AN EXPLORATORY ANALYSIS OF LOG-IN CONSISTENCY FOR SECONDARY STUDENTS ENROLLED IN AN ONLINE COURSE

Abstract

In order to sustain motivation and resilience, students enrolled in online courses are expected to demonstrate higher levels of self-regulated learning (SRL) skills than those enrolled in traditional courses. Previously research has relied on data through the Motivated Strategies for Learning Questionnaire (MSLQ), but concerns have been voiced about the reliability and bias of this self-collected data. Learning analytics, collected from trace data in the learning management system (LMS) , provides a reliable, timely source of temporal data that demonstrates SRL behaviors. The purpose of this study is to determine trends in temporal behaviors during the course and how these trends are influenced by student demographics. Participants were enrolled in an online course at an independent high school in the southeastern United States (n = 238). A one-way repeated measures ANOVA identified trends in the temporal behaviors of students including when, how often and for how long students studied. A two-way mixed ANOVA resulted in these trends being influenced by a student's gender, grade level and previous online experience. This study supports the collection of trace data at multiple points during an online course to construct trends in student pacing that impact learning outcomes.

Introduction

Online learning provides students with the flexibility to study at a time and location that is best suited for them. Without a designated schedule, students can schedule study sessions at their leisure, choosing the time of day and day of the week they log into the online learning management system (LMS). With this freedom, students are expected to rely on self-regulated learning skills such as time management, goal setting, motivation, and persistence to successfully meet course expectations (Broadbent & Poon, 2015). More than in traditional courses, online students must have a strong sense of learner agency to be successful (Lehmann et al., 2014; Rienties et al., 2019).

Instructors can utilize information regarding a student's self-regulation to support their success in online courses. Previous research on self-regulated learning (SRL) traits relied on student self-report questionnaires, such as the *Motivated Strategies for Learning Questionnaire* (MSLQ) to analyze relationships between these behaviors and course outcomes (Broadbent et al., 2021). However, studies using self-reported data have raised concerns about reliability and potential biases (Rosenman et al., 2011). To offer a more objective measurement of SRL behaviors, researchers have increasingly turned to analyzing clickstream data gathered from the LMS (Li et al., 2020). Clickstream data including when students access their online course, materials viewed and for how long, provides researchers with a proxy for how a student engages in their learning.

Learning analytics provides a foundation for analyzing data collected through the online learning environment (Bienkowski et al., 2012; Li et al., 2020). One area of focus is on the development of learner dashboards that can provide insight to individual learning characteristics related to SRL behaviors (Park & Jo, 2015). Through monitoring student engagement online, instructors can provide targeted feedback and intervention techniques to help students to be successful.

While learning analytics has gained traction in higher education, its application in K-12 online environments is less common, with only 17.4% of articles published between 2011-2017 focusing on this demographic (Du et al., 2021). While these two environments share similarities in their design and facilitation, the self-regulated learning behaviors of each population are inherently different, necessitating a need for additional research specifically in the K-12 environment (Carter et al., 2020).

The purpose of this study is to utilize K-12 learning analytics to provide insight to individual trends of high school students enrolled in online courses. By examining student SRL behaviors over time, this study contributes to understanding how online learning behaviors vary for high school students over the duration of a course. The insights derived from this study can be used to support high school personalized learning online to foster student success.

Literature Review

Self-Regulated Learning

Self-regulation is the process in which learners actively monitor their learning to achieve their goals (Boekaerts, 1992; Pintrich & De Groot, 1990; Zimmerman, 1986). Encompassing cognitive, metacognitive, motivational, and behavioral aspects, self-regulated learning (SRL) is a robust area of research in the field of educational psychology. Originating from the work of Zimmerman (1986) and Pintrich and De Groot (1990), researchers have studied how SRL behaviors influence learners of all ages and in various learning environments both in-person (Pardo et al., 2016b) and online (Li et al., 2020). *Zimmerman's Social Cognitive Model of Self-Regulation* focuses on three phases: forethought, performance, and self-reflection (Zimmerman, 1986). In the *Forethought Phase* learners analyze the task provided, set specific goals, and develop plans to complete these tasks. Learners are expected to reflect on their personal interest in the task, leverage their confidence in the ability to complete the task and self-assess their motivation to achieve the goal. During the *Performance Phase*, learners engage their self-control by managing their time and effort in completing the learning plan. Learners should judge their progress and adjust when needed. In the *Self-Reflection Phase* learners reflect on the outcomes of their performance and if they reach their identified goal. Learners think about the causes of their outcome and identify adjustments needed for future tasks. As learners engage in this cyclical process, they generate strategies and perspectives that may positively or negatively affect how they engage in future learning tasks (Panadero, 2017).

Pintrich and De Groot (1990) developed a four-phase model of self-regulated learning that includes Forethought, Monitoring, Management and Reflection. Each of the four phases interacts with four areas of regulation: Cognition, Motivation, Behavior and Context. In his model he proposed a four-by-four matrix of phases and areas of regulation to categorize measures of SRL. Traits such as goal setting, cognitive awareness and monitoring, persistence, help-seeking, and evaluation are included in the matrix.

While the phases appear to be sequential, Pintrich and De Groot (1990) contest that these areas of SRL do not need to be carried out linearly and the phases do not occur in a specific order. Phases may overlap with some phases interacting during the learning process. Additionally, all four phases may not occur during every SRL event (Nodoushan, 2012). Pintrich's model of SRL was used as the theoretical framework for the development and validation of self-reported student questionnaires of SRL skills including the MSLQ (Li et al., 2020). The MSLQ includes both a motivation and a learning strategies section to understand how learners approach tasks, their motivation, and the strategies they engage during the process. The MSLQ is the most used instrument in SRL studies (Roth et al., 2016).

Research in SRL has predominately relied on using self-report instruments, such as the MSLQ, to identify skills and behaviors that promote self-regulation. Goal setting, time management, help seeking, self-efficacy and persistence have been attributed to a learner's ability to successfully complete a given learning task (Kocdar et al., 2016). Alavi et al. (2009) identified the importance for students to engage in SRL strategies both during and outside of class time to be successful.

One area of interest in research is how self-regulated behaviors influence the success of learners in online courses. Students enrolled in online courses have a higher responsibility for managing their learning process, as they have agency in when and where they engage in their course with limited presence of an instructor (Lehmann et al., 2014; Rienties et al., 2019). In a survey conducted by Howland and Moore (2002), online students reported that self-management, self-monitoring, and motivation were more essential to their success in online courses in comparison to courses that were face-to-face. Research has identified nine common strategies of SRL in online courses including time management, peer learning, elaboration, effort regulation, metacognition, critical thinking, organization, rehearsal, and help seeking (Broadbent & Poon, 2015). Researchers agree that self-regulated learning skills are teachable, highlighting the importance in identifying these behaviors to provide learners with proper support (Azevedo & Cromley, 2004; Dignath & Büttner, 2008; Zimmerman & Schunk, 2001).

Identifying and presenting data regarding student SRL skills is necessary for teachers to provide support through course design, feedback, and interventions (Li et al., 2020). Previous studies have primarily relied on self-reported data collected through the MSLQ to identify the presence of SRL skills in online courses (Roth et al., 2016). A meta-analysis conducted by Broadbent and Poon (2015) examined the relationship between self-reported SRL behaviors and achievement in online courses, identifying a positive correlation between SRL skills and achievement. Conversely, other studies found no significant relationship between self-reported SRL skills and achievement (Cicchinelli et al., 2018), causing researchers to question the reliability of self-reported SRL data. A potential limitation of gathering information via self-reported measures is that individuals might introduce bias when recounting their personal experiences (Rosenman et al., 2011). Additionally, students are oftentimes asked to indicate their SRL behaviors at the beginning of a course, which can lead to misrepresentations in their actual behaviors during the course (DiBenedetto & Bembenutty, 2013).

To provide a more objective measure of SRL behaviors, researchers have begun to rely on the analysis of trace data collected through the online learning environment. Trace data represents student learning activity by reporting time-stamped data associated with clicks in the learning environment.

Based in the field of learning analytics, the analysis of trace data presents a reliable source of information for researchers to analyze SRL behaviors online. In this study, trace data will be utilized to measure SRL behaviors.

Learning Analytics

Learning analytics is a powerful tool for researchers and practitioners to examine data collected through educational platforms and tools (Du et al., 2021). In looking at a student's online interactions, trends and patterns can be analyzed to predict behaviors and determine best practices in online learning (Hung et al., 2020). When students click through the course, data is logged by the learning management system (LMS) including page views, time stamps, interactions performed, device and browser information, etc. Previous studies have utilized trace data as a proxy for unobservable student behaviors in an online learning environment (Malmberg et al., 2017; Ricker, 2019; Bainbridge et al., 2015). While it is widely accepted that trace data cannot capture all learning activity for a student, as some may occur outside of the learning management system (LMS), the monitoring of student clicks provides an advantage to better understand otherwise unobservable online behaviors (Liu & Cavanaugh, 2012).

Student interactions in the online learning environment provide significant variables that represent broader learning constructs that are important to further research (Pardo et al., 2016a). Kim et al. (2018) utilized learning analytics to identify student profiles through the analysis of trace data related to self-regulated learning behaviors in an online course. These behaviors included total study time, log-in frequency, test scores, etc. In a similar study conducted by Kizilcec et al. (2017), trace data was utilized to analyze how students of different demographics utilized SRL processes differently. Using trace data to monitor student SRL behaviors online can provide a more individualistic approach to supporting students in online learning environments. Additionally, the use of trace data provides a more accurate method for tracking SRL behaviors, as they occur in real-time rather than waiting on the results collected through self-reports.

Since learning analytics is based on data generated by the user, it has the potential to serve as a tool to enhance educational outcomes. Du et al. (2021) conducted a systematic literature review of 901 journal articles and conference papers published between 2011-2017 to determine how learning analytics has been used to support the management of teaching and learning in online environments. From this analysis, Du and colleagues identified three major directions of learning analytics research including utilizing: (a) learning analytics to predict performance, (b) descriptive analysis to support teaching and learning, and (c) learning analytics data to detect behavior patterns in learning.

Of the studies focused on predicting performance, most utilized online behavioral data, student demographics, educational records, and self-reported data as inputs into their predictive model (Du et al., 2021). A majority (95%) of these studies utilized the course final grade as the target variable. From these findings, researchers report that the frequency in when and how students participate in the online course has a positive effect on achievement. A common limitation of these studies was the aggregation of data at the end of the course rather than over time, which limits the ability for these models to predict performance, and rather than focus on identifying key factors.

Another focus of learning analytics research is focused on providing descriptive analytics to support teaching and learning (Du et al., 2021). Many studies included the use of the LMS learner dashboard to provide a visual of learning behaviors to identify at-risk students. Dashboard analytics typically include ranking, percentile, and course mean to provide a comparison of an individual's behavior in relation to their peers (Duan et al., 2022).

Learning behaviors and patterns were a focus of learning analytics research as determined by Du et al. (2021). Common variables measured include the frequency of student logins, the duration of learning, the learning materials accessed and course interactions. Many studies focused on classifying student behavior by analyzing patterns in their learning (Li et al., 2021; Sher et al., 2022) providing insight into their motivation (Karaoglan et al., 2021), time management (Gurung et al., 2022) and help seeking behaviors (Miller et al., 2015).

K-12 Learning Analytics

While learning analytics has gained momentum in higher education, its application in K-12 online environments has not been as common (Du et al., 2021; Hung et al., 2020; Sousa et al., 2021). Du et al. (2021) identified that only 17.4% of the articles published between 2011-2017 were focused on K-12 and most of these studies relied on smaller sample sizes (less than 500 participants). Researchers have noted that this disparity may be the result of data privacy concerns for minors and a lack of involvement of stakeholders in understanding the value of learning analytics (Sousa et al., 2021). Privacy concerns may relate to working with data that includes personally identifiable information (PII). Researchers must carefully follow privacy concerns and abide by federal legislation put in place to protect students (Gross & Francisco, 2016). A recent framework designed by Krumm et al. (2018) provides guidelines for handling large data sets in K-12 including deidentification and parental consent.

As the demand for K-12 online learning opportunities continues to grow, school administrators and teachers should consider factors that affect student success. Previous research has indicated that student demographics, including gender, ethnicity, previous experience, and GPA influence student behavior in an online course (Cavanaugh, 2001; Moore & Kearsley, 2012; Ward, 2018) but additional research is needed to better understand the learning process of K-12 online students (Sousa et al., 2021).

Learning analytics provides a framework for analyzing clickstream data to identify SRL behaviors that influence student success in online K-12 courses (Carter et al., 2020). While similar to those identified in higher education settings, SRL behaviors relating to time management, motivation, help seeking and goal setting are uniquely different due to the developmental differences between higher education and K-12 groups, as well as due to the differences in course design. One of the main differences in the instructional design between these groups was a focus on instruction in K-12 environments and a focus on discussion in higher education (Hung et al., 2020).

Learning analytics, specifically the analysis of trace data, has been used by researchers as a proxy of student engagement in online K-12 courses (Barenberg et al., 2018; Monroy et al., 2014). Recognizing and predicting educational success relies on the construct of student engagement. Nevertheless, research indicates challenges in aligning data-driven insights on engagement with both observed and self-reported levels of student engagement as data obtained through the LMS provides a one-dimensional aspect of engagement and struggles to align with the non-observable aspects of the motivation construct (Bond et al., 2023). Lowes et al. (2015) used login frequency as a predictor of course success, as measured by final grades in twelve online high school courses. Leite et al. (2022) utilized structural equation modeling (SEM) to analyze log data of high school student engagement with course videos and student achievement. Additional behaviors such as viewing course materials (Lara et al., 2014), time spent in the course (Kim et al., 2018) and total number of course sessions (Li et al., 2020) were positively associated with student achievement. Yet, students who are engaged go beyond mere attendance and academic performance; they exhibit persistence in the face of challenges, self-regulate their behavior to achieve goals, strive for a comprehensive mastery of content, and find enjoyment in the learning process (Klem & Connell, 2004).

While the field of learning analytics has made strong progress in identifying demographic, academic and behavioral variables that influence outcomes, additional research is called upon to expand the influence of learning analytics beyond its reliance on learner-adjacent data (Baker et al., 2020). Besides predicting, learning analytics facilitates the presentation of dynamic feedback to tailor individual learning experiences and enhance intervention strategies in online courses (Kew & Tasir, 2022). One of the promising developments in supporting personalized behavioral analysis is through the creation and implementation of learner analytics dashboards.

Learner Analytics Dashboards

Learner analytics dashboards (LADs) are designed to provide administrators, teachers, and students with visual data representations in relation to specified learning behaviors and intended outcomes (Valle et al., 2021). Based on trace data collected through the learning management system (LMS), the goal of LADs is to provide an easier way for online constituents to be able to view, interpret and act upon patterns identified in the data (Wiley, 2020).

LADs that are teacher-facing can be designed to provide information on when and for how long learners are accessing the course to recognize students who are lacking engagement (Rice & Carter, 2016). By providing individualized information about each learner teachers can differentiate instruction for different learning preferences and provide personalized support (Harvey & Kumar, 2019). For example, Harvey and Kumar (2019) identified that students who lack SRL behaviors related to time management may be identified by infrequent logins, missing or late submissions, and reduced time in the LMS. Teachers would use this information to provide learners with strategies to address their individual behaviors and traits to help them be successful in the course. Teacher-facing LADs are often designed to align with pedagogical scripts (Hung et al., 2020). These scripts prescribe the precise role, location, action, and sequence that online students must follow, and teachers are then expected to follow this script to address deviations in student behavior (Fischer et al., 2013). The reliance on scripts though promotes teachers in getting students back on script (Wiley, 2020) rather than providing support in individualized student needs and the development of self-regulated learning behaviors (Baker et al., 2020; Hung et al., 2020).

Student-facing learner analytics dashboards provide data visualizations that assist in reflecting upon their online learning behaviors and outcomes (Park & Jo, 2015). These types of dashboards can provide students with the ability to see themselves in comparison to their peers, typically in relation to their behavior (log frequency and time spent) and achievement (average assignment grades). In a study conducted by Park and Jo (2015), online students were expected to self-monitor their learning progress in comparison to their peers to promote SRL behaviors. Researchers argued though that providing comparisons between a learner and their peers does not provide a full scope of student engagement in the online learning environment and additional variables should be included in LADs to provide a more comprehensive approach (Barthakur et al., 2023). LADs inform learner profiles. The identification and development of learner profiles can support a more holistic analysis of the learner's abilities and knowledge.

Learner Profiles

Learner profiles characterize students based on demographic, academic and temporal factors to identify personal attributes that affect individual learning styles (Barthakur et al., 2023). Based on the need for personalized learning, learner profiles can identify strengths and weaknesses that influence learning. Every learner possesses unique intrinsic motivations, interests, and cognitive capabilities, encompassing individual learning speed, ability, and differing levels of self-regulation that affect their learning progress in an online course (Winne et al., 1998). While the allure of personalized learning has attracted many educators, the ability to enact at scale has been problematic (Barthakur et al., 2023). With advancements in technology and availability of learning analytics, the development of learner profiles has become more promising (Li & Wong, 2021).

To support the effectiveness of learner profiles in personalized learning, researchers emphasize the need to examine SRL patterns over time. Many previous studies focus on collecting trace data at a single point during the course, most often at its conclusion (Kim et al., 2018), but this process fails to account for how SRL behaviors can vary during the course. Data collected at multiple time points can reveal how student learning changes over a period (Bienkowski et al., 2012). Understanding how SRL strategies vary over time is critical to providing timely support to improve learning (Kim et al., 2018).

To better understand how SRL behaviors can vary during a course, Kim et al. (2018) analyzed the study regularity and help seeking behavior of undergraduate students enrolled in an online statistics course. Students were classified according to their SRL behaviors into one of three learning profiles: self-regulation, partial self-regulation, and non-self-regulation. While the total time spent studying was generally consistent across the three profiles, there was a significant difference in learning outcomes related to when students studied. Learners in the non-self-regulation profile were more likely to log into the course right before an exam, inferring a pattern of procrastination. How students manage their time is correlated with SRL traits of goal setting, motivation, and perseverance. Additionally, study regularity was more sporadic in the non-self-regulation profile group in comparison to students in the other two groups, reflecting a lack of persistence in this group.

Researchers have focused on the importance of consistency in online learning behaviors as a representation of perseverance (Gurung et al., 2022; Lara et al., 2014). Login consistency, identified as a common time that students logged into the LMS, has been positively linked to course completion in a MOOC (Veletsianos et al., 2021). Similarly, study regularity, defined by accessing course materials at regular intervals was a significant predictor of achievement, reflecting the importance of persistence in learning (Jo et al., 2016). To further understand the variance in study behaviors, Sher et al. (2022) explored trends in the time-of-day learners accessed their online course and the device modality (mobile vs. computer) used. They identified patterns of behaviors related to those that were computer-dominant and computer-limited. For both groups they identified consistency in use of mobile devices in the afternoon for shorter learning sessions, and longer sessions occurring on computers in the evening. The underlying goal of their study is to promote the use of personalized recommendations for individuals based on their learning preference.

Understanding the temporal patterns of online learners holds significant implications for online course design and learning support. Nevertheless, current studies have examined only certain temporal aspects of online learning, neglecting to provide a comprehensive understanding of how learners utilize and arrange their time for online learning, particularly in K-12 learning environments (Li et al., 2022). The purpose of this article is to address the gap in K-12 learning analytics knowledge by providing an exploratory analysis of how online learning behaviors vary over time for high school students.

Statement of Problem and Research Questions

Enrollment in K-12 online environments continues to grow, providing flexible learning opportunities to a diverse population of students (Henke-Greenwood, 2006; Metz, 2011). Research indicates that online students require stronger self-regulation behaviors than those enrolled in traditional classes (Lehmann et al., 2014; Rienties et al., 2019), though additional research is needed to identify how SRL patterns of online learners vary during the course. The purpose of this study is to examine how SRL patterns change over time for students enrolled in a high school course. A quantitative research design was used to analyze the research questions and test the hypotheses. The research questions guiding this study are:

a. To what degree do high school learners vary their study patterns between quarters while enrolled in an online course?
b. Do associations exist between student demographics and temporal behaviors for high school learners in an online learning environment?

Hypothesis

It is hypothesized that students do not maintain a consistent study pattern during the duration of their online course, varying the amount of time, time between sessions and number of study sessions each week. In relation to student demographics, it is hypothesized that gender, grade level and previous experience affect student login behaviors in an online course.

Methods

This quantitative study explored the temporal behaviors of students enrolled in an online course at an independent school in the southeastern United States during the 2021-2022 and 2022-2023 school years. Trace data including when a student accessed their online course, what they viewed, and the type of device (mobile vs. computer) was collected from the institution's learning management system, Canvas. There were a total of 238 students enrolled in a total of 18 online courses during the two school years studied.

Study Context

The online courses were designed and facilitated internally by instructors (subject matter experts) in collaboration with the school's online learning and design team (trained in learning design). Courses spanned multiple content areas including Science, World Language, Mathematics and Social Sciences.

Participants and Context

Courses were one- or two-semesters in length and delivered asynchronously through the school's LMS, Canvas. Online courses provided a semi-structured course pacing, with a new module releasing on Friday each week and one to three assignment deadlines scheduled each week. All content and assessments were facilitated through the LMS, and students could plan their schedule based on the posted deadlines. Most students were experienced in using the LMS because they had used it in previous courses at the school. A three-day orientation was provided in each course as a guide for navigating the course, explaining an overview of the course expectations, and sharing tips to be successful learning online.

Study participants include students in grades 9 through 12 that were enrolled in at least one online course during the 2021-2022 or 2022-2023 school years. Typically, students at the school are enrolled in five or six traditional, face-to-face classes and permitted to enroll in one online course each year. Student demographics including gender, grade level, accommodations status, gifted status and previous online experience were collected through the school's student information system (SIS).

Demographic variables for each school year (Table 4) indicate that the student groups across both years were similarly distributed in grade level, accommodation status, gifted status, and previous online experience. The 2022-2023 school year had a larger percentage of female students (n=83) than male students (n=49) in comparison to the previous school year.

Table 4

Student Demographics for each School Year

Student Demographics	2021-2022	2022-2023	Total*
Gender			
Male	56	49	99
Female	60	83	125
Grade Level			
9th Grade	21	30	51
10th Grade	18	19	33
11th Grade	31	38	60
12th Grade	46	45	80
Accommodations			
With Accommodations	27	28	34
Without Accommodations	89	104	190
Gifted			
Identified Gifted	6	11	15
Not Identified Gifted	110	121	209
Previous Online Experience			
Yes	59	66	102
No	57	66	122

* The total column presents demographic information for each unique participant. If a student took a course in both 2021-22 and 2022-23, they are only counted once in the total.

Temporal Variables

Canvas, the school's learning management system (LMS), served as the primary platform for the delivery of course content and assessments. Student engagement and course interactions were tracked through clicks within the online course. Each data point offers a record of a student's engagement in the course including the start time, end time, content viewed, and the device type (mobile or desktop). Like the process used by Sher et al. (2022), trace data was processed to create study sessions that represented a student's continuous learning event where two clicks were within 60 minutes of one another. A 60-minute interval was selected as it aligns with the time interval of the school's face-to-face class schedule. For each session, the following temporal variables were created:

- **Session Length:** The length of time a student is active in the LMS. The end of a session is identified as a period of inactivity of at least 60 minutes.
- **Day of Week Accessed:** The day of the week that a study session occurs. If a study session occurs over two days (e.g., 11:53 pm Tuesday to 12:10 am Wednesday) it is recorded based on the initial day the session begins (i.e., Tuesday).
- **Time of Day Accessed:** Like the process utilized by Sher et al. (2022), the time of day that a study session is initiated was categorized into one of three time of day (TOD) categories. The TOD segments correlate with a student's natural school day schedule and are defined below:
    - Morning/School: 5:00 am - 3:59 pm
    - Afternoon: 4:00 pm - 9:59 pm
    - Night: 10:00 pm - 4:59 am
- **Device Type:** The type of device used during the study session, as indicated by either iOS or browser access. Sessions identified as iOS were completed on a mobile device, either phone or tablet. Study sessions identified as browser based were accessed on a laptop or desktop. Study sessions are identified as either mobile (iOS), desktop (browser) or mixed (a combination of iOS and browser access in the same session).

Data Analysis

Temporal data was organized using Microsoft Excel prior to entering into IBM SPSS Statistics, version 29. ANOVA tests were conducted on within-subject factors (study behaviors over time) and between-subject factors (participant demographics) in relation to the study's research questions. To determine whether participant study behaviors change over time (RQ1), one-way repeated measures ANOVAs were conducted for each of the behaviors being analyzed: Average Number of Sessions, the Time Between Sessions, the Number of Sessions, Total Time in Study Sessions, Frequency of Weekday Login, Frequency of School-time Login, Frequency of Afternoon-time Login, Frequency of Night-time Login, Frequency of Mobile Device Use. If a significant difference between the time periods was determined, data was then analyzed using two-way mixed ANOVAs to determine if these changes are related to participant demographics including Gender, Grade Level and Previous Online Experience (RQ2).

Study Behaviors Over Time

Researchers in the field of learning analytics often study course behaviors in online courses as a proxy for student engagement (Broadbent & Poon, 2015) but these analytics are typically generated at the end of a course (Du et al., 2021). To determine if there is a need to capture data more often during an online course, repeated measure ANOVAs were conducted to identify how participant study behavior varies over time. Prior to running each ANOVA, the quarterly within-factor variables were plotted to identify outliers. Outliers in each were removed from the data set and each ANOVA was conducted on the original data set and the new one then compared. For each within-factor variable, there was not a significant difference in the outcomes, so all identified outliers were removed prior to conducting each ANOVA test.

Results

The present study examined how SRL patterns changed over time for students enrolled in an online high school course. Statistics were calculated for each temporal variable being studied during the two school years (Table 5). The average length of each study session across each year was 17.38 minutes and ranged between an average of 5.65 minutes per session to 32.38 minutes per session. Students had an average of 22.10 hours between study sessions, logging in approximately once per day on average. The minimum average time between sessions was 9.24 hours, approximately 2.5-3 times each day and the maximum average time between sessions was 64.3, approximately 2.5 days between sessions. The average number of sessions and average total study time were similar for both school years. Login frequencies indicate that students logged in more often on the weekends during the 2022-2023 school year. Additionally, students during the 2022-2023 school year had 5% more logins via mobile device than their peers in the 2021-2022 cohort.

Table 5

Temporal Behavior Data by Year

Temporal Behaviors	2021-2022	2022-2023	Total
Average Session Length (in minutes)			
Minimum	8.44	5.65	5.65
Maximum	32.38	31.03	32.38
Average	18.49	16.14	17.38
Average Time Between Sessions (in hours)			
Minimum	9.87	9.24	9.24
Maximum	50.81	64.3	64.3
Average	20.71	23.67	22.10
Average Number of Sessions			
Minimum	52	43	43
Maximum	543	543	543
Average	204	213	238
Average Total Study Time (in hours)			
Minimum	32.7	37.0	32.7
Maximum	149.4	154.6	154.6
Average	74.4	81.6	78.5
Day of Week Accessed (Frequency)			
Monday	16.31%	16.05%	16.19%
Tuesday	17.09%	16.58%	16.85%
Wednesday	17.84%	16.95%	17.42%
Thursday	17.54%	17.67%	17.60%
Friday	17.58%	15.13%	16.43%

Weekday	**86.36%**	**82.38%**	**84.49%**
Saturday	6.03%	7.28%	6.62%
Sunday	7.61%	10.34%	7.26%
Weekend	***13.64%***	***17.62%***	***15.51%***
Time of Day Accessed (Frequency)			
Morning/School	31.20%	28.52%	29.94%
Afternoon	33.21%	35.98%	34.51%
Night	35.58%	35.5%	35.54%
Device Type (Frequency)			
Mobile	19.84%	24.97%	22.25%
Computer	71.74%	66.88%	69.45%
Mixed	8.42%	8.15%	8.29%

One-Way Repeated Measures ANOVA

To determine if a student's pattern of online behavior changes over time (RQ1), one-way repeated measures ANOVA were conducted for each temporal variable.

Average Length of Sessions.

A participant's average length of session was recorded by identifying the time between when they first clicked into the course and their last click of that study session. The average length of study sessions for all participants was 17.38 minutes. The average length of study session for quarter 1 was 20.6 minutes, quarter 2 was 18.3 minutes, quarter 3 was 17.5 minutes and quarter 4 was 15.5, which indicates that the average time participants spent in each session declined over time. Mauchly's Test of Sphericity indicated that the assumption of sphericity had been violated, $\chi^2(5) = 16.409$, $p < .05$, and therefore, a Greenhouse-Geisser correction was used. There was a significant main effect of time on average session length, $F(2.779, 17.110) = 31.849$, $p < .05$. Pairwise comparison effects were then studied using Bonferroni adjusted alphas. Results indicated a statistically significant difference in the average session length between quarter 1 and 2, 2.270 95% CI [.964, 3.576], quarter 1 and 3, 3.054 95% CI [1.513, 4.594], quarter 1 and 4, 5.046 95% CI [3.552, 6.540], and quarter 2 and 4, 2.776 95% CI [1.340, 4.212].

Time Between Sessions.

The amount of time between sessions was calculated by taking the difference in time of the last click of the previous session and the first click of the new session. This variable represents time management in online student behavior (Broadbent & Poon, 2015). The average time between sessions for the group was 22.10 hours and the averages per quarter were as follows: 16.3 hours (Quarter 1), 18.4 hours (Quarter 2), 19.7 hours (Quarter 3) and 22.2 hours (Quarter 4). As the year progressed, students, on average, increased the amount of time between each study session in their online course. Mauchly's Test of Sphericity was insignificant, violating the assumption of sphericity ($p < 0.05$) so the Greenhouse-Geisser correction was used instead. There was a statistically significant difference in the average time between study sessions in each quarter, $F(2.491, 256.537) = 56.741$, $p < .05$. Utilizing Bonferroni adjustments, pairwise comparisons were calculated and significant differences in the time between study sessions of each quarter. This posthoc test identified significant differences in the time between study sessions for quarter 1 and 2, -2.155 95% CI [-3.116, -1.193], quarter 1 and 3, -3.471 95% CI [-4.637, -2.304], quarter 1 and 4, -5.900 95% CI [-7.328, -4.472], quarter 2 and 3, -1.316 95% CI [-2.319, -0.313] and quarter 2 and 4, -3.476 95% CI [-5.075, -2.417].

Total Time.

The total time spent in the course was calculated by adding the time per session for each of the participant's study sessions. The average total time spent in the online course was 78.5 hours. The average time spent in quarter 1 was 25.9 hours, quarter 2 was 20.6 hours, quarter 3 was 16.7 hours and quarter 4 was 12.2 hours, showcasing a negative trend in study time over the course of the year. The assumption of sphericity was violated under Mauchly's Test of Sphericity, and the Greenhouse-Geisser test was used instead. The Greenhouse-Geisser test indicated a statistically significant difference in the total time studied in each quarter ($p < 0.05$). Additionally, pairwise comparisons using Bonferroni's adjustment indicated significant differences between quarter 1 and 2, 5.263 95% CI [3.321, 7.205], quarter 1 and 3, 9.225 95% CI [6.986, 11.464], quarter 1 and 4, 13.694 95% CI [11.157, 16.230], quarter 2 and 3, 3.962 95% CI [2.531, 5.394] and quarter 2 and 4, 4.469 95% CI [2.765, 6.172].

Number of Study Sessions.

Study sessions were identified as a time in which a participant was actively clicking in the online course with less than 60 minutes between clicks. If a participant is idle for 60 minutes, a new study session will be created. The mean number of study sessions for the study was 238. In analyzing each quarter separately, the average number of study sessions was 78 (Quarter 1), 73 (Quarter 2), 63 (Quarter 3) and 52 (Quarter 4). Mauchly's Test of Sphericity indicated that the assumption of sphericity was violated, so the Greenhouse-Geisser adjustment was used to identify relationships between quarters. As the Greenhouse-Geisser adjustment was significant, $F(2.533, 260.917) = 99.259$, $p < .05$, this indicates that there is a significant difference in the number of study sessions in each quarter. By analyzing Bonferroni's adjustment in the pairwise comparisons, significant differences were determined between quarter 1 and 2, 5.587 95% CI [1.784, 9.390], quarter 1 and 3, 15.5 95% CI [10.949, 20.051], quarter 1 and 4, 26.087 95% CI [20.599, 31.574], quarter 2 and 3, 9.913 95% CI [6.240, 13.587] and quarter 2 and 4, 20.500 95% CI [16.327, 24.673].

Weekday.

The frequency of when students logged in each week was measured and summed to determine the percentage of study sessions that occurred during the week (Monday through Friday). The average frequency of weekday study for the participants of this study was 84.5%, indicating that the average frequency of weekend study was 15.5%. The frequencies varied slightly over the course of the year: 83.7% (Quarter 1), 84.01% (Quarter 2), 87.11% (Quarter 3), 84.0% (Quarter 4). The assumption of sphericity was violated under Mauchly's Test of Sphericity, so the Greenhouse-Geisser adjustment was consulted. There was a significant difference in weekday frequencies between quarters, according to the Greenhouse-Geisser Test ($p < 0.05$). Pairwise comparisons indicate a significant relationship between quarter 1 and 3, -0.34 95% CI [-0.054, -0.014], quarter 2 and 3, -0.031 95% CI [-0.047, -0.015] and, quarter 3 and 4, 0.031 95% CI [0.013, 0.050].

Time of Day.

The frequency of when students logged in each day was measured and collated according to one of three groups: Morning/School* (5 am - 3:59 pm), Afternoon (4:00 pm - 9:59 pm) and Night (10:00 pm - 4:59 am). These times were selected to align with the school day times, as well as the time students typically wake up and go to bed each evening. The original data set had separated times for Morning (5 am - 7:59 am) and School (8 am - 3:59 pm) but due to the limited frequency of morning study sessions, these two groups were combined for the study. The average login frequency for each of these time periods was 30.0% during School hours, 34.5% during Afternoon hours and 35.5% during Night hours. Three repeated measure ANOVAs were conducted on each of the time frequencies groups. Student login behavior during school varied slightly during each quarter, as 28.7% logged in during school hours in quarter 1, 28.2% during quarter 2, 23.9% in quarter 3 and 30.4% in quarter 4. Afternoon frequencies were stabler across the quarters as 35.8% logged in during the afternoon in quarter 1, 34.7% during quarter 2, 34.3% in quarter 3 and 32.7% in quarter 4. Like the school group, nighttime login frequencies varied more between quarters as 35.1% logged in during this time in quarter 1, 37.1% during quarter 2, 41.3% in quarter 3 and 36.4% in quarter 4. Mauchly's Test of Sphericity was insignificant ($p < 0.05$), so the Greenhouse-Geisser adjustment was utilized to determine a significant difference between school login-frequencies between quarters for each of the groups. A statistically significant difference between quarters was determined for each of the time groups: school ($F(2.746, 304.783) = 22.164$, $p < .05$), Afternoon ($F(2.729, 305.657) = 4.131$, $p < .05$) and Night ($F(2.710, 303.488) = 17.651$, $p < .05$). Pairwise comparisons indicated significant differences between quarter 1 and 3, 0.048 95% CI [0.025, 0.071], quarter 2 and 3, 0.043 95% CI [0.022, 0.063], quarter 2 and 4, -0.022 95% CI [-0.042, -0.002], and quarter 3 and 4, -0.064 95% CI [-0.089, -0.040] for the school hours group. For the afternoon group, a significant difference was only determined between quarter 1 and 4, 0.031 95% CI [0.005, 0.056]. For the Night group, significant pairwise comparisons were present between quarter 1 and 2, -0.019 95% CI [-0.039, 0.000], quarter 1 and 3, -0.061 95% CI [-0.087, -0.036], quarter 2 and 3, -0.042 95% CI [-0.064, -0.020] and quarter 3 and 4, 0.049 95% CI [-0.073, -0.024].

Mobile.

Students could access their online course using either a desktop or mobile device. Students at the school are issued a school laptop for use in their in-person and online courses but some choose to utilize their mobile device (phone or tablet) in substitution or addition to their laptop. The frequency of mobile usage was collected for each study session, averaging 22% of the total study sessions for all participants. This average varied slightly each quarter, as students utilized their mobile devices for 18.9% of their study sessions in quarter 1, 19.8% of their study sessions in quarter 2, 19.6% of their study sessions in quarter 3 and 21.1% of their study sessions in quarter 4. There was a violation of the assumption of sphericity under Mauchly's Test of Sphericity, so the Greenhouse-Geisser adjustment was consulted. There was not a significant difference in mobile frequency use between quarters, $F(2.608, 286.892) = 2.431$, $p > .05$.

Two-Way Mixed ANOVA

Changes in online behavior were determined to be statistically different between quarters for study session length, time between study sessions, total study time, weekday frequency and time of day frequency. To determine whether these differences were related to a participant's gender, grade level or previous online experience, two-way mixed ANOVA tests were performed (RQ2).

Gender.

Two-way mixed ANOVA tests were conducted for each of the significant study behaviors listed above, with gender as the between-groups factor. There was a significant effect of time on weekday frequency, in agreeance with the one-way repeated measures ANOVA conducted prior, $F(2.718, 208.003)$

= 12.355, $p < 0.05$, partial $\eta^2 = .107$. There was not a significant effect of gender on weekday frequency, $F(1,103) = 0.238$, $p > 0.05$. There was a significant interaction effect and gender was determined to be a significant factor in explaining the variance in quarterly weekday frequencies over the duration of the course, $F(2.718, 280.003) = 4.490$, $p < .05$, partial $\eta^2 = .042$. Post-hoc tests were performed to further analyze the interaction effect of gender and time on weekday frequency. Pairwise comparisons using Bonferroni adjustments indicate a statistically significant difference in weekday frequency for males between quarter 1 and 4, 0.028 95% CI [0.004, 0.052], quarter 2 and 3, -0.029 95% CI [-0.055, -0.003] and quarter 3 and 4, 0.042 95% CI [0.13, 0.72]. For females, significant differences were identified between quarter 1 and 3, -0.047 95% CI [-0.073, -0.021], quarter 1 and 4, -0.020 95% CI [-0.039, 0.00], quarter 2 and 3, -0.037 95% CI [-0.058, -0.015] and quarter 3 and 4, 0.028 95% CI [0.003, 0.052]. Two-way mixed ANOVA tests were conducted on gender and the remaining temporal variables and no significant interaction outcomes were identified ($p>0.05$).

<u>Grade Level.</u>

Two-way mixed ANOVA tests were conducted to determine whether grade level had an interaction effect with the temporal variables presented in the study. Separate tests were run for average session length, weekday frequency, total study time and total number of sessions.

<u>Average Session Length.</u>

A significant relationship between quarters was confirmed for the average length of study sessions in an online course, $F(2.824, 316.338) = 22.686$, $p < 0.05$, partial $\eta^2 = .168$. There was not a significant relationship between grade level and average session length, $p > 0.05$. The interaction effect of grade level and average session length was significant, $F(8.473, 316.338) = 3.132$, $p < 0.05$, partial η^2 = .077. Posthoc Bonferroni adjustments were conducted to further examine these interactions. Significant differences were identified for tenth graders between quarter 1 and 2, 4.294 95% CI [1.670, 6.917], quarter 1 and 3, 5.369 95% CI [1.670, 6.917], quarter 1 and 4, 5.973 95% CI [2.972, 8.973], eleventh graders between quarter 1 and 2, 3.283 95% CI [.795, 5.772], quarter 1 and 3, 4.523 95% CI [1.597, 7.449], quarter 1 and 4, 6.337 95% CI [3.491, 9.184], and quarter 2 and 4, 3.054 95% CI [.325, 5.783]. Students in twelfth grade had significant differences in session length between quarter 1 and 4, 5.030 95% CI [2.706, 7.354], quarter 2 and 4, 4.405 95% CI [2.176, 6.644], and quarter 3 and 4, 3.755 95% CI [1.480, 6.030]. No significant differences were identified between quarters for freshman student.

Weekday Frequency.

To further understand the changes in weekday frequency between each quarter, a two-way mixed ANOVA was performed with grade level as the between-subject factor. This confirmed a significant difference between quarters for weekday frequency, $F(2.765, 309.661) = 0.021$, $p < 0.05$, partial η^2 = .064. There was a significant relationship between grade levels, $F(3, 112) = 19.065$, $p < 0.05$, partial η^2 = .338. Additionally, there was a significant interaction effect between grade level and weekday frequency, $F(8.295, 309.661) = 2.156$, $p < 0.05$, partial η^2 = .055. For twelfth graders, a difference between weekday frequency was significant for quarter 1 and 2, -0.064 95% CI [-0.095, -0.033], quarter 2 and 3, -0.62 95% CI [-0.088, -0.036], and quarter 3 and 4 0.47 95% CI [0.016, 0.044]. Significant differences were not identified between quarters for grades 9, 10 or 11.

Total Study Time.

The two-way mixed ANOVA resulted in a significant main effect between quarters for total study time, $F(2.757, 308.782) = 092.394$, $p < 0.05$, partial η^2 = .452. There was a significant main effect of grade level, $F(3,112) = 8.897$, $p < 0.05$, partial η^2 = .192, as well as a significant interaction between grade level and total study time between quarters, $F(8.271, 308.782) = 8.184$, $p < 0.05$, partial η^2 = .180. To further examine these interactions, a posthoc test of pairwise comparisons using Bonferroni adjustment was performed. No significant differences were identified between quarters for students in grade 9. For grades ten, eleven and twelve, significant differences were identified for some quarters ($p < 0.05$) as indicated in Table 6 below.

Table 6

Pairwise Comparisons between Grade Level and Total Study Time per Quarter

Grade Level	Pairwise	Mean Difference	Significance	Lower Bound	Upper Bound
10	Quarter 1 & 2	4.294	<.001	1.670	6.917
10	Quarter 1 & 3	5.369	<.001	2.285	8.453
10	Quarter 1 & 4	5.973	<.001	2.972	8.973
11	Quarter 1 & 2	6.396	<.001	2.650	10.141
11	Quarter 1 & 3	11.994	<.001	7.944	16.044
11	Quarter 1 & 4	16.833	<.001	12.484	21.182
11	Quarter 2 & 3	5.598	<.001	2.505	8.691
11	Quarter 2 & 4	10.438	<.001	6.961	13.914
11	Quarter 3 & 4	4.839	.004	1.094	8.585
12	Quarter 1 & 2	4.601	<.001	1.542	7.659
12	Quarter 1 & 3	7.612	<.001	4.305	10.919
12	Quarter 1 & 4	14.589	<.001	11.028	18.130
12	Quarter 2 & 3	3.011	0.011	0.486	5.537
12	Quarter 2 & 4	9.979	<.001	7.140	12.817
12	Quarter 3 & 4	6.967	<.001	3.909	10.025

*Based on estimated marginal means
**Adjustment for multiple comparisons: Bonferroni

Number of Study Sessions.

There was a significant difference in the number of study sessions between quarters, $F(2.683, 300.499) = 73.813$, $p < 0.05$, $\eta^2 = .397$. There was a significant main effect of grade level, $F(3,112) = 8.153$, $p < .05$, $\eta^2 = .179$. As well as a significant interaction effect between grade level and average number of study sessions $F(8.049, 300.499) = 6.018$, $p < .05$, $\eta^2 = .139$. Pairwise comparisons were conducted to examine the interaction effect and significant differences were identified between many quarters for grades ten, eleven and twelve ($p < 0.05$) (Table 7). No significant differences were identified between quarters for grade 9 ($p > 0.05$).

Table 7

Pairwise Comparisons for Grade Level and Total Study Sessions

Grade Level	Pairwise	Mean Difference	Significance	Lower Bound	Upper Bound
10	Quarter 1 & 3	23.148	<.001	13.544	32.752
10	Quarter 1 & 4	29.704	<.001	19.303	40.104
10	Quarter 2 & 3	16.704	<.001	8.495	24.913
10	Quarter 2 & 4	23.259	<.001	14.675	31.844
11	Quarter 1 & 3	18.867	<.001	9.756	27.978
11	Quarter 1 & 4	29.033	<.001	19.167	38.900
11	Quarter 2 & 3	14.167	<.001	6.379	21.954
11	Quarter 2 & 4	24.333	<.001	16.189	32.477
11	Quarter 3 & 4	10.167	.005	2.176	18.157
12	Quarter 1 & 2	11.289	<.001	5.311	17.267

12	Quarter 1 & 3	18.022	<.001	10.583	25.461
12	Quarter 1 & 4	34.400	<.001	26.344	42.456
12	Quarter 2 & 3	6.733	0.032	0.375	13.092
12	Quarter 2 & 4	23.111	<.001	16.462	29.761
12	Quarter 3 & 4	16.378	<.001	9.853	22.902

*Based on estimated marginal means
**Adjustment for multiple comparisons: Bonferroni

Two-way mixed ANOVA tests were used to examine the relationships between gender and mobile device frequency, average session length, and time of day frequencies (Night, School, Afternoon) yet no significant interactions were identified.

Previous Online Experience.

Two-way mixed ANOVA tests were conducted to determine whether grade level had an interaction effect with the temporal variables presented in the study. Separate tests were run for total study time and number of study sessions.

Total Study Time.

There was a significant difference in the total study time between quarters, $F(2.593,295.649) = 99.462$, $p < .05$, $\eta 2 = .466$. There was not a significant main effect of previous online experience ($p < 0.05$) but there was a significant interaction effect between previous online experience and total study time, $F(2.593,295.649) = 5.025$, $p < .05$, $\eta 2 = .042$. To examine these interactions more in depth, posthoc comparisons were calculated using the Bonferroni adjustment. Significant differences were identified between all quarters for both students that did and did not have previous online experience, as indicated in Table 8 below.

Table 8

Pairwise Comparisons for Grade Level and Total Study Sessions

Previous Online Experience	Pairwise	Mean Difference	Significanc e	Lower Bound	Upper Bound
No	Quarter 1 & 2	4.541	0.003	1.170	7.913
No	Quarter 1 & 3	8.900	<.001	5.017	12.784
No	Quarter 1 & 4	10.193	<.001	5.972	14.414
No	Quarter 2 & 3	4.359	<.001	1.605	7.113
No	Quarter 2 & 4	5.652	<.001	2.468	8.836
Yes	Quarter 1 & 2	5.925	<.001	3.479	8.370
Yes	Quarter 1 & 3	10.281	<.001	7.464	13.099
Yes	Quarter 1 & 4	16.037	<.001	12.975	19.099
Yes	Quarter 2 & 3	4.357	<.001	2.359	6.355
Yes	Quarter 2 & 4	10.112	<.001	7.802	12.422
Yes	Quarter 3 & 4	5.755	<.001	3.335	8.176

*Based on estimated marginal means
**Adjustment for multiple comparisons: Bonferroni

Number of Study Sessions.

The number of sessions differed significantly between each quarter, $F(2.593,295.574) = 85.350$, $p < .05$, $\eta^2 = .428$. The main effect of previous online experience was not statistically significant ($p < 0.05$), but the interaction effect of previous online experience and number of sessions was significant, $F(2.593,295.574) = 5.292$, $p < .05$, $\eta^2 = .044$. Pairwise comparisons were calculated using Bonferroni adjustment to examine the relationships between quarters for students with and without previous online experience. There was a statistically significant relationship between quarter 1 and 3, 13.325 95% CI [5.221, 21.429], quarter 1 and 4, 18.550 95% CI [9.327, 27.773] and quarter 2 and 3, 11.625 95% CI [4.698, 18.552] for students without previous online experience. There was a significant difference between quarter 1 and 2, 8.947 95% CI [4.235, 13.660], quarter 1 and 3, 19.829 95% CI [13.949, 25.708], quarter 1 and 4, 32.474 95% CI [25.783, 39.165], quarter 2 and 3, 10.882 95% CI [5.856, 15.907], quarter 2 and 4, 23.526 95% CI [18.194, 28.858] and quarter 3 and 4, 12.645 95% CI [7.405, 17.885] for students with previous online experience.

Two-way mixed ANOVA tests were conducted between previous online experience and mobile frequency, previous online experience and average session length, previous online experience and weekday frequency and previous online experience and time of day frequencies (Night, School, Afternoon) but no significant interaction effects were identified.

Discussion

This study utilizes clickstream data collected from the learning management system of 10 online courses for students in grades 9-12 during the 2021-2022 school years. The purpose of this exploratory quantitative analysis was to identify if student login behavior in online courses changed over the duration of the course. Previously researchers have utilized clickstream data as a proxy for self-regulated learning behaviors in online courses, but most often this data is collected at one point in time, typically at the conclusion of the course (Kim et al., 2018). By collecting and analyzing data at multiple points during the course, we can better understand how SRL behaviors change over time (Bienkowski et al., 2012).

To determine how clickstream behaviors change over time, one-way repeated measures ANOVA tests were conducted to determine if there was a significant difference in temporal variables during each quarter of the school year. Two-way mixed ANOVA tests were then used to analyze whether student demographics influenced the temporal changes between variables. Based on previous studies, the demographic between-group factors studied were gender, grade level and previous online experience (Veletsianos et al., 2021; YeckehZaare et al., 2022b).

Average Session Length

The average length of a study session in an online course was determined by a period of continuous activity (clicks) in the course LMS with fewer than 60 minutes of inactivity. A significant difference was found between quarters in relation to the student's average study session length. On average students spent more time in each study session during quarter 1, with the average length falling in each subsequent quarter. This trend is opposite previous studies that indicate students tend to increase the amount of study time and frequency towards the latter half of the course, signaling the behavior of massing (Li et al., 2021; Kim et al., 2018). The difference in these studies could be related to the use of course deadlines and adaptive release. In previous studies students were expected to self-manage their pacing, with an end of course assessment as the only deadline. The courses for this institution included multiple deadlines each week as well as adaptive release, opening a new content module each week of the course. Aligned with the findings of Barenberg et al. (2018), students enrolled in courses with multiple assignment deadlines access course materials more regularly than those with an end-of-course test.

The decreasing trend in average session length was influenced by a student's grade level and gender. Students in grade 10 had the most significant decline in average session length as the course progressed. Similarly, female students tended to have more sessions in quarter 1 then a larger decline in quarter 2, 3 and 4 than their male peers. The differences in these self-regulated temporal behaviors align with previous findings indicating that younger students had more difficultly in acquiring self-regulation competence (Dignath & Büttner, 2008; Radovan, 2010), as well as gender differences that exist between male and female students (Pérez et al., 2017).

Time Between Sessions

The length of time between sessions was measured by the last click of the previous session and the first click of the new session, with at least 60 minutes of inactivity between sessions. Based on the results of this study, there is a significant difference in how students space their learning each quarter, as measured by the average time between study sessions. The average time between study sessions increased as the school year progressed, highlighting a change in student time management and engagement. The impact of these changes is important for course designers and instructors to consider as they design and facilitate online courses. Login frequency has had a positive effect on student achievement, as measured by final course scores (Lowes et al., 2015), but the exact frequency that is desired has not been defined. While increased login frequency supported learning in a study of online courses by Lowes et al. (2015), Cavanaugh et al. (2016) found that there was an intermediate frequency (not too often and not too spread), that optimized course performance. Unlike the findings in the study conducted by YeckehZaare et al. (2022b), the variability in the spacing of study sessions in this study was not related to a student's gender, grade level or previous online activity.

Total Study Time

Analyzing the total time spent in the course was determined by adding the individual session times for each student. There was a statistically significant difference in total study time between quarters for students, with each quarter averaging less study time than the previous ones. Similar to the previous discussion of changes in average length of the study session, changes in total study time are opposite previous findings (Li et al., 2021; Kim et al., 2018), but align with the suggestion that multiple course deadlines encourage students to spread their behavior rather than mass at the end of the course (Barenberg et al., 2018).

Changes in this behavior were influenced by a student's grade level and previous online activity. Students in grade 12 had a larger difference between quarters than their peers in grades 10 and 11. The difference in behavior between grade levels partially illustrates the behavior of "senioritis", a colloquial term to describe the senior slump (Blanchard, 2013). High school seniors tend to disengage from school, particularly after the first quarter. Their trend in decreasing time spent in their online course aligns with the patterns that occur across other courses as well (Blanchard, 2013). Additionally, students with previous online experience had more significant differences in their study time than their peers without previous experience. This behavior was unexpected, as previous studies indicate that students with previous experience have better self-regulated skillsets than those that are new to online learning (Li et al., 2021).

Number of Study Sessions

The number of study sessions was summed for each participant in an online course. As the school year progressed, students logged into the course fewer times during each quarter. Most notably, quarter 1 had the largest number of study sessions logged and this number declined in each subsequent quarter. Again, this result was not aligned with previous findings (Li et al., 2021; Kim et al., 2018), but may be explained by the structure of the course deadlines and adaptive content release.

Like total study time, the number of study sessions was influence by a student's grade level and previous online experience. Students in grades 10 and 11 had larger differences between study sessions compared to seniors. Students without previous online experience also had larger differences in the number of study sessions compared to their peers with previous experience. These changes in engagement behavior are supported by the differences in self-regulated learning due to age (Dignath & Büttner, 2008; Radovan, 2010) and technology self-efficacy (Wang et al., 2013)

Weekday Frequency

Each online course in this study included 2-3 deadlines each week, with at least one occurring during the school week (Monday through Friday). Students were encouraged to log into their course throughout the week to meet course deadlines and expectations. To determine how students spread their learning throughout the week, frequencies were tallied to determine the frequency of study sessions that occurred during the school week (Monday through Friday) out of the total number of sessions. Student login behavior differed during the year based on their preference of weekday vs. weekend studying. Most differences were found in quarter 3, as students increased their frequency of weekday studying compared to weekend. Previous research has indicated that login frequency of weekday vs. weekend changes over time in relation to the device modality (Sher et al., 2022), but specificity in the changes during specific time frames during the course has not been investigated to date. Understanding the frequency of when student's login to study can help course designers and teachers best design for assignment deadlines that meet student behavior trends.

Gender and grade level both had a significant effect on the changes of weekday login frequency during the duration of the course. Female students were more likely to login during the weekend in quarter 1 and increasingly during the week with each subsequent quarter. Male students exhibited the opposite behavior, increasing the frequency of weekend logins as the course progressed. While differences in self-regulated behaviors due to gender have been identified (Pérez et al., 2017), differences in login trends between genders have not previously been identified. Understanding these differences support teachers in early identification of students that need to modify their study patterns to be successful in an online course. Students in grade 12 also increased their weekday frequency as the school year progressed, spending less time in the course on weekends. The trend in seniors to spend less time studying on the weekend aligns with the phenomenon of senior slump (Blanchard, 2013), and reduced engagement from this student group as they progress closer to graduation.

Time of Day

Similar to weekday login frequency, the time-of-day students logged in was analyzed to determine how frequently they were studying during the school day (5 am - 3:59 pm), during the afternoon (4 pm - 9:59 pm) and evening (10 pm - 3:59 am). There was a statistically significant difference in login frequencies for each quarter during the designated time frames. When students login to their online course is related to both time management (Kim et al., 2018) and circadian learning preferences (Smies et al., 2022). Additional research should be conducted to better understand the causes of these variances, as the differences in these behaviors were not related to a student's gender, grade level or previous online experience.

Mobile

One of the benefits of online learning for students is the flexibility to learn anywhere at any time (Henke-Greenwood, 2006; Metz, 2011). As a result, students are utilizing their mobile devices more often for school-related purposes, including online learning (Sher et al., 2022). While students at this school were issued school-laptops for their studies, students spent an average of 22% of their study sessions on a mobile device. The increased use of mobile technology in online learning has been supported by recent research, as the improvements in technology and network connectivity provide greater flexibility for students to learn when and where it is best for them (Milheim et al., 2021). While this behavior did not differ significantly over time, student use of mobile technologies is important for teachers and course designers to consider while analyzing student temporal behaviors.

Limitations and Future Research

The purpose of this study was to determine if temporal behaviors in online learning change over time and if these changes are related to student demographics (i.e., gender, grade level or previous online experience). Statistical differences in student behavior between quarters in their online course were determined, yet additional research is needed to understand when and why these behaviors change. The trace data collected for this study was based on a collection of 18 online courses facilitated at an independent school in the southeastern United States. The courses were structured to include 2-3 due dates each week, as well as weekly release of new content, limiting the level of flexibility that is oftentimes associated with online learning. A recommendation for future research is to conduct a similar study in an online learning environment that has less structure in course pacing.

While differences were identified for temporal behaviors between quarters, additional research is needed to determine the impact of these changes on student outcomes. Previous research in temporal behaviors have indicated a conflicting perspective on whether increasing online engagement is associated with higher final grades in the course (Lowes et al., 2015) or whether there is a median level of frequency that best supports academic success in online courses (Cavanaugh et al., 2016). A study to analyze the relationships between these changing temporal behaviors and academic outcomes over the duration of the course would help identify optimal behaviors to promote success.

Conclusion

Online students are expected to have strong self-regulated skill sets to manage their time and engage in their course despite the limited real-time presence of their instructor (Lehmann et al., 2014; Moore & Kearsley, 2012; Rienties et al., 2019). Course engagement has been shown to be a significant factor in student success (Bond et al., 2023), satisfaction (LaTour & Noel, 2021) and retention (Pardo et al., 2016a). To support the development of self-regulated skills in K-12 online students, this study focused on analyzing how student behaviors change over time during a school year. Previous studies have focused on utilizing data that is collected at a single point in time and averaged for the span of the course, but this doesn't account for differences in behavior that occur within the course time frame (Du et al., 2021). Research indicates that SRL skills are adaptable and can be influenced by the inclusion of metacognitive strategies during the learning experience (Zimmerman & Schunk, 2001).

To support the inclusion of metacognitive strategies, teachers and learning designers need to be aware of how student engagement behavior changes over time. This exploratory study has focused on identifying the presence of change and possible demographic factors that may influence these changes. From this study, student behavior indicates the highest engagement during quarter 1 (longest average study sessions, least amount of time between study sessions, highest average total study time and highest number of overall sessions on average). As the course progresses, these behaviors change, typically indicating less engagement into quarters 2, 3 and 4.

Student demographics including gender, grade level and previous online experience have some relation to these temporal behaviors, influencing average session lengths, total time spent studying, the number of study sessions and the frequency in which they study during the school week. By better understanding factors related to these behavioral changes, specific strategies can be incorporated to help students enhance their course engagement.