results complement prior findings that students who increased their study activities earlier before exams and relevant deadlines outperformed their peers (Li et al., 2020; Rodriguez et al., 2021). The relevance of engagement extends not only to the period before exams but also to the time after exams. While all students experienced a decrease in behavioral engagement following the midterm exams, those who maintained relatively higher levels of engagement in the LMS achieved better grades. This suggests that some students were able to sustain higher levels of behavioral engagement when most of their peers disengaged from studying. Students with a one-standard-deviation smoother decline in click-activities compared to their peers in the week after a midterm exam obtained nearly 1.5 points better final course grades. This finding emphasizes the theoretical assumptions of Fredricks et al. (2004) and Pintrich (2004) about the relevance of continued and regulated behavioral engagement for performance outcomes compared to unregulated behavior and crammed engagement shortly before exams.

Finally, we explored interindividual differences in students' learning activities and performance by demographic background variables (RQ3a). Consistent with prior studies (Nguyen et al., 2020), female students had higher levels of behavioral engagement overall than their male peers, but the amounts of intraindividual variation in the weeks before, during, and after the exams were comparable across genders. No gender differences in performance emerged. The similarities in intraindividual variation of male and female students' click activities may be one reason why female students did not outperform their male peers, despite having higher overall click activities.

First-generation students had proportionally higher behavioral engagement in the first week of the quarter but a more substantial decline over time and they obtained lower grades than continuing-generation students. Similarly, URM students had less favorable patterns of behavioral engagement, with stronger decreases in click actions after midterm exams. Both findings are consistent with the current literature (Nguyen et al., 2020; Rodriguez et al., 2021). For first-generation students, the performance gap remained after controlling for click activities across the quarter; hence, lower performance could not solely be explained by maladaptive study behaviors of these students (Sabnis et al., 2022; Yu et al., 2020). Lack of knowledge about efficient learning strategies, conflicting obligations, and time constraints might interfere with students' regular study activities. It is relevant to note that data were collected during the COVID-19 pandemic when remote instruction introduced new challenges for many students. During the pandemic, first-generation students and URM students were particularly affected by financial hardships and difficulties with accommodating remote learning from home (Soria et al., 2020; Soria & Horgos, 2020), which could have amplified existing gaps in efficient learning habits and performance.

Finally, students with higher high school GPAs had higher levels of behavioral engagement in the first course week but did not differ in the slopes of click activities across the weeks of the quarter. When click activity was controlled for, high school GPA was not predictive of students' end-of-term grades. Thus, academically well-prepared students obtained better end-of-term grades potentially because they displayed efficient study behaviors.

5. Study 1b

In *Study 1b*, we combined digital trace data with survey data to explore associations between the intended use of *goal-engaging* or *goal-adjustment control strategies* with changes in students' behavioral engagement when preparing for the final exam. We used data from a subsample of 51 students who participated in the survey study of the UCI-MUST project and selected the chemistry courses as particularly important and challenging for them. After the midterm exam, students were asked if they planned to use goal-engaging or goal-adjustment control strategies when preparing for the next course exam. We expected that students who intended to use goal-engaging strategies (e.g., increasing time and effort) should have increased behavioral engagement in the weeks after the midterm and before the final exam. We expected no increased engagement in those weeks for students who reported intentions to use goal-adjustment strategies.

5.1. Study 1b. Statistical analysis

To address our research question in *Study 1b*, we conducted multilevel analysis with random slopes and random intercepts with a subsample of $N_S = 51$ students in $N_C = 4$ courses. We used a highly similar analytical approach as in *Study 1a*. First, we estimated a baseline model to examine students' behavioral engagement patterns across the fall quarter (Model 1b). Second, we estimated multilevel regression models with random intercepts and random slopes to investigate if self-reported intentions to use control strategies after the midterm exam were predictive for students' click activities in the weeks after the midterm and before the final exam (Models 2b, 3b, see Supplemental Material B for the Mplus code). In Model 2b, we added intentions to use selective goal-engaging control strategies when preparing for the next course exam as a predictor for students' behavioral engagement. In Model 3b, we added intentions to use goal-adjustment control strategies.

Because self-report data was assessed after the midterm exams, we used reported control strategies as predictors for behavioral engagement only in the weeks after the midterm and before the final exam. We allowed correlations of reported control strategies with click activities before and during midterm exam weeks.

5.2. Study 1b. Results

5.2.1. Self-reported intentions and behavioral engagement before exams (RQ1b)

Table 6 shows a correlation matrix with background variables, control strategies, end-of-term grades, and click activities in the entire term and selected weeks. Higher intentions to use goal-engaging control strategies were negatively correlated with click activities during exam weeks and positively correlated with click activities in weeks after the midterm exams.

In Model 1b, we specified the baseline model to examine variation in behavioral engagement in sample 1b (see Table 7). Students' click activities declined significantly across the ten weeks of the academic term ($b = -0.85$, $SE = 0.20$, $p < .001$). Click activities spiked during exam weeks ($b = 16.98$, $SE = 4.24$, $p < .001$), and dropped in weeks after midterm exams ($b = -2.29$, $SE = 0.1.19$, $p = .05$).

Results of Model 2b (Table 8) show that students who intended to use goal-engaging control strategies had higher click activities in the week after midterm exams compared to students who did not endorse goal-engaging control strategies ($b = 1.9$, $SE = 0.77$, $p = .04$). But no statistically significant difference in the click activity emerged in the week before the final exams ($b = 0.96$, $SE = 2.29$, $p = .67$). Results of Model 3b (Table 9) showed that, as expected, intentions to use goal-adjustment control strategies were not associated with increased click activities after the midterm exams or in the week before final exams. For visualization purposes, we used a median split to plot the click activities of students who reported higher intentions against the click activities of students who reported lower intentions of using a particular control strategy (Fig. 7).

5.3. Study 1b. Discussion

We focused on a small subsample of students who selected the chemistry course as their most important or most challenging course. Slightly lower end-of-term grades of students in sample B compared to all students in the courses indicate that these students struggled academically. Therefore, adaptive learning strategies and regulation of behavioral engagement may be particularly important for them.

For RQ1b, we found negative correlations between the endorsement of goal-engaging control strategies and end-of-term performance, which deviate from prior evidence showing positive associations between goal-engaging control strategies and subsequent learning outcomes (Daniels et al., 2014; Hamm et al., 2013). The measurement point of control strategies in the present study likely explains this negative correlation. We asked students after their midterm exam to rate the likelihood of using control strategies to prepare for subsequent exams in the course. Students who struggled during the midterm exams were probably more inclined to endorse control strategies and make changes to their study strategies because they had a greater need to do so than students who performed well in the midterm exam.

Results from the multilevel regression analysis revealed that students who endorsed more goal-engaging control strategies exhibited increased behavioral engagement in the weeks immediately following the midterm exams, aligning with their intention to enhance their learning effort. Consequently, these students experienced a significantly smaller

Table 6
Study 1b. Correlation matrix on student background characteristics, self-reported intentions of using control strategies for future exams, grades, and click activities in sample B.

	first-gen.		urm		hs gpa		goal eng.		goal adj.		grade		overall click activity		week 1 click activity		exam week click activity		post midterm week click activity		pre final week click activity	
	r	95 % CI	r	95 % CI	r	95 % CI	r	95 % CI	r	95 % CI	r	95 % CI	r	95 % CI	r	95 % CI	r	95 % CI	r	95 % CI	r	95 % CI
female	−0,11	[−0.37, 0.16]	0,18	[−0.09, 0.42]	−0,24	[−0.48, 0.02]	0,11	[−0.17, 0.37]	−0,05	[−0.32, 0.23]	−0,09	[−0.35, 0.19]	0,07	[−0.01, 0.16]	0,12	[−0.15, 0.38]	0,06	[−0.10, 0.21]	0,12	[−0.09, 0.33]	0,08	[−0.20, 0.34]
first-gen			−0,16	[−0.42, 0.11]	−0,13	[−0.39, 0.15]	−0,09	[−0.36, 0.19]	−0,24	[−0.49, 0.04]	0,02	[−0.25, 0.29]	0,03	[−0.06, 0.11]	0	[−0.27, 0.27]	−0,03	[−0.18, 0.13]	0,03	[−0.18, 0.25]	0,12	[−0.16, 0.38]
urm					−0,13	[−0.39, 0.14]	0,08	[−0.20, 0.35]	−0,02	[−0.29, 0.26]	−0,14	[−0.39, 0.14]	0,05	[−0.04, 0.13]	0,07	[−0.21, 0.33]	0,13	[−0.02, 0.28]	0,14	[−0.07, 0.34]	−0,08	[−0.34, 0.20]
hs gpa							−0,16	[−0.41, 0.12]	0,07	[−0.21, 0.34]	0,17	[−0.11, 0.42]	−0,07	[−0.15, 0.02]	−0,15	[−0.40, 0.12]	−0,12	[−0.27, 0.04]	−0,03	[−0.24, 0.18]	−0,01	[−0.28, 0.26]
goal eng.									0,2	[−0.08, 0.45]	−0,16	[−0.42, 0.12]	0,01	[−0.07, 0.10]	−0,07	[−0.34, 0.21]	**−0,17**	**[−0.32, −0.02]**	**0,32**	**[0.11, 0.50]**	0,19	[−0.09, 0.45]
goal adj.											−0,18	[−0.44, 0.10]	−0,04	[−0.13, 0.04]	0,03	[−0.25, 0.30]	−0,04	[−0.20, 0.12]	0,11	[−0.11, 0.31]	−0,25	[−0.49, 0.03]
grade													0,07	[−0.01, 0.16]	0,19	[−0.08, 0.44]	0,07	[−0.08, 0.22]	−0,11	[−0.32, 0.10]	0,24	[−0.03, 0.49]

Note. Sample 1b ($n = 51$). First-generation = first generation college student status. urm = historically underrepresented minority status. hs gpa = high school GPA. goal eng = goal engagement control strategies. goal adj. = goal adjustment control strategies. Final grade and variables on click activities are within-course centered. Bold font $p < .05$.

Table 7
Study 1b. Baseline model on intraindividual variation in click-activities in fall 2020 in sample 1b.

Model 1b			
		Estimate	(SE)
level 2	action cnt	−0.39	(0.74)
	slope week (linear)	**−0.85**	**(0.20)**
	slope exam	**16.98**	**(4.24)**
	slope post midterm	**−2.29**	**(1.19)**
	slope pre final exam	1.08	(1.81)
	AIC	4013	
	BIC	4076	
	Adjusted BIC	4029	

Note. Sample 1b ($N_S = 51$; $N_C = 4$). Intercept week was week 1 of the quarter. AIC = Akaike's Information Criterion. BIC = Bayesian Information Criterion. Bold font $p < .05$.

decline in click activities after the midterm exams compared to peers who did not endorse goal-engaging strategies. In the week preceding the final exams, the intention to use goal-engaging control strategies did not lead to more elevated behavioral engagement. Possibly, these students encountered challenges in implementing their intentions over the long term. As expected, intentions to adjust performance goals in the course were not associated with changes in behavioral engagement.

These findings are noteworthy for two reasons. First, they indicate that students faced challenges in implementing intended changes in their learning behavior over an extended period in the course. Thus, struggling students who endorse goal-engaging control strategies could benefit from targeted support to effectively implement adaptive strategies to regulate behavioral engagement in the long term.

Second, research on the convergence of learning strategy measures from multiple data sources has produced mixed results (Du et al., 2023; Winne & Jamieson-Noel, 2003), and self-report data has been criticized for limited validity due to memory biases or social desirability (Baker et al., 2020). While self-reports on self-efficacy often exhibit little to no correlation with course-specific measures of SRL behavior with digital trace data (Cicchinelli et al., 2018; Huang et al., 2022), more specific self-reports on learning behavior, such as time management or self-assessments overlap with SRL measures based on digital trace data (Cicchinelli et al., 2018; Ifenthaler et al., 2022; Tempelaar et al., 2020). Li et al. (2020) highlight that the timing of data collection is relevant for the conformity of measured constructs with multiple data sources. Their study revealed that only self-reports on learning behavior assessed *after* the college course showed a significant overlap with digital trace measures. Our findings emphasize the importance of specificity and timing as self-reported measures of course-specific self-regulatory intentions measured in the middle of the quarter corresponded with behavioral traces data.

6. General discussion

The study was guided by four research questions to investigate a) intraindividual variation in students' behavioral engagement in the course LMS across one academic term, b) associations of intraindividual variation of behavioral engagement in the LMS and end-of-term grades, c) differential patterns of behavioral engagement and performance by demographic backgrounds, and d) whether self-reported intentions to regulate learning behavior was associated with subsequent changes in behavioral traces of study activities.

Supporting prior empirical findings (Ifenthaler et al., 2022; Nguyen et al., 2020; Park et al., 2018), students' study activities in the LMS decreased across the academic term and spiked during exam weeks. Hence, students' behavioral engagement declined in these classes. Nevertheless, students were very sensitive in their study activities to relevant course exams. However, our findings highlight that the "lower decrease" in click activities was much more relevant to higher end-of-

Table 8
Study 1b. Multilevel model to investigate how intentions of using selective goal-engaging control strategies predict click activities.

Model 2b		week 1 click activities		slope week		slope exam		slope post midterm		slope pre final	
		Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
level 2	Intercept	−6.02		−0.19		16.89		−12.58		−6.98	
	female	5.58	(3.64)	−0.72	(0.47)	−0.54	(5.44)	1.58	(5.38)	3.42	(2.72)
	first-generation	**3.51**	**(1.47)**	−0.30	(0.64)	−0.99	(3.62)	−0.06	(2.26)	1.62	(4.34)
	urm	−2.46	(2.26)	0.34	(0.60)	4.15	(4.89)	2.00	(1.30)	−2.85	(5.16)
	hs gpa	−2.12	(7.58)	−0.33	(1.02)	−6.38	(12.52)	3.21	(6.49)	4.83	(8.51)
	goal engagement cs							**1.59**	**(0.77)**	0.96	(2.29)
	AIC	4393									
	BIC	4635									
	Adjusted BIC	4454									

Note. Sample B ($N_S = 51$; $N_K = 4$). first-generation = first generation college student status. urm = historically underrepresented minority status. hs gpa = high school GPA. cs = control strategies.
Bold font $p < .05$.

Table 9
Study 1b. Multilevel model to investigate how intentions of using goal adjustment control strategies predict click activities.

Model 3b		week 1 click activities		slope week		slope exam		slope post midterm		slope pre final	
		Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
level 2	Intercept	−5.86	(3.61)	−0.23	(0.66)	16.99	(7.33)	−9.85	(6.15)	2.34	(8.63)
	female	5.49	(4.28)	−0.69	(0.59)	−0.69	(6.23)	1.83	(9.28)	2.88	(2.10)
	first-generation	**3.52**	**(1.55)**	−0.32	(0.64)	−0.82	(3.61)	0.12	(1.39)	0.85	(4.29)
	urm	−2.50	(2.16)	0.33	(0.60)	4.19	(4.84)	2.67	(2.18)	−2.62	(5.06)
	hs gpa	−2.19	(7.68)	−0.32	(1.04)	−6.39	(12.43)	1.35	(9.24)	3.84	(8.40)
	goal adjustment cs							1.06	(1.23)	−0.67	(1.09)
	AIC	4428									
	BIC	4682									
	Adjusted BIC	4492									

Note. Sample 1b ($N_S = 51$; $N_K = 4$). first-generation = first generation college student status. Urm = historically underrepresented minority status. hs gpa = high school GPA. cs = control strategies.
Bold font $p < .05$.

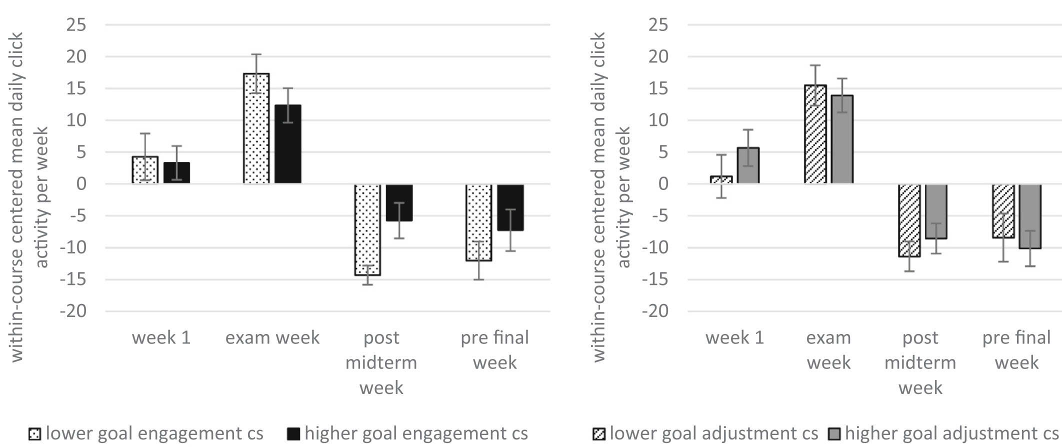

Fig. 7. Study 1b. Within-course centered click activity plotted by intentions of using goal engagement and goal adjustment control strategies for future course exams. *Note.* Sample 1b. For visualization purposes, students were divided into two groups using a median split. Intentions of using control strategies for future exams were assessed after the midterm exam.

term grades than a "steeper increase" during exam weeks. Put differently, students who maintained regular behavioral engagement throughout the quarter and who increased their study activities longer in advance of relevant deadlines attained better grades, which aligns with previous empirical findings (Jovanovic et al., 2019; Li et al., 2020; Rodriguez et al., 2021). These findings are consistent with theories on behavioral engagement and regulation that highlight the importance of regulated engagement for learning and performance (Fredricks et al., 2004; Pintrich, 2004). Our findings suggest that many students in the examined chemistry courses might have benefitted from targeted support for effectively regulating their learning behavior throughout the academic term. Particularly students with first-generation student backgrounds and URM students, who had a higher risk of showing maladaptive patterns of behavioral engagement. Findings from the small subsample in study 1b further indicate that students' intentions to change their behavioral engagement when preparing for the next exam were not always implemented in study routines before the final exams.

Promising approaches for targeted intervention programs are, for example, the studies by Bernacki et al. (2020) and Cogliano et al. (2022) who implemented an SRL intervention in the LMS of science college courses at US universities to provide information about effective regulation strategies in combination with guided practice tasks to apply those strategies in the ongoing courses. Another example from the European context is the work by Bellhäuser et al. (2022, 2023), who implemented a web-based online training with learning diaries to support college students in their SRL.

Findings from our study indicate that interventions should be embedded early in the course to provide students with necessary information about effective regulation strategies from the course beginning. As many students showed declines in behavioral engagement over time and massed learning activities before several course exams, the interventions should provide ongoing practice opportunities (see e.g., Cogliano et al., 2022) or guidance on how to implement regulation strategies across the academic term (e.g. with learning diaries, Bellhäuser et al., 2023). To tailor the support to students' needs, it would be relevant to know the reasons why students struggle with implementing consistent and regular study activities (i.e., time constraints, lack of knowledge, or challenges to implement intentions into daily learning routines), and provide the relevant support on either improved time management strategies or volition strategies. Future studies should address this gap.

6.1. Limitations and outlook

We used a quantitative measure of students' click activity in the course to operationalize behavioral engagement. This allowed us to observe inter- and intraindividual variation in students' interaction with the LMS across the academic term. However, a limitation is that we obtained a measure for the frequency of students' activities in the LMS, but we gained no further information on how they were using the LMS. Future research should use more fine-grained measures of specific aspects of students learning activities that allow to describe study behavior more precisely (e.g., clicks on study materials, lecture videos, practice quizzes, etc.). In addition, further self-reported information on students' concentration or level of distraction during learning activities in the course would be valuable variables to improve our understanding of how students cognitively engaged with the learning materials.

We used data from four chemistry courses at one university. Courses had common structures of science classes with weekly lecture videos, assignments, and repeated quizzes. However, associations between behavioral traces of learning activities with performance outcomes are context-specific and can vary between courses, domains, and universities (Gašević et al., 2016). The generalizability of our findings to other educational contexts should therefore be explored in future research. Our findings supported prior results on less favorable study patterns and lower course performance of first-generation and URM students, even after controlling for prior achievement. Our data provides limited information on the potential mechanisms of these differential findings, and future research should collect more information on further explanatory factors.

Analysis of *Study 1b* focused on a small subsample of students who perceived the courses as particularly challenging. These students formed a selective convenience sample of students who consented to participate in the survey-data collection of the UCI-MUST project, and who selected the examined chemistry courses in their surveys. This sample was of great interest to address our research question, but it is important to keep in mind that this subsample was not representative of all students in the courses. Furthermore, the relatively small sample size limited our possibilities to include more complex models in this study, and findings from the regression analysis should be interpreted with caution, as low statistical power may lead to unstable effects (Lakens & Evers, 2014). An interesting question for future studies with a larger sample would be, whether increased learning activities in the LMS as a result of goal-engaging control strategies after an experienced setback in a midterm exam would facilitate better end-of-term performance. Moreover, the potential promotive effect of targeted interventions to sustain goal-engaging strategies across multiple weeks into the preparation for the final exam should be investigated. Based on prior studies with self-report data (Daniels et al., 2014; Hamm et al., 2013), we would expect positive mediation effects.

7. Conclusion

Our study shows that students' behavioral engagement on a course LMS declined across the academic quarter except for large spikes shortly before course exams. Increased behavioral engagement earlier before exams and maintained behavioral engagement after midterm exams were related to better course grades, which emphasizes the relevance of consistent engagement for academic success. Students who obtained higher high school GPAs and female students showed higher behavioral engagement, whereas first-generation and URM students showed steeper declines in behavioral engagement across the course. Findings from study 1b suggest, that intentions to increase behavioral engagement did not lead to changes in learning behavior in the long run. Because of a small sample size and the selective character of the sample in study 1b, these findings should be interpreted with caution and need elaboration with larger and more representative samples. Future research should expand on our findings and examine the reasons for individual differences in patterns of behavioral engagement and the discrepancy between intentions and behavior in the university context and examine possibilities to support students in regulating their behavior in class.

CRediT authorship contribution statement

Luise von Keyserlingk: Writing – original draft, Project administration, Formal analysis, Data curation, Conceptualization. **Fani Lauermann:** Writing – review & editing, Writing – original draft, Conceptualization. **Qiujie Li:** Writing – review & editing, Writing – original draft. **Renzhe Yu:** Writing – review & editing, Project administration, Data curation. **Charlott Rubach:** Writing – review & editing, Data curation. **Richard Arum:** Writing – review & editing, Project administration, Funding acquisition. **Jutta Heckhausen:** Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lindif.2024.102598.

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