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The transition patterns of learners' behavior and the association with motivation and cognitive engagement in online learning

Jingwen He [1], Zilu Jiang [2], Zilong Pan [3], Qiwei Men [4] and Kui Xie [1] *

*Correspondence:
xiekui@msu.edu
Department of Counseling, Educational Psychology, and Special Education,
Michigan State University,
449 Erickson Hall, 620 Farm Lane,
East Lansing, MI 48824,
United States
Full list of author information is available at the end of the article

Abstract

This study investigated the transitions in behavioral patterns of students participating in online learning throughout a semester. We analyzed the page view behavior of 283 students enrolled in a course designed to enhance online readiness at a Midwestern university. Utilizing K-means cluster analysis, we tracked page view frequency across various tasks, including assignments, overviews, and reading resources. Our findings indicate a decline in page view frequency for all tasks. Four distinct clusters were identified: active, passive, assignment-oriented, and overview-oriented groups. A notable shift was observed with the majority of students transitioning to the passive group in the second half of the semester. Examining the factors influencing this shift, we employed motivation constructs from Self-Determination Theory (SDT) and measures of cognitive engagement. The results revealed that deep learning strategies and identified motivation positively correlate with the maintenance of active and engaged behaviors. Conversely, shallow learning strategies are associated with decreased active engagement and a focus on specific tasks. External motivation served as a predicting factor for remaining passivity. These insights contribute to understanding the dynamics of student engagement in online learning environment.

Keywords: Behavioral engagement, Motivation, Deep learning strategy, Shallow learning strategy

Introduction

Behavioral engagement is an important factor in understanding students' learning activities in online learning contexts (Liang et al., 2023; Pilotti et al., 2017). Students who have a high level of behavioral engagement are more likely to stay focused and engaged, leading to a better online learning performance (Hollister et al., 2022). Behavioral engagement in online learning environments can be captured by usage log behaviors such as frequency of page views (Li & Tsai, 2017). Accessing course materials frequently indicates that an individual actively interacts with course content. By leveraging data on the frequency of page views, researchers are able to develop insights into the ways in which students engage with course materials and navigate online learning environments. To identify and analyze patterns of behavior exhibited by learners, cluster analysis has been widely used as a valuable technique (Moubayed et al., 2020; Yoon et al., 2021).

Students' engagement is longitudinal in nature. It changes from time to time influenced by students' characteristics and the context in which learning occurs (Xie et al., 2023). While some studies have explored the changing nature of student engagement (Barthakur et al., 2021; Lust et al., 2013; Saqr & López-Pernas, 2021), they often present a generalized view of the changing pattern of the level of engagement (e.g., high, low), overlooking the importance of task-focused transitions. This oversight can result in missed opportunities to address learning struggles and individual differences, ultimately leading to suboptimal educational outcomes. Therefore, in order to gain a comprehensive understanding of how students' engagements changed overtime and the underlying factors associated with the transition, it is essential to consider both the level of engagement and task-focused engagement when examining transition patterns.

Long-term changes in behavioral engagement may be associated with motivation (i.e., the reasons that drive behavioral engagement; Xie et al., 2006) and cognitive engagement (i.e., deep and shallow learning strategies use while learning; Kucuk & Richardson, 2019). Motivation drives learners to initiate and direct their behaviors toward their learning goals. Different types of motivation can influence behaviors in varied ways. Existing literature examining the relationship between motivation and behavioral engagement in online learning often focuses on the two primary categories motivation (i.e., intrinsic and extrinsic motivation), lacking a nuanced understanding of how different types of Self-Determination Theory (SDT) motivation (e.g., identified motivation and introjected motivation) affect engagements. Understanding these differences allows for more effective interventions that can improve engagement and learning outcomes. Additionally, cognitive engagement addresses how students interact and process the learning tasks. It involves the use of various learning strategies that promote the understanding of the contents. Understanding how cognitive engagement relates to the behavioral changes is important as it reflects the learning process where learners adapt their behaviors to retain and internalize the new information. Despite its importance, few studies have taken into account the role of cognitive engagement in association with behavior change. Examining both nuanced motivation and cognitive engagement together can uncover critical insights for the behavior change as motivation influences the initiation and persistence of behavior while cognitive engagement concerns the quality and the depth of those behaviors.

To examine the underlying mechanisms that drive the changing patterns of behavioral engagement in online environments, we conducted a study in a seven-week undergraduate online course. We examined the trends related to the changing pattern of level-based and task-focused engagement in an online course in higher education. Specifically, we analyzed the transition pattern between the first and second halves of the course. The course covers various aspects of self-regulation and strategies for successful online learning. During the initial three weeks, students engage in learning psychological concepts such as time management and setting SMART goals. The final three weeks are dedicated to working on their e-portfolio as part of the final project, highlighting a shift from learning to application. We applied cluster analysis to identify nuanced behavioral clusters and explored both the degree and task-focused changes in engagement, which sheds light on the intricate behavioral changes and dynamics in online learning.

This study aims to uncover the changing patterns of behavior in students throughout the entire course. We specifically examine distinct clusters of learners in the first and second halves of the semester, providing a detailed exploration of how motivation and cognitive engagement impact shifts in behavioral engagement. The following research questions guided the design of this study:

1.How do different task frequency change in the first and second half semester?

2.What are the page view frequency patterns (clusters) in the first and second half semester?

3.What are the transition patterns among different clusters?

4.How do motivation and cognitive engagement influence the transition patterns?

Literature review

Using log data to identify behavioral engagement in Learning Management System

Student engagement is a multifaceted concept crucial to understanding the dynamics of learning, particularly in higher education (Xie et al., 2019). At its core, student engagement represents an active and continuous effort made by students in the process of understanding and assimilating content (Trowler, 2010). This engagement is not just a passive reception of information but rather an active, deliberate, and ongoing process of interaction with knowledge. One key aspect of student engagement is behavioral engagement, which is well articulated by Fredricks et al. (2004). They define behavioral engagement as encompassing the observable actions that are necessary for academic success, such as consistent attendance, active participation in class, and the completion of homework and assignments (Fredricks et al., 2004).

A Learning Management System (LMS) serves as a digital hub for course materials and interactions. These systems produce web logs, offering granular, near-real-time records of student behavior as they interact with online course materials. These log data are essentially a comprehensive record of a user's activity within the system, detailing actions such as click or page view counts, time spent on specific tasks, and performance results like quiz scores (Siemens, 2012). Such trace data are considered more reliable indicators of learner engagement compared to self-reported or observational data (Bodily & Verbert, 2017). Analyzing these digital traces allows educators to gain a deeper understanding of student interactions with course content, identify the most engaging material aspects, and pinpoint areas where students might struggle or disengage (Saqr et al., 2023).

Building on the foundational understanding of log data in LMS, various empirical studies have used the interaction frequency as a key indicator for engagement (Hung & Zhang, 2008; Koster et al., 2016). For example, Koster et al. (2016) utilized interaction frequencies with tablet-installed applications—including actions like opening and closing the application, accessing materials, and responding to questionnaires—as measures to assess student engagement. Similarly, Murray et al. (2012) observed that the frequency of interaction with online resources could significantly facilitate learning and enhance students' progress. Hung and Zhang (2008) explored online learning behaviors by examining a diverse range of student activities. Their study focused on six key indicators of student effort: the number of LMS logins, frequency of accessing course materials, number of messages posted and read, participation in synchronous discussions, and students' final grades. By analyzing these multiple facets of student interaction with the LMS, they were able to differentiate between active and passive learners, effectively categorizing students based on their engagement level across various tasks.

In summary, log data in LMS is crucial for identifying behavioral engagement, allowing educators to discern different types of learners and further provide personalized instruction for more effective online learning experiences in higher education.

Cluster analysis and cluster transition of behavioral engagement

Previous studies have explored using cluster analysis to understand students' engagement characteristics (Moubayed et al., 2020; Yoon et al., 2021). For example, Moubayed et al. (2020) aimed to determine student engagement levels in an e-learning environment using frequency-related metrics. The researchers analyzed data from 486 enrolled students, encompassing a total of 305,933 records. They utilized a variety of metrics, including the number of logins, content reads, forum reads and posts, quiz reviews, lateness, and duration to submit assignments. By employing the K-means clustering algorithm, they identified two distinct levels of engagement: high and low. Their findings highlighted that the two-level model offered the best performance in terms of clear cluster separation, providing a nuanced understanding of engagement in e-learning contexts. Yoon et al. (2021) focused on a more specific context, video-based online learning. They tracked a range of interactions, such as frequency of clicks on various functions including play, pause, bookmarking, and commenting. Using Partitioning Around Medoids (PAM) clustering method, they identified two clusters: active and passive learners. Active learners exhibited higher learning achievement compared to passive learners. Additionally, the study revealed that factors such as learners' gender, major, and prior knowledge did not significantly predict cluster membership. These studies underscore the utility of cluster analysis in online learning research, offering valuable insights into the varying degrees and dimensions of student engagement.

Engagement is not static; it can be influenced by factors such as learner motivation, educational environment, teacher influence, peer interaction, social context, and the nature of the learning tasks (Fredricks et al., 2004). However, most studies perceive engagement as a static state, overlooking its dynamic nature. Few studies have delved into the trajectory of engagement (Barthakur et al., 2021; Lust et al., 2013; Saqr & López-Pernas, 2021). For example, Lust et al. (2013) explored the use patterns of an online learning tool across two different phases of a blended learning course. They identified a shift in student engagement patterns, with an additional cluster emerging in the second phase of the course. This finding underscores the changing nature of student engagement, highlighting how it can vary even within the same course. Transitioning to a broader timeframe, Barthakur et al. (2021) analyzed student engagement over a full year in a Massive Open Online Course (MOOC). They found three distinct clusters of learners, each exhibiting different engagement strategies: consistently engaged, disorganized, and 'get-it-done' students. This study illustrates how engagement can fluctuate over a longer period, revealing patterns that might not be apparent in shorter-term studies. Further extending this perspective, Saqr and López-Pernas (2021) employed Hidden Markov Models to investigate engagement states in a full program, uncovering mostly-engaged, intermediate, and troubled trajectories. Similarly, Saqr et al. (2023) identified three distinct program-level learning trajectories. The first was a stable and intense trajectory linked to deep learning, where students used diverse strategies and achieved the highest grades. The second was a fluctuating interactive trajectory, characterized by a focus on course requirements and average grades. The third was a light trajectory associated with surface learning, marked by minimal effort, lower grades, and a relatively stable engagement pattern.

Investigating engagement transition patterns is crucial for us to optimize instructional strategies for different types of learners. The insights from the engagement pattern shifting allows us to identify common trends of how students move from different levels of engagement and underlying factors that associate with change. Detecting these critical factors is particularly helpful for designing target-intervention. Moreover, tracking and evaluating these changing patterns provides valuable feedback for the current instructional environment, which helps developing learning experience that adapts to the evolving trends and students' diverse needs.

It is essential for research studies to consider both the transition of level of engagement and task-focused engagement (e.g., how consistently students remain focused on specific tasks over time) to fully realize the benefits of investigating engagement patterns. However, most of the existing literature, as discussed above, while providing valuable insights into how engagement trajectories change over time, tends to focus more on the transition of levels of engagement (e.g., high/low of engagement) rather than trends related to task-focused engagement. Lacking insights into the task-focused engagement can lead to an incomplete understanding of students' learning process (Boekaerts, 2016). A student can have a high level of overall engagement while being engaged less in certain tasks. The level of engagement alone only reflects partial information regarding students' overall engagement level, revealing less precise information about how their learning experience about how they interact with learning activities. Consequently, when overlooking the changing patterns of the task-focused engagement, educators may miss the critical opportunities to identify key areas for targeted-intervention, as they may not be able to understand the specific evolving needs of different types of learners. Additionally, the targeted-intervention may be less effective when they are solely based on general level of engagement rather than tailoring to specific changing patterns of task-focused behaviors. Therefore, capturing the nuanced differences of tasks-focused engagement can ensure a more comprehensive support to foster students' academic performance.

The association between SDT motivation, cognitive engagement and behavioral engagement

Self-determination theory and behavioral engagement

Self-Determination Theory (SDT) provides a comprehensive framework for understanding the relationship between different types of motivation and student engagement. Based on the Self-Determination Theory's taxonomy of motivation, there is a continuous internalization from extrinsic motivation to intrinsic motivation, which includes external regulation (behaviors driven by externally imposed rewards and punishments), introjection (behaviors driven by the internal rewards of self-esteem for success and by avoidance of anxiety, shame, or guilt for failure), identification (behaviors driven by the value of an activity and thus experience a high degree of volition or willingness to act) and integration (behaviors driven by not only the value of the activity, but also interests and values) (Ryan & Deci, 2020). SDT posits that the type and quality of motivation significantly influence the level and quality of engagement in learning activities. Intrinsic and identified motivations, being more autonomous, are typically associated with higher engagement levels, characterized by persistence, deep learning, and enjoyment (Niemiec & Ryan, 2009; Ryan & Deci, 2000). In contrast, introjected and external motivations, being more controlled, may lead to less effective engagement (Deci et al., 1991).

The empirical research on student engagement in online learning from the SDT perspective aligns with and expands upon these theoretical foundations. For example, Xie et al. (2006) conducted two studies focusing on students' motivation and participation in an online discussion board as part of a traditional course. They found that students' participation was linked to their intrinsic motivation. Over time, students' intrinsic motivation for participating in online discussions declined steadily. The findings indicated that if students perceived the online discussion as valuable and enjoyable, they were more likely to participate, supporting SDT's hypothesis that intrinsically motivating tasks lead to higher engagement levels. A more recent study conducted by Liu et al. (2023) explored the learner engagement mechanism in MOOCs. Their findings highlighted that intrinsic motivation (interest) and certain forms of extrinsic motivation (perceived knowledge value) were crucial for learner engagement and satisfaction. Interestingly, the motivation for self-development, another form of extrinsic motivation, did not significantly impact learner engagement.

Examining the nuanced differences among types of motivation (intrinsic, identified, introjected, and external) is crucial because different types of motivation influence engagement in distinct ways (Deci & Ryan, 2000; Howard et al., 2021). Intrinsic motivation, driven by internal satisfaction and interest, often leads to higher levels of engagement and success (Ferrer et al., 2022). Identified motivation, where learners recognize the value of the activity, also promotes persistence (Combette et al., 2021; Howard et al., 2021). In contrast, introjected and external motivations, driven by internal pressures and external rewards or punishments, respectively, may not be related to engagement (Ferrer et al., 2022) or lead to lower quality engagement (Howard et al., 2021). Understanding these differences is vital for designing effective targeted motivation interventions aimed at improving student engagement, particularly for those exhibiting low-quality engagement (Reeve, 2012).

While previous studies have examined the relationship between motivation and engagement, few have provided valuable insights into the relationship between different types of Self-Determination Theory (SDT) motivation and behavioral engagement in online learning environments. There is an oversight of the nuanced impacts of the four types of motivation as outlined by SDT and their individual effects on student engagement. Addressing this gap, the current study aims to explore how intrinsic, identified, introjected, and external motivations individually influence engagement changes, thereby providing a more detailed understanding that can inform targeted interventions. By tailoring interventions to foster higher quality motivations, educators can better support students with low-quality engagement, ultimately enhancing learning outcomes and optimizing resource allocation.

Cognitive engagement and behavioral engagement

Social Cognitive Theory provides a comprehensive framework for understanding the relationship between cognitive engagement and behavioral engagement. It proposes that learning occurs in a social context with a dynamic and reciprocal interaction of the person, environment, and behavior (Bandura, 1986). Cognitive engagement is reflected in how individuals process and reflect on the information they observe. Behavioral engagement, on the other hand, is demonstrated through actions that are influenced by observing others and the consequences of those actions.

Cognitive engagement incorporates deep learning strategy and shallow learning strategy (Greene et al., 2015). Deep learning strategies, which involve a comprehensive understanding and integration of concepts, align with the cognitive processes that individuals actively construct knowledge through observation and interaction (Bandura, 1986). Consequently, students who engage deeply in their learning exhibit behaviors like persistent effort in challenging tasks, active participation in discussions, and application of knowledge in diverse contexts (Schunk, 2001). On the other hand, shallow learning strategies, characterized by surface-level processing such as rote memorization, represent a more passive form of engagement with limited cognitive processing. This approach can lead to restricted behavioral engagement, where students might participate only in basic tasks and avoid deeper, more challenging activities. Their learning behavior tends to focus on task completion rather than meaningful engagement with the learning material (Zimmerman, 2002).

There are limited studies exploring the relationship between cognitive engagement and behavioral clusters using learning analytic method. One relevant study was from Sun et al. (2023). They conducted a study focusing on Self-Regulated Learning (SRL) in asynchronous online courses, particularly on identifying student subgroups based on their SRL behaviors and examining the differences in cognitive load and student engagement. The study tracked 101 graduate students using SRL-enabling tools in an online course. Through sequence and cluster analysis, two distinct subgroups were identified: a high SRL (H-SRL) group and a low SRL (L-SRL) group. The H-SRL group demonstrated lower extraneous cognitive load, higher learning performance, higher germane cognitive load, and greater cognitive engagement compared to the L-SRL group. This study shed light on the relationship between SRL behavioral pattern and cognitive engagement. However, there is a research gap in using cognitive engagement as a predictor for changes in students' behavioral patterns. Understanding the relationship between cognitive engagement and behavioral changes is crucial as it illustrates the learning process wherein learners adjust their actions to assimilate and internalize new information. Our research aims to fill this gap by focusing on how deep and shallow learning strategy influences the change of behavioral patterns in online learning.

Methods

Participants

There were 307 students initially enrolled in the course, after 24 students dropped out, 283 students completed the course. This was an online course designed to prepare students for online readiness at a Midwestern university. There were 152 females (53.7%), 126 males (44.5%), and 5 missing (1.8%). The age of participants ranged from 18 to 54, with a mean of 20.94. The sample consisted of 49.5% White (140), 29% Asian (82), 18% African American (51), 5.3% Hispanic (15), 1.4% Native American (4), and 1.1% Other (3). Students enrolled in the course came from a variety of majors, including business, engineering, nursing, and education.

Context

The course was a seven-week undergraduate course hosted on Canvas. Unlike subject-specific courses, this course covered various aspects of self-regulation and strategies for successful online learning without a progression from easy to hard or strong connections between each unit. During the initial three weeks, students engaged in learning psychological concepts. The final three weeks were dedicated to working on their e-portfolio as part of the final project, highlighting a shift from learning to application.

The Canvas learning management system automatically tracked and recorded time-stamped clickstream data when students interacted with the course content. This data included Student ID, Course ID, Page ID, Session Start Time, and Session End Time. The original dataset contained log history for all users in 11 course sections during 2020. We filtered out logs from non-student users, such as instructors and course managers, and excluded non-learning activities like clicks on student evaluations of instruction. User-generated behavioral log data (n = 68,386) were collected on a learning management system (LMS) and included four task types: overview, reading, assignment, and resource.

Overview: This category includes the home and module overview pages. These pages are designed to guide students by providing an overview of the module's content and structure. They serve as a navigational aid, especially for those unfamiliar with the topics, by offering a brief description of the module's purpose, main topics, and links to more detailed pages or resources. The presence of learning maps further supports effective navigation and comprehension of the module.

Reading: These pages are central to the academic component of the course, containing reading materials and resources like lecture videos, book chapters, or articles. The diversity in reading content is tailored to the specific topics of each module. Students are expected to engage with these materials to prepare for quiz questions that assess their understanding of the reading content.

Assignment: The assignments are a practical application of the learned concepts. These vary across modules and include activities such as discussion boards, quizzes, self-assessment, technology tools trials, and e-portfolio development. These tasks are designed to demonstrate students' understanding and application of course material in real-world scenarios.

Resource: These pages provide supplementary materials to enhance and deepen students' learning. While not mandatory, these resources offer additional insights and tools related to the module topics, including videos, articles, and technology tools lists. This category helps students explore topics more comprehensively and at their own pace.

Measurement and procedure

Students completed a self-reported survey at the end of the semester during 2020, reflecting on their learning experiences in this course. The measures included their academic motivation for college study, deep and shallow strategy use in the current course. They also filled out a consent form allowing the researchers to use their log data for this study.

Academic motivation was measured by 16 items adapted from Ratelle et al. (2007) on a 6-point Likert scale (1=strongly disagree, 6= strongly agree). This scale assessed students' motivation toward being in college and included four subconstructs: intrinsic motivation, identified regulation, introjected regulation, and external regulation. Four items from each subscale were used in this study. Sample intrinsic motivation item was "Because I experience pleasure and satisfaction while learning new things." Sample identified regulation item was "Because I think that a college education will help me better prepare for the career I have chosen." Sample introjected regulation item was "To prove to myself that I am capable of completing my college degree." Sample external regulation item was "Because I need at least a college degree in order to find a good paying job later on." The McDonald's omega (ω) reliability coefficients were 0.909 for intrinsic motivation, 0.844 for identified regulation, 0.907 for introjected regulation, and 0.887 for external regulation.

Deep and shallow learning strategies were assessed by items adapted from Greene et al. (2015) on a 7-point Likert scale (1=never, 7=Daily). This scale assessed students' frequency of different learning strategies use while studying and thinking. It included seven items measuring deep strategies and six items measuring shallow strategies. Sample deep strategy item was "When learning new material, I summarized it in my own words." Sample shallow strategy item was "I tried to memorize answers to questions from test study guides." The McDonald's omega (ω) reliability coefficients were 0.895 for deep strategies and 0.867 for shallow strategies.

Data analysis

In this study, K-means clustering method was employed to analyze the frequency of page views on four distinct categories: overview, reading, resource, and assignment. K-means is one of the most popular unsupervised clustering algorithms. This algorithm operates by determining the centroid of a cluster (or the cluster mean) and associating data points nearest to this centroid. Within the realm of online learning, K-means is utilized to categorize students with similar online activity and interaction patterns into distinct levels of engagement.

Notably, in order to optimize the accuracy and relevance of our findings, we made the decision to merge the reading and resource pages into a single category. This choice was based on two key factors: first, the pages displayed a consistent pattern of usage over time, and second, the total number of these two pages was relatively limited in comparison to other categories. By merging these categories, we were able to streamline our analysis and improve the precision of our results. All page views were standardized using z-scores. Outliers that exceeded the absolute value of three standard deviations were removed. There were 8 outlier students in the first half semester, and 4 outlier students in the second half. Two students were outlier in both time points. Therefore, we included 273 students in the following cluster transition analysis.

After the cluster analysis, multinomial logistic regression was used to explore how motivation and cognitive engagement influence students' behavioral pattern change. SPSS 28.0 was used to finish all the analysis.

Results

RQ1: How do different task frequency change in the first and second half semester?

We examined the means, standard deviations, and Pearson's correlations for our focal variables (see Table 1). There were significant positive correlations between deep learning strategy and three page view frequency in both time points. Intrinsic motivation was found correlated with both assignment and reading-resource page view frequency in the first half semester, and correlated with only assignment page view frequency in the second half semester. Identified motivation and introjected motivation were also found significantly related to certain page view frequency. Though these findings were significant, the correlations ranged from very weak (less than 0.2) to weak (less than 0.4).

Table 1 Means, standard deviations, and Pearson's correlations

	M	SD	1	2	3	4	5	6	7	8	9
First half of semester											
1.Overview	1.70	1.88	1.00								
2.Assignment	34.15	17.22	.47***	1.00							
3.Reading-Resource	13.73	.57	.55***	.66***	1.00						
4.Intrinsic motivation	4.82	.89	.06	.14*	.13*	1.00					
5.Identified motivation	5.17	.76	.08	.09	.10	.60***	1.00				
6.Introjected motivation	4.72	1.07	.15*	.14*	.10	.57***	.52***	1.00			
7.External motivation	5.06	.90	.02	.03	-.01	.37***	.67***	.46***	1.00		
8.Deep learning strategy	5.63	.93	.14*	.14*	.20**	.55***	.47***	.39***	.27***	1.00	
9.Shallow learning strategy	5.16	1.13	-.06	-.01	-.01	.44***	.41***	.42***	.40***	.47***	1.00
Second half of semester											
1.Overview	1.31	1.98	1.00								
2.Assignment	29.87	14.45	.44***	1.00							
3.Reading-Resource	8.90	.45	.76***	.56***	1.00						
4.Intrinsic motivation	4.82	.89	.04	.20**	.08	1.00					
5.Identified motivation	5.17	.76	.11	.15*	.14*	.60***	1.00				
6.Introjected motivation	4.72	1.07	.09	.16*	.18	.57***	.52***	1.00			
7.External motivation	5.06	.90	.04	.05	.02	.37***	.67***	.46***	1.00		
8.Deep learning strategy	5.63	.93	.16*	.17**	.16**	.55***	.47***	.39***	.27***	1.00	
9.Shallow learning strategy	5.16	1.13	-.00	.01	-.09	.44***	.41***	.42***	.40***	.47***	1.00

Note. $^{*}p$<.05. $^{**}p$<.01. $^{***}p$<.001.

Three repeated measures ANOVAs were performed to evaluate the differences in task frequency between the first and second half semester. The page view frequency refers to the number of times students visit a certain page. There was a significant decrease on average overview page view frequency ($F(1, 282) = 14.85$, $p < .001$, partial eta-squared = 0.050) from 1.70 times to 1.31 times, indicating a small to moderate effect. The average assignment page view frequency decreased from 34.15 times to 29.87 times ($F(1, 282) = 34.64$, $p < .001$, partial eta-squared = 0.109), indicating a moderate to large effect. The average reading-resource page view frequency decreased from 13.73 times to 8.90 times ($F(1, 282) =131.78$, $p < .001$, partial eta-squared = 0.318), indicating a large effect. The significant decrease in mean frequency from the first to the second time period, indicates that students were less engaged with the overview, assignment and reading-resource pages.

RQ2: What are the page view frequency patterns (clusters) in the first and second half semester?

Dunn Index was used to determine the optimal number of clusters. The Dunn Index is a metric used to evaluate the quality of clustering in a dataset. It measures the ratio of the minimum inter-cluster distance to the maximum intra-cluster distance. A higher Dunn Index indicates better clustering because it suggests that clusters are compact (small intra-cluster distances) and well-separated (large inter-cluster distances). We found that the Dunn Index was highest when the number of clusters was set to 4, at 0.055 (See Figure 1).

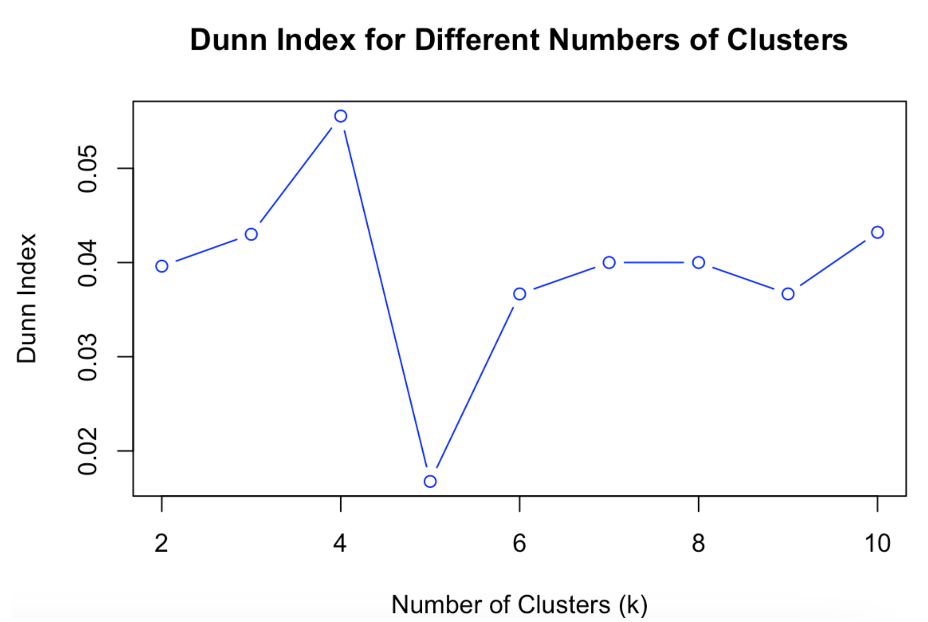

Fig. 1 The Dunn Index for different numbers of clusters

The cluster analysis of learner page view behaviors revealed four distinct engagement patterns, as shown in Table 2 and Figure 2. Active learners demonstrated a relatively even engagement across all page types, with a marginal preference for overview and reading-resource pages over assignment pages. In contrast, passive learners displayed consistently low engagement, suggesting a general disinterest or lack of interaction with the course material. Assignment-oriented learners were notably more engaged with assignment-related pages, showing some interest in reading resources but less in overview content. Lastly, overview-oriented learners predominantly engaged with overview pages, indicating a preference for a broader understanding of course material rather than focusing on specific assignments or reading resources.

RQ3: What are the transition patterns among different clusters?

Among 273 students, there were 141 stayers and 132 movers. To determine if this difference was statistically significant, we performed a chi-square test. The results indicated that the difference between the proportions of stayers and movers is not statistically significant ($\chi^2 = 0.297$, $p = 0.586$).

Table 2 Means and standard deviations by clusters (Unstandardized)

Variable	Active	Passive	Assignment-oriented	Overview-oriented
First half of semester				
Number in group (%)	41 (15%)	89 (32%)	83 (30%)	62 (23%)
Overview	3.63 (1.59)	.34 (.58)	.80 (.73)	2.97 (1.01)
Assignment	51.15 (12.12)	19.55 (8.33)	40.14 (8.73)	30.48 (7.76)
Reading-Resource	25.95 (5.46)	4.98 (3.89)	14.73 (5.44)	13.65 (4.88)
Second half of semester				
Number in group (%)	19 (7%)	134 (48%)	75 (27%)	51 (18%)
Overview	4.63 (1.57)	.20 (.46)	.81 (.75)	3.04 (1.15)
Assignment	42.95 (10.42)	20.54 (9.24)	40.69 (10.26)	29.92 (7.05)
Reading-Resource	22.32 (6.40)	4.11 (3.66)	10.23 (4.71)	12.20 (3.76)

Note. M(SD).

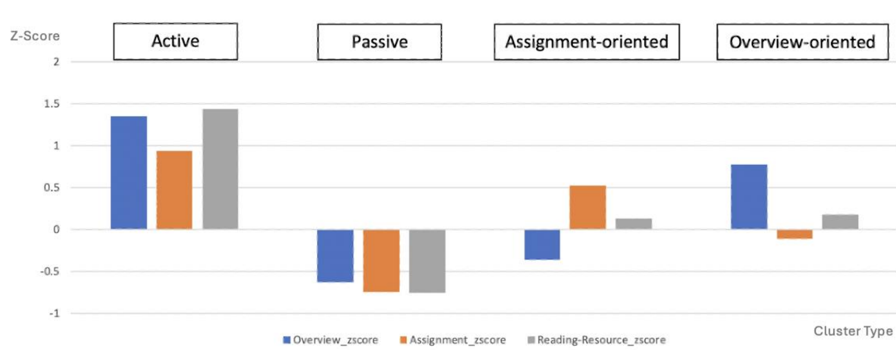

Fig. 2 Average Standardized Page view scores by four types of learners

We found 15 transition patterns. The transition pattern frequency showed that 141 students (52%) remaining in the same engagement category: 72 stayed passive (26.37%), 37 stayed assignment-oriented (13.55%), and 22 stayed overview-oriented (8.06%), while 10 remained active (3.66%). The transition pattern of movers (132, 48%) indicated changes between different types of engagement, with the most common shift being from assignment-oriented to passive (35, 12.82%), followed by overview-oriented to passive (24, 8.79%), and active to assignment-oriented (15, 5.49%) (see Table 3). The sankey chart presented a visualization of the transition pattern (see Figure 3). The flows between clusters indicate transition from every cluster to the passive group, which is the only cluster that grows, while the others shrink. This pattern suggests a trend towards increasing passivity among the participants over time.

RQ4: How do motivation and cognitive engagement influence changing behavioral patterns?

A multinomial regression analysis that controlled for the effects of gender and student status (full-time or part-time) was conducted to investigate the impact of motivation and cognitive engagement on students' patterns of behavioral transition (see Table 4). The motivational variables included intrinsic, identified, introjected, and external motivation. For cognitive engagement, the analysis considered the use of deep and shallow learning strategies. Staying passive transition category served as the reference category in the analysis. The model conducted was a significant improvement in fit over a null model $\chi^2(81) = 103.912$, $p = .044$, Nagelkerke $R^2 = .38$. Based on the model result, deep learning strategies, shallow learning strategies, identified motivation, and external motivation have been found to be the significant predictors for students' patterns of behavioral transition.

Table 3 Transition pattern frequency and percentage

Transition Pattern	Frequency	Percentage
1.Stay Passive	72	26.37%
2.Stay Assignment-oriented	37	13.55%
3.Assignment-Passive	35	12.82%
4.Overview-Passive	24	8.79%
5.Stay Overview	22	8.06%
6.Active-Assignment	15	5.49%
7.Active-Overview	12	4.40%
8.Overview-Assignment	11	4.03%
9.Stay Active	10	3.66%
10.Passive-Assignment	10	3.66%
11.Assignment-Overview	10	3.66%
12.Passive-Overview	7	2.56%
13.Overview-Active	5	1.83%
14.Active-Passive	2	0.73%
15.Assignment-Active	1	0.37%
Total	273	100%

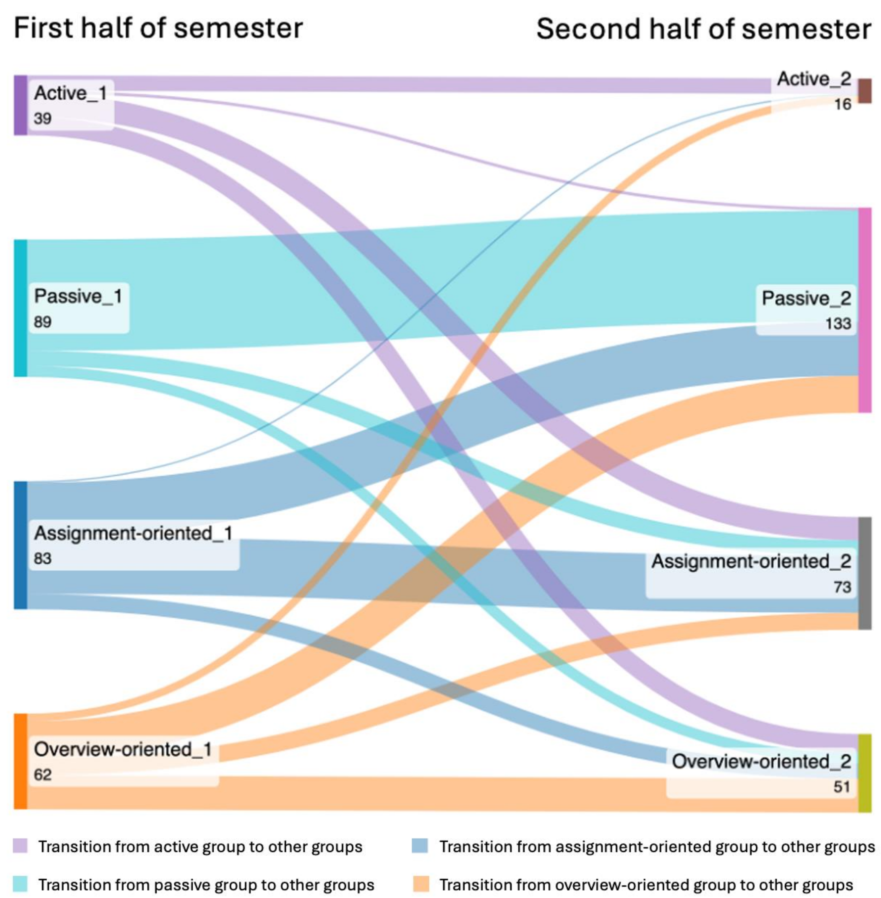

Fig. 3 Characteristics of behavioral pattern transition

Adopting deep learning strategies was found to be associated with an increased likelihood of students remaining involved in an online learning environment. For a one-unit increase in the use of deep learning strategies, the odds of a student staying active (relative to the stay passive group) are predicted to increase by a factor of 2.8, 95%CI [1.06, 7.38]. Likewise, with each one-unit increase in deep learning strategies, students are 2.92 times more likely to transit from the active group to the overview group rather than remaining passive, 95%CI [1.04, 8.15].

Conversely, the adoption of shallow learning strategies was consistently associated with an increased likelihood of students remaining in the stay passive category. For each unit increase in shallow learning strategies, students were .45 times as likely to remain active compared to staying inactive, 95%CI [.24, .85]. Moreover, the odds of a student transitioning from an active to an assignment-oriented group were reduced by a factor of .51, 95%CI [.27, .94]. Similarly, the likelihood of moving from an overview-oriented group to an assignment-oriented group compared to remaining inactive was .45, 95%CI [.23, .86].

Identified motivation was a crucial factor significantly related to whether students can stay actively engaged in the online learning environment. Students who perceived a one-point increase in identified motivation were 3.86 times more likely to stay active rather than staying passive, 95%CI [1.05, 14.12].

External motivation, conversely, was identified as a predictor negatively associated with the likelihood of students remaining passive. With a one-unit increase in external motivation, the odds of a student transitioning from overview-oriented learners to passive learners, relative to staying passive, are expected to decrease by a factor of 0.41, 95%CI [.17, .96].

Table 4 Results of the multinomial regression

	B	Std. Error	Sig.	Exp(B)	95% CI
Stay Active					
Intrinsic motivation	-.92	.53	.08	.40	[.14, 1.11]
Identified motivation	1.35*	.66	.04	3.86	[1.05, 14.12]
Introjected motivation	.27	.36	.46	1.30	[.65, 2.62]
External motivation	-.58	.43	.18	.56	[.24, 1.31]
Deep learning strategy	1.03*	.50	.04	2.80	[1.06, 7.38]
Shallow learning strategy	-.79*	.32	.01	.45	[.24, .85]
Male	-.45	.71	.53	.64	[.16, 2.57]
Female	-1.52	.00	.	.22	[.22, .22]
Part-time student	.09	1.24	.95	1.09	[.10, 12.41]
Active—Assignment					
Intrinsic motivation	.84	.50	.10	2.31	[.86, 6.20]
Identified motivation	-.47	.60	.43	.62	[.19, 2.00]
Introjected motivation	.12	.33	.72	1.12	[.59, 2.13]
External motivation	.18	.47	.71	1.19	[.48, 2.97]
Deep learning strategy	.52	.40	.20	1.68	[.77, 3.68]
Shallow learning strategy	-.68*	.32	.03	.51	[.27, .94]
Male	-.36	.61	.56	.70	[.21, 2.30]
Female	-.67	.00	.	.51	[.51, .51]
Part-time student	-.70	1.39	.62	.50	[.03, 7.55]
Active—Overview					
Intrinsic motivation	-.40	.53	.46	.67	[.24, 1.91]
Identified motivation	.52	.73	.48	1.68	[.40, 7.00]
Introjected motivation	.34	.43	.42	1.41	[.61, 3.26]
External motivation	-.76*	.52	.15	.47	[.17, 1.30]
Deep learning strategy	1.07*	.52	.04	2.92	[1.04, 8.15]
Shallow learning strategy	.20	.40	.62	1.22	[.56, 2.65]
Male	.44	.72	.55	1.55	[.38, 6.39]
Female	-1.24	.00	.	.29	[.29, .29]
Part-time student	-.97	1.40	.49	.38	[.3, 5.91]

Stay Assignment					
Intrinsic motivation	-.09	.41	.83	.92	[.41, 2.04]
Identified motivation	.52	.55	.34	1.69	[.58, 4.92]
Introjected motivation	.40	.30	.18	1.50	[.84, 2.69]
External motivation	-.08	.43	.84	.92	[.40, 2.12]
Deep learning strategy	-.05	.33	.88	.95	[.50, 1.80]
Shallow learning strategy	-.10	.30	.75	.91	[.51, 1.62]
Male	-.55	.48	.25	.58	[.22, 1.48]
Female	-.94	.00	.	.39	[.39, .39]
Part-time student	.30	.75	.69	1.35	[.31, 5.85]
Assignment—Overview					
Intrinsic motivation	-.59	.62	.34	.56	[.17, 1.86]
Identified motivation	1.01	.99	.31	2.75	[.40, 19.12]
Introjected motivation	.42	.48	.38	1.53	[.59, 3.93]
External motivation	-.07	.75	.93	.94	[.21, 4.10]
Deep learning strategy	.41	.58	.49	1.50	[.48, 4.72]
Shallow learning strategy	.22	.51	.67	1.25	[.46, 3.42]
Male	-23.20*	.76	.00	.00	[.00, .00]
Female	-23.94	.00	.	.00	[.00, .00]
Part-time student	.00	1.23	1.00	1.00	[.09, 11.23]
Assignment—Passive					
Intrinsic motivation	.02	.42	.96	1.02	[.45, 2.34]
Identified motivation	-.06	.55	.92	.94	[.32, 2.79]
Introjected motivation	.27	.30	.36	1.31	[.73, 2.37]
External motivation	.34	.46	.46	1.41	[.57, 3.47]
Deep learning strategy	.02	.34	.96	1.02	[.53, 1.98]
Shallow learning strategy	.01	.32	.98	1.01	[.54, 1.87]
Male	-.54	.49	.28	.58	[.22, 1.54]
Female	-.63	.00	.	.53	[.53, .53]
Part-time student	.49	.74	.51	1.63	[.38, 6.93]
Stay Overview					
Intrinsic motivation	-.73	.47	.12	.48	[.19, 1.20]
Identified motivation	.63	.68	.35	1.88	[.50, 7.10]
Introjected motivation	.64	.37	.08	1.89	[.92, 3.89]
External motivation	.44	.55	.42	1.56	[.54, 4.52]
Deep learning strategy	.33	.41	.41	1.40	[.63, 3.11]
Shallow learning strategy	-.28	.33	.39	.75	[.39, 1.44]
Male	-1.20*	.56	.03	.30	[.10, .91]
Female	-1.81	.00	.	.16	[.16, .16]
Part-time student	1.84*	.70	.01	6.29	[1.61, 24.61]

Overview—Assignment					
Intrinsic motivation	-.59	.53	.27	.56	[.20, 1.58]
Identified motivation	.20	.70	.78	1.22	[.31, 4.83]
Introjected motivation	.21	.35	.55	1.24	[.62, 2.47]
External motivation	.77	.59	.19	2.17	[.69, 6.81]
Deep learning strategy	.68	.45	.13	1.96	[.82, 4.70]
Shallow learning strategy	-.81*	.34	.02	.45	[.23, .86]
Male	-.90	.68	.18	.41	[.11, 1.54]
Female	-1.65	.00	.	.19	[.19, .19]
Part-time student	1.70*	.80	.04	5.60	[1.07, 29.01]
Overview—Passive					
Intrinsic motivation	.00	.47	1.00	1.00	[.40, 2.53]
Identified motivation	.96	.64	.13	2.61	[.75, 9.05]
Introjected motivation	.62	.37	.10	1.86	[.90, 3.83]
External motivation	-.90*	.44	.04	.41	[.17, .96]
Deep learning strategy	.06	.38	.88	1.06	[.50, 2.24]
Shallow learning strategy	-.18	.32	.59	.84	[.45, 1.58]
Male	-.24	.56	.67	.79	[.26, 2.37]
Female	-1.11	.00	.	.33	[.33, .33]
Part-time student	.15	.86	.86	1.16	[.22, 6.21]

Note. * $p < .05$.
[a]The reference category is the Stay passive group.

Discussion

The current study explored students' behavioral pattern transitions in online learning over a semester. We found students' page view frequency decrease in all tasks, including assignment, overview and the reading-resource. Using page view frequency, we identified four clusters, including active group, passive group, assignment-oriented group and overview-oriented group. Then we examined the behavioral pattern transition over the half semester, and found most students changed to the passive group, which align with the trend of decreasing page view frequency. We further examined the cause of this transition, using motivation constructs from SDT and cognitive engagement, and found deep learning strategies and identified motivation are positively associated with maintaining or adopting active and engaged behaviors. In contrast, shallow learning strategies are linked to a decrease in active engagement and a focus on specific tasks such as assignments or overviewing content. External motivation serves as a predictive factor for remaining passivity.

The changing nature of behavioral engagement

In our study, we observed a noteworthy trend: a significant decrease in students' page view frequency across various tasks like assignments, overviews, and reading-resources over the semester. This trend aligns with previous research suggesting a decrease in behavioral engagement over time (Wigfield et al., 2006). Several factors may contribute to this decrease. One possible explanation is the diminishing novelty effect (Fredricks et al., 2004). Initially, students might engage enthusiastically with new course materials, but this interest could wane as the novelty wears off. Additionally, as the semester progresses, students often face increasing academic demands from other courses, leading to time constraints and prioritization issues (Trowler, 2010). This juggling of responsibilities may lead to a decrease in the time and attention they can allocate to each course.

The observed decrease in student engagement over time in our study highlights the necessity of examining changes in behavioral patterns within online learning in higher education. This investigation is particularly crucial when employing a learning analytics approach. Learning analytics offer a robust framework for tracking and analyzing these behavioral patterns, providing educators with actionable insights (Siemens, 2012). By leveraging data-driven methodologies, educators can uncover underlying trends, identify at-risk students, and tailor interventions more effectively (Dawson et al., 2018). Such an approach is not just beneficial for understanding student engagement trajectories, but it is also crucial for improving educational outcomes and fostering a more engaging and responsive learning environment (Gašević et al., 2015).

Four types of clusters and cluster transitions

In our study, we identified four distinct clusters of learners based on their page view frequency in online learning environment. These clusters are: Active Learners who exhibited a high frequency of page views across all tasks, indicating a consistently active engagement with the course materials; Passive Learners who showed low frequency of page views in all tasks, suggesting a generally passive engagement with the course content; Assignment-Oriented Learners who were characterized by a high frequency of assignment page views but fewer page views in other areas. This suggests a focused approach primarily on completing assignments; and Overview-Oriented Learners who predominantly viewed overview pages, such as the Home page and module overview pages, but engaged less with other types of course content.

These findings align with and expand upon previous research in online learning engagement. For instance, Moubayed et al. (2020) and Yoon et al. (2021) distinguished between high and low levels of engagement and active versus passive learners, respectively. Consistent with these studies, our research also identified active and passive learners. However, we present unique findings with the assignment-oriented and overview-oriented groups.

The context of our course design provides insights into these patterns. The assignments in our course were diverse, including discussion boards, quizzes, self-assessments, technology tool try-outs, and e-portfolio development, all followed mastery-based design and aimed to assist students applying learning concepts to real-world scenarios and demonstrate understanding of course material. The overview pages served as a guide, offering a concise description of module content, main topics, and effective navigation strategies. These designs likely influenced the emergence of the assignment-oriented and overview-oriented clusters, as these components were crucial for planning and mastering course content in an asynchronous setting.

We further examined students' behavioral pattern transition and observed a notable cluster transition pattern, indicating the dynamic nature of engagement in online learning. Among the 'stayers', the majority (72 in total) were in the passive learner cluster, followed by 37 in the assignment-oriented group, 22 in the overview-oriented group, and only 10 in the active group. Notably, there was an increase in students transitioning to the passive learner cluster, rising from 89 to 133, and no student transitioned from being a passive to an active learner.

These findings showed both similarities and differences with previous studies. In terms of stayers, Barthakur et al. (2021) identified three distinct clusters of consistently engaged, disorganized, and 'get-it-done' students, while Saqr and López-Pernas (2021) found mostly-engaged, intermediate, and troubled trajectories. Similarly, Saqr et al. (2023) noted that students using the Intense diverse strategy were likely to continue this approach in subsequent courses. These findings resonate with our results, showing that behavioral patterns in online learning can indeed change, but also that students may persist as active, passive, or task-focused.

For the movers, we found approximately 48% of the students (132 in total) shifted their engagement clusters over the course. We noted various transition patterns: some students moved from active to passive, others from passive to task-focused, and vice versa. The quality of these changes varied, with some students shifting to more engaged strategies while others became less engaged. This aligns with Saqr et al. (2023), who found a considerable likelihood (40.2%) of students shifting to an Intensely diverse strategy, illustrating that instability in engagement is a common occurrence among students with varying levels of engagement quality.

In general, most students moved to the passive group. However, it is important to acknowledge that a small portion of students transitioned from passive to task-focused engagement. Specifically, 10 students transitioned from the passive to the assignment group, and 7 students transitioned from the passive to the overview group.

The four cluster types and their later transition pattern highlight the complexity of student engagement in online learning and the importance of considering individual course designs and contexts when interpreting engagement patterns. Understanding these dynamics is important for educators to tailor interventions and support strategies effectively.

How motivation and cognitive engagement predict behavioral pattern change

In the final section of our discussion, we delve into how and why motivation and cognitive engagement influence changes in behavioral patterns. Our results reveal distinct correlations between these factors and students' engagement transitions.

Deep learning strategies, which involve critical thinking, synthesis, and application of knowledge, are conducive to a higher level of cognitive engagement (Greene et al., 2015). Students with higher deep learning strategies tend to keep staying active compared to the students who were in staying passive group. The design of the course incorporated various learning materials such as book chapter, journal paper, videos and mastery-based assignments, providing students opportunities to utilize deep learning strategies. Students likely engaged in deep learning when interacting with the content, which required not only comprehension but also the integration of knowledge from different sources to successfully answer quiz questions. Students with higher deep learning strategies were also less likely to stay in passive group, but tend to shift to the Overview-focused group from the Active group. Overview pages often provide a clear learning objectives and structured summary of the learning topic, which may guide students' learning and help them connect different aspects of the course. This design can be particularly useful for students employing deep learning strategies.

Conversely, students with a higher reliance on shallow strategies, such as rote memorization and surface-level processing, are more likely to stay passive, and less likely to maintain active engagement or become members of the "Active to Assignment-oriented" and "Overview-oriented to Assignment-oriented" groups. Shallow strategies are often associated with lower levels of cognitive engagement (Greene et al., 2015). The course's requirement for weekly assignments, which included discussions, quizzes, and portfolio work, likely demanded more than memorization or superficial understanding. Thus, students relying on shallow strategies might find themselves less engaged over time, as these strategies were not sufficient for applying concepts to real-world situations or demonstrating a deep understanding of the material.

Identified motivation is characterized by personal identification with the task's value, leading to engagement that is more self-determined and intrinsically motivated (Ryan & Deci, 2000). The significant positive effect of identified motivation on predicting staying active group implied that when students recognize and value the relevance of their learning activities, they are more likely to continue engaging with the course material actively. The course's e-portfolio assignments, for instance, allowed students to showcase their skills and reflect on their learning, activities that are well-suited to fostering identified motivation (Xie et al., 2006). This internalized motivation supports students' sustained attention and persistence in learning activities, enhancing their behavioral engagement (Wolters, 2004).

Compared to students who consistently remained passive, those with higher external motivation were less likely to transition out of a low-quality engagement state. External motivation, driven by factors such as rewards, grades, or external approval, often leads to superficial engagement and compliance rather than deep, intrinsic involvement in learning activities (Ryan & Deci, 2000). Students motivated by external factors may engage in tasks only to achieve external rewards or to avoid negative consequences, rather than out of genuine interest or personal value. As a result, their engagement remains at a surface level, lacking the depth and persistence associated with intrinsic motivation. Consequently, students are less likely to develop a sustained interest in the learning task, which can negatively impact their overall learning trajectory. The reliance on external motivation can hinder the development of deep, meaningful engagement in learning activities.

Conclusion, implication & limitation

This study was primarily aimed at identifying behavioral patterns in online learning and understanding how these patterns shift over the course of a semester. Additionally, we sought to explore the underlying influences of motivation and cognitive engagement on these changes in behavioral engagement. Our findings revealed a notable trend of decreasing page view frequency across various course tasks. By analyzing page view frequencies, we successfully identified four distinct clusters of student engagement: active, passive, assignment-oriented, and overview-oriented. Further examination of the behavioral patterns change over the semester indicated a significant shift towards passive cluster. We found deep and shallow learning strategies, identified and external motivation may explain some of the changes. In summary, our study sheds light on the dynamic nature of student engagement in online learning environments and the complex interplay of motivational and cognitive factors influencing it.

One of the main challenges in online learning, particularly in asynchronous courses, is the decline in student engagement over time. To address this issue, curriculum designers and instructors should consider both motivational and cognitive aspects. From the motivation perspective, identified motivation has been shown to positively impact student engagement, whereas external motivation often has a negative effect. Identified motivation occurs when students perceive the value and importance of their learning activities. For instance, designing final projects that integrate previously learned concepts can enhance identified motivation by demonstrating the relevance and application of past knowledge. Additionally, providing students with autonomy and choices in their learning activities, such as selecting topics for projects or choosing how to demonstrate their understanding, can further support the development of intrinsic motivation. In contrast, an overemphasis on external motivators, such as performance goals, can lead students to become disengaged and passive. Therefore, curriculum design should prioritize mastery learning, which focuses on students understanding and mastering the material rather than merely aiming for high grades. Mastery learning encourages deeper engagement with the content, as it values comprehension and application over rote memorization and standardized testing metrics. Furthermore, instructors should provide personalized support, particularly during the application stage of learning, to address individual student challenges and enhance overall motivation and engagement.

From a cognitive perspective, deep learning strategies are beneficial for maintaining active engagement and promoting meaningful learning. Students who employ deep learning techniques, such as summarizing material in their own words, mentally associating new ideas with prior knowledge, and thinking of practical applications, tend to be more engaged and better at regulating their learning activities. These strategies help students to plan and organize their studies effectively, fostering a more active and thoughtful approach to learning. On the other hand, shallow learning strategies, which focus on memorization and surface-level understanding, should be minimized as they prevent students from making meaningful connections and applying their knowledge in practical contexts. Examples of shallow strategies include rote memorization of definitions, copying lecture notes verbatim, and focusing solely on potential test questions. Curriculum designers and instructors should therefore emphasize deep learning strategies in their course materials and activities, helping students to develop a robust understanding of the subject matter and apply it in various contexts.

Our study also has several limitations that should be considered when interpreting the findings. First, the scope of our research was limited to two time points – the first and second half of the semester. This binary division aligns with our research goal of observing general trends in changes to engagement patterns and their association with motivation. It also corresponds to the class structure, where the first three weeks focus on learning and the last three weeks emphasize application and working on the final assignment. However, this approach potentially overlooks more nuanced changes in engagement that could occur at different stages or at more frequent intervals during the semester. A more granular temporal analysis might reveal subtler shifts in student engagement and provide a deeper understanding of its dynamics.

Secondly, the context of our study is restricted to a specific course and sample characteristics, limiting the generalizability of our findings. Different courses design or technology-supported environment, as well as varying age levels and cultural backgrounds, may exhibit distinct patterns of engagement and motivation. Therefore, applying these findings to other educational contexts should be done with caution, and further research in diverse settings is necessary to validate and expand upon our results.

Thirdly, there were also several changing behavioral patterns cannot be explained by the motivation and cognitive engagement, suggesting that these factors alone might not fully explain the engagement patterns in these particular cases. Looking ahead, future research should explore additional variables that could impact engagement patterns in online learning environments. These might include factors such as individual differences in learning modes, emotional and psychological well-being, socio-economic backgrounds, or the influence of peer and instructor interactions. Furthermore, technological aspects, such as the usability and design of the learning platform, could also play a crucial role in shaping engagement.

Lastly, our study predominantly relied on quantitative data, specifically page view frequencies, as indicators of student engagement. Although page view frequency provides distinct clusters, it is important to consider multiple log-data features, such as time and page view sequence. Also, the incorporation of qualitative data types, such as student interviews or open-ended survey responses, could enrich the findings. Qualitative insights would allow for a more comprehensive understanding of the reasons behind students' engagement patterns, their perceptions of the learning experience, and the subjective factors influencing their motivation and cognitive strategies.

Addressing these limitations in future research will not only strengthen the findings but also broaden the scope of understanding regarding student engagement in online learning environments. It will enable a more holistic view of how various factors interplay to shape the learning experience, thus offering richer, more nuanced insights for educators, curriculum designers, and policymakers in the field of online education.

Abbreviations

LMS: Learning Management System; MOOC: Massive Open Online Course; PAM: Partitioning Around Medoids; SDT: Self-Determination Theory; SRL: Self-Regulated Learning.

Authors' contributions

Jingwen He: Data Analysis, Conceptualization, Manuscript Writing, Manuscript Revision

Zilu Jiang: Data Collection, Data Cleaning and Analysis, Conceptualization, Manuscript Writing

Zilong Pan: Data Cleaning, Conceptualization, Manuscript Writing

Qiwei Men: Data Cleaning, Manuscript Revision

Kui Xie: Data Collection, Manuscript Review, Manuscript Revision

Authors' information

JH is a PhD Candidate at Education Psychology and Education Technology Program at Michigan State University. Her research interest is motivation, engagement, student-teacher relationships, and teacher feedback in traditional and technology-supported learning environments. She is a quantitative researcher and specialized in data management and analysis.

ZJ is a Postdoctoral Fellow at the Everyone Graduates Center at the Johns Hopkins University School of Education. She received her Ph.D. in Educational Studies from The Ohio State University. Her research lies at the intersection of educational psychology and learning technologies. She is committed to developing translational research that connects educational theories with practice. Her research delves into the contextual supports affecting the teaching and learning process, both in traditional classroom settings and online learning environments. She examines students' motivation and engagement, technology integration in the classroom, and educational program evaluations. She aims to equip educators with evidence-based strategies for enhancing students' academic engagement and achievement.

ZP is an assistant professor of teaching, learning and technology at Lehigh University. He has spent his academic career researching emerging educational technologies and innovative methodological approaches in educational practices and studies in STEAM (science, technology, engineering, arts, and mathematics) disciplines. The innovative

methodological approaches include game-based learning, project/problem-based learning; data-informed decision-making; learning analytics incorporating pedagogical approaches.

QM is a PhD student at The Ohio State University. He has a master of Applied Statistics with 3 more years of professional experience in data analysis. His research interest is data mining in learning management system in higher education, machine learning, NLP, and self-regulated learning.

KX is Red Cedar Distinguished Professor and Chairperson of Department of Counseling, Educational Psychology, and Special Education at Michigan State University. His research investigates areas related to motivation and engagement in digital learning, K-12 technology integration and teacher professional development, technology intervention and learning environment, learning analytics and research methods. He has published extensively in flagship journals in crossover fields of Educational Technology, Educational Psychology, and others.

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The data used in this study will not be shared publicly, as it contains sensitive personal information about students. Protecting the privacy and confidentiality of the participants is a priority, and the data will remain securely stored in accordance with institutional and ethical guidelines.

Declarations

Competing interests
The authors declare that they have no competing interests.

Author details
[1] Michigan State University, United States

[2] Johns Hopkins University, United States

[3] Lehigh University, United States

[4] The Ohio State University, United States

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