EdataWeave: Collecting Learning Behaviors Across Multiple Platforms

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Abstract

Modern courses require students to use multiple digital learning platforms, but traditional learning analytics often focuses on single, specific platforms. Thus, there is a limited understanding of how students integrate information across sources. We present an alternative approach using a browser extension, which collects behavior information across multiple web-based learning platforms simultaneously. We tested the extension in a college-level introductory statistics course with 27 students over 15 weeks. Using the information collected by the extension, we found that students navigate multi-platform learning environments in diverse ways, which can inform curriculum design and the effectiveness of learning platforms.

CCS Concepts

• **Information systems** → *Open source software*; *Data stream mining*; • **Software and its engineering** → Software design engineering.

Keywords

learning analytics, multiplatform data collection, student behavior

ACM Reference Format:
Frank Stinar, Ruohan Zong, Dong Wang, and Nigel Bosch. 2026. EdataWeave: Collecting Learning Behaviors Across Multiple Platforms. In *Proceedings of the Thirteenth ACM Conference on Learning @ Scale (L@S '26), June 29–July 3, 2026, Seoul, Republic of Korea.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3774398.3811562

1 Introduction

Modern university courses require students to navigate between multiple digital platforms [3, 8]. These platforms can be learning management systems, course-specific websites, communication platforms, and any other platform that the instructor or university prescribes to the students [1]. For example, an introductory statistics course we explored in this study uses a learning management system, a course website, a website for assessments, and a student collarboration tool. To succeed, students must integrate information from these four sources, yet it is often unclear how students are (or are not) integrating information.

Different online course platforms can provide valuable functions and contribute to the learning experience. Modern learning is thus rarely confined to one system and is instead distributed across learning plaforms [9]. However, the fragmented course information makes it difficult to track student engagement for research and practice. For instance, instructors often provide multiple ways to interact with course content without sufficient tools for knowing how effective the different platforms are for learning. Traditional behavioral analytics tools focus on information extracted from a single or a small number of platforms [6, 15, 18]. Thus, we developed and tested **EdataWeave**, a browser extension which enables tracking behavioral information across multiple platforms simultaneously. EdataWeave captures student activity on any browser-based learning platform and provides integrated information on how students are navigating multiple learning platforms while giving researchers and instructors the ability to supply interventions to their students.

We tested EdataWeave in an introductory college-level statistics course that used four learning platforms over 15 weeks. From the in-depth longitudinal data we collected, we extracted diverse types of student interactions and, using case studies, we describe notably different ways students behave with the learning platforms.

2 Related Work

Modern classrooms are increasingly blended (i.e., containing both online and in-person components, often in multiple forms), which has inspired research on ways to specifically improve blended learning. Whether that is understanding engagement on specific learning platforms [16], challenges for students [7, 14, 21], or how to scale learning platforms [11, 12, 19], researchers work to improve blended learning. Yet, the shift to multi-platform learning has created fragmented learning systems where course content is no longer centralized, and thus data about students interactions with course content is also not centralized, and can often be incomplete. To handle decentralized information, we developed a way to collect student behaviors from multiple online learning platforms synchronously.

Alongside improving blended and decentralized classrooms, this study is also motivated by the need to better understand online learning behaviors. Previous studies have identified engagement patterns [4, 8, 10], collaboration changes [5], self-regulated learing

ACM ISBN 979-8-4007-2293-6/2026/06
https://doi.org/10.1145/3774398.3811562

[2, 17, 20], and dependencies on learning goals [13] as points where online learning can differ from in-classroom learning.

3 Method

We tested the browser extension in a college-level introductory statistics course as a means to study overall differences in student interactions with course content (given multiple course websites) alongside differences in individual student's behavior. The open-source code for the browser extension is available at https://osf.io/k8cdt/overview?view_only=313f9cfeb6ce4f13a3b78f153fbf67ad.

3.1 Browser Extension

We developed a cross-browser extension that collects behavioral data in online learning environments. The extension is available in any Quantum (Mozilla Firefox), Chromium-based (Google Chrome, Microsoft Edge, Opera), or Webkit (Safari) web browser. The extension allows for passive data collection and intervention deployment.

To uphold privacy, EdataWeave assigns anonymized participant IDs that are unique to each student. As long as a student is using the browser extension, their participant ID is only stored locally within the browser's storage. For activity tracking, that browser-stored participant ID is then validated (to determine whether it exists) against a remote server before data collection begins. This allows for activity tracking while still maintaining student anonymity through behavior tracking. Furthermore, the browser extension only works with a set of predefined URL prefixes, as described below, to avoid course-irrelevant tracking.

The behavioral data are collected by tracking browser-level and page-level interactions on predefined course-related webpages. The predefined webpages can be updated without modifying the browser extension's source code, allowing for flexibility across different courses. Browser-level events include when course-related browser tabs are opened, closed, or refreshed. Page-level behavioral events count the number of mouse clicks, keypresses, and inactivity periods on the predefined webpages. All of the interactions are timestamped and sent to the remote server with the participant ID.

To administer survey items or deploy interventions on the browser extension, instructors add their content to a text file on the remote server. The browser extension periodically queries the server to fetch newly posted interventions. Thus, once an intervention is pushed to the server, that intervention will be given to all of the students in the form of a pop-up from the extension. The pop-up can collect text-based input from the students, provide students with HTML-formatted text, or display a link to a more complex web-based intervention hosted outside of the browser extension. The browser extension handles question presentation, validating the student responses, and edge cases where students might close the intervention without submission.

All collected data from the browser extension are transmitted to a remote server through HTTPS requests.

3.2 Data

After obtaining IRB approval, we tested the browser extension in an introductory statistics course at a large public university in the United States. Students in the course could opt in to the study and recieve **$25** as compensation for their participation. Due to this being a pilot study, we included multiple checks to make sure the extension was working correctly and participants were engaging as expected. From 65 students who participated, 8 were removed from the analyses for not completing an introductory survey. Since the extension was collecting information whenever the student was on a course website, each student had thousands of data points. Thus, any students who did not have at least 10,000 activities tracked over the course were removed, as they were not consistently using extension. This resulted in 27 student participants for analysis.

The demographics of the 27 student participants are as follows: all students were 18 to 22 years old; 16 students were women, 10 were men, and 1 was nonbinary; 15 students were Asian, 7 were white, 2 were Hispanic, 2 were multiracial, and 1 was Middle Eastern. Demographics were collected as free response questions in the introductory survey.

The statistics course used four online tools. First, students used the Instructure Canvas™ learning management system (Canvas). The students had a course-specific Canvas page that contained the gradebook and course information. Second, the students collaborated in a Discord (an online communication platform) community to ask questions and discuss course content. Third, the course website hosted the main learning material and supplemental learning material (e.g., data science guides and videos). Fourth, students completed assignments and exams on an assignment hosting platform.

4 Case Studies

Before analyzing specific students, we evaluated if there were any usage trends in the course platforms. When comparing between students, the course platforms were inconsistently used together. The course website and Canvas were most often engaged together with 57% of students having their highest coordinated usage per week on these two platforms. We then examined specific students to see how individuals interacted with the course platforms. While we did not find any patterns in how students used course platforms, the assignment platform had the most usage, Discord had the least, and the other two had similar usage rates. Overall course content usage is displayed in Figure 1.

In the following case studies, we measured correlations with Spearman's ρ to determine if there were similar trends in platform usage. These correlations are intended to measure association between the activities of each individual student, not to generalize from one student to a population, so we omit significance.

4.1 Case 1: Student Erasmus

Student Erasmus (a pseudonym for anonymity) focused on collaborative learning using Discord more than any other student. Analyzing correlations between interactions across the four platforms revealed the strongest correlation between Discord and the assignment platform (ρ = .654). This indicates some coordinated usage of these two platforms when Erasmus is engaging with course content. However, there was a correlation between course website usage and the Canvas (ρ = .532) as well, which denotes similarly coordinated usage. Erasmus's usage of the course platforms over time is represented as the red line in Figure 2.

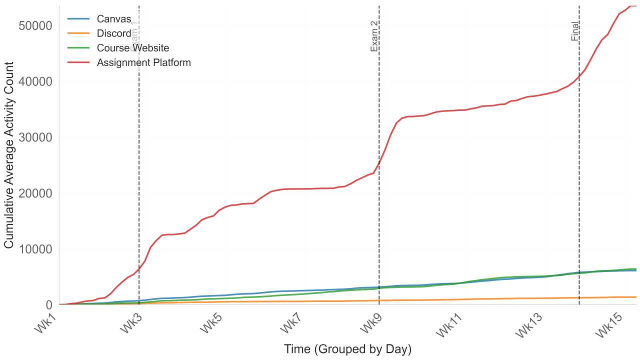

Figure 1: Cumulative average activities on each course platform for all students.

As the semester went on, Erasmus engaged with course content at different rates. Compared to before the first exam, average activity on course content increased three times between the first and second exams. These interactions suggest that Erasmus shifted towards more consistent course content engagement after the first exam. Alonsgide this, in the week leading up to the exams, Erasmus had a spike in Canvas usage. Then, in the week after an exam, there was an increase in Discord usage. These patterns could signify that Erasmus's learning is dependent on exams. That is, Canvas review occurs before exams, and that is followed by social engagement related to the course after exams (e.g., discussion and possible exam clarification).

Erasmus engaged with Discord more than most other students. Erasmus's high number of keypresses and clicks on Discord suggest active posting, replying, and collaborating. Their Discord usage increased between exam 2 and the final, which could be related to Erasmus either needing more time with the content, or taking on a more "teaching assistant" role to collaborate and help their fellow classmates with course content.

Erasmus's interactions are summed up as "platform dependent." Erasmus might have learned well via Discord despite not engaging much with the assignment platform. Thus, the nature of Erasmus's experience with course content cannot be captured within the analytics of one platform. If behavior information was collected from only one platform, nuanced engagement with course content would be missed.

4.2 Case 2: Student Orolo

Student Orolo demonstrated a practice-focused learning pattern because their most-used platforms are the course website and assignment platform. Futher exemplifying this, Orolo's highest correlation is between those two platforms (ρ = .434). This pattern contrasts with Erasmus who prioritized a collaborative learning style throughout the semester. Orolo's activity information is denoted by the blue line in Figure 2.

Alongside the strong course website and assignment platform correlation, Orolo also used other course platforms in tandem (except Discord). This suggests Orolo integrated each of these three content platforms while learning course content. Furthermore, Discord activity counts negatively correlated with activity counts for each of the other platforms (Course Website–Discord: ρ = -.062; Assignment Platform–Discord: ρ = -.371). These correlations suggest that Orolo either preferred independent study over collaborative learning, or Orolo collaborated outside of the course Discord.

Orolo's engagement in course content changed throughout the semester. Cumulative activity was low before the first exam, peaked between exams 1 and 2, and then decreased before the final exam. Like Erasmus, this suggests that Orolo was initially under-engaged until they recieved feedback on their first exam. Furthermore, Orolo consistently used Canvas but their course website and assignment platform usage decreased. This indicates reduced engagement in course content and reduced practice-focused learning for Orolo.

Orolo's activities demonstrate that students can maintain consistent usage of some course platforms while engaging less with others. In cases where only certain course platform activies are tracked, Orolo would previously be noted as lacking engagment, when, in reality, their engagement is focused in other course platforms.

4.3 Case 3: Student Tulia

Student Tulia focused on the assignment platform over the semester. Tulia engaged 3.5 times more after exam 2 compared to the time before the first exam and 1.5 times more compared to the time between exams 1 and 2.

Tulia also had negative or minimal correlations between their Discord usage and the other course platforms (Canvas–Discord: ρ = .139; Course Website–Discord: ρ = -.287; Assignment Platform–Discord: ρ = -.124). However, Tulia still observed the course Discord throughout the semester. This suggests a type of "lurking" behavior where Tulia passively monitored the collaborative discussions without active engagement.

Tulia engaged with course content more around exams. Tulia's activities increased by 47.0% in the week before and following an exam. This pattern suggests strategic engagement around assessments and possible cramming behavior. Thus, EdataWeave highlighted Tulia's passive engagement, exam-focused cramming, and increased engagement by combining activies across all the course platforms.

5 Discussion and Future Work

Using data collected with EdataWeave, we observed examples of distinct behaviors from students across course websites. Erasmus collaboratively learned using Discord, Orolo learned using course platforms in pairs, and Tulia's learning revolved around exam dates. Furthermore, the learning platforms were far from equally utilized. While each of the learning platforms were useful for some students (e.g., Discord for Erasmus), Discord was underutilized by the students, on average. Thus, the extension extracts unique learning behaviors by combining information from multiple data sources.

Variation in engagement behaviors across students suggests that there is not a single way to integrate information across platforms. Instead, students develop their own integration strategies based on their learning preferences. Thus, students integrate information from multiple sources in personalized ways.

The cross-platform behavior tracking provided by EdataWeave reveals integration patterns. For instance, Erasmus's strong Canvas–course website correlation indicates some coordinated usage that

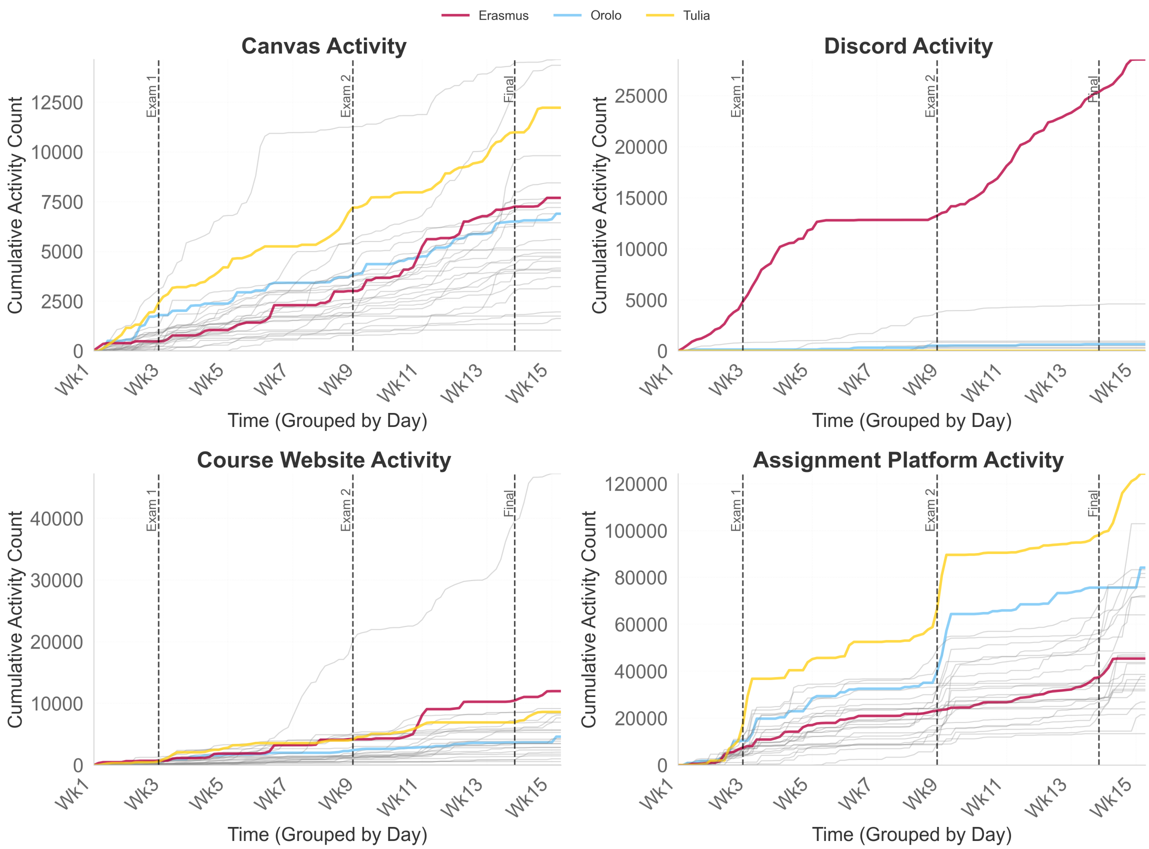

Figure 2: Cumulative activities separated by course platform. Each line is a specific student's trajectory, and the highlighted lines are the case studies.

single-platform learning analytics would fail to find. Similarly, the inverse relationship between Discord and the other learning platforms for the other two case studies reveal how engagement in one platform impacts the engagement in another. The browser extension's ability to extract unfragmented behavior information across multiple course platforms thus leads to previously unavailable insights related to how students integrate different course tools.

Longitudinal behavior tracking suggests that integration strategies can also change over the semester. These changes could suggest that students find more effective ways to engage with course content. In the case studies, students focused on the platforms in different ways. Potentially, students could learn which platform combinations best support their learning. Orolo's decreasing engagement over time could also suggest they were challenged with maintaining effective platform integration or motivation the course.

While the case studies show EdataWeave can measure the diverse ways students behave with multiple learning platforms, they only represent a few students from the larger class. Future research should examine how the diverse integration patterns found generalize to larger populations or other courses. Additionally, our analyses depend on the behavior data extracted. Linking the behaviors to learning outcomes (e.g., grades or assignment completion rates) could lead to understanding if certain behaviors are effective for success in a course. Furthermore, future work could also examine factors that influence integration behaviors such as course design, collaboration tendencies, or other individual differences.

EdataWeave enables behavioral tracking across multiple platforms. Case studies show distinct integration strategies: some students prioritize collaboration platforms, others coordinate content platforms in pairs, and some engage primarily around assessments. These patterns are not visible in single-platform analytics. The variation across students indicates that effective platform integration is personalized rather than uniform, and longitudinal tracking shows that integration strategies can evolve over the semester. EdataWeave provides a tool for understanding how students navigate cross-platform learning environments and can inform both learning analytics research and educational practice.

6 Acknowledgments

This material is based upon work supported by the National Science Foundation under Award No. IIS-2202481.

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