Journal of Online Learning Research (2020) **6**(2), 155-170

Student Clickstream Data: Does Time of Day Matter?

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The relationship between student activity data and performance in the online classroom is well-documented, yet the parameters of this relationship and their implications for K-12 online schools are not yet well understood. This study examined the role of student chronotype (defined here as the time of day a student is most active in an online course) and overall activity level on course performance. Clickstream data captured by a Learning Management System from 414 students enrolled in an eleventh-grade English course in the fall of 2018 at two Midwestern full-time K-12 virtual schools were used to determine chronotype and activity level. Students were classified as one of four possible chronotypes given the mode of their click activity. Results of an ANCOVA showed that students who were most active in the morning significantly outperformed students who were most active in the afternoon and evening. Morning students also tended to be the most active overall. The results of a hierarchical regression revealed that, while chronotype was related to student performance, total student activity had an even greater impact on performance suggesting an interesting interplay between the two factors.

INTRODUCTION

Online learning is known for its flexible nature (Horzum, Önder, & Beşoluk, 2014). Courses are largely asynchronous, particularly at the high school level, and allow students to move through material at their own pace (Lowes, Lin, & Kinghorn, 2015). This feature makes full-time virtual education an appealing option for students who simply prefer a flexible pacing option or whose life circumstances impact the amount of time, and time of the day, that they can devote to their education (Carver, Mukherjee, & Lucio, 2017).

This flexibility, however, may have important implications for student performance that are not yet well understood. One potential influence may be the time of day a student prefers to work, also known as chronotype. Defined as a person's preference for activity, responsibilities, bedtimes, and other actions related to the time of day, chronotype can vary with age, circumstances, and environment, but eventually stabilizes over time (Zerbini & Merrow, 2017). Student chronotype has been found to have a significant relationship with performance in both brick-and-mortar and online higher education environments; students who prefer to work in the evening tend to perform lower than their peers who prefer to work in the morning (Davidson & Ritchie, 2016; Preckel et al., 2013; Rahafar, Maghsudloo, Farhangnia, Vollmer, & Randler 2016; Valladares, Ramírez-Tagle, Muñoz, & Obregón, 2018; Zerbini & Merrow, 2017).

Although chronotype is most easily assessed subjectively via questionnaire, one of the affordances of an online program is the ability to use student data to approximate student activity (Cerezo, Sánchez-Santillán, Paule-Ruiz, & Núñez, 2016; Shelton, Hung, & Lowenthal, 2017). Student activity in online courses is often extracted from clickstream data (i.e., mouse clicks, or hits) and can provide useful information about the amount and type of activity occurring as well as the time and duration of that activity (Dickinson, 2005; Lowes et al., 2015). The variability of student activity in online courses can also lead to a wide variety of performance outcomes (Carver et al., 2017; Li & Tsai, 2017; Pardo, Han, & Ellis, 2017); all of which, the online teacher has little insight into. Student differences on factors such as chronotype can have an impact on learning (Jonassen & Grabowski, 2012; Preckel et al., 2013). By exploring the relationship between the time of day students are most active, their level of activity in their course, and their associated performance, we can provide teachers insight into key student differences.

The current study employed student activity data as a means of establishing student chronotype and tested whether the time of day a student is most active in a course was related to final course performance. Prior research has found a significant, albeit relatively weak, association between the time of day a student works and performance (Valladares et al., 2018; Zerbini & Merrow, 2017; Zerbini et al., 2017). However, current research is based on a mixture of brick and mortar, online, and blended programs and has generally focused on higher education students. The current study sought to expand the existing literature by focusing on students enrolled at full-time K-12 virtual schools and by using learning management system (LMS) student activity data as a means of identifying student chronotype.

Participants in the current study were eleventh-grade students enrolled in an English course at two Midwestern, full-time, K-12 virtual schools. Both locations use the same course, curriculum, and proprietary LMS from which student performance and clickstream data were extracted. The purpose of this research is to go beyond identifying the impact chronotype may have on student performance and to generate insights about how, and to what degree, student activity within a course can help educators provide data-driven support and foster higher engagement and performance (Dvorak & Jia, 2016; Quinn & Gray, 2020).

BACKGROUND

Online learning is a growing option for many students, especially for primary and secondary education (Curtis & Werth, 2015; Liu & Cavanaugh, 2011, 2012; Shelton et al., 2017). Currently, full-time virtual schools can operate in 37 states (National Center for Education Statistics, 2017), and as most recently measured, 295,518 students were enrolled in full-time virtual schools during the 2016-17 school year (Miron, Shank, & Davidson, 2018). As enrollment in these institutions is expected to expand, more research is needed to understand how to deliver an effective learning experience and optimize student performance. Student activity captured by the LMS provides a unique and valuable opportunity for educators to generate data-driven insights about online learning (Lowes et al., 2015).

LITERATURE REVIEW

Clickstream Data and Learning Analytics

Unlike brick and mortar classrooms, student behavior in the online environment is often not directly observable. Clickstream data captured by an LMS, or peripheral tracking software, are used to approximate student behavior in the virtual classroom (Cerezo et al., 2016; Il-Hyun, Kim, & Yoon, 2015; Kim, Park, Yoon, & Jo, 2016). Types of activity data can include login times and duration, discussion posts, resources used, multimedia usage, video playback behavior, and overall ‘hits’ in the online course. Learning analytics has emerged as a way for researchers and educators to glean actionable insights from this type of student activity data (Gasevic, Dawson, & Siemens, 2015; Jorno & Gynther, 2018; Rogers, Dawson, & Gasevic, 2016; Siemens, 2013). These insights can be used to support educators with a more data-driven instructional experience and enable them to better personalize, support, predict, and intervene in student learning(Cerezo et al., 2016; Reyes, 2015).

One important goal of learning analytics research is to explain student outcomes to better support student learning and intervene where appropriate (Firat, 2016; Lu et al., 2018). However, while student activity data has been a popular data source (Carver et al., 2017; Colthorpe, Zimbardi, Ainscough, & Anderson, 2015; Dvorak & Jia, 2016; Lowes et al., 2015; Shelton et al., 2017; Xing, Guo, Petakovic, & Goggins, 2015), researchers have cautioned against reducing students down to their data points at the risk of overinterpreting or losing important contextual information related to the learning process (Gasevic et al., 2015; Lara, Lizcano, Martínez, Pazos, & Riera, 2014). Clickstream data can also mask underlying factors that impact activity levels and subsequent performance (Lara et al., 2014; Perrotta & Williamson, 2018; Tempelaar, Rienties, & Nguyen, 2017). That said, there remains a growing interest within learning analytics research to utilize student activity data, especially within K-12 online education, to glean insights into how varying levels of activity impact student outcomes (Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014; Lowes et al., 2015).

Several studies have successfully demonstrated the relationship between student clickstream data and course performance (Dickinson, 2005; Dvorak & Jia, 2016; Lu et al., 2018; You, 2015). In particular, the amount of activity in online courses has been shown to relate to student outcomes (Agudo-Peregrina et al., 2014; Cerezo et al., 2016; Li & Tsai, 2017; Liu & Cavanaugh 2011, 2012; Lowes et al., 2015). Hrastinski (2009) posited in his theory of online learning as online participation, that to increase online learning, participation online also needs to be increased. Interestingly, while obvious differences exist between directly observing brick-and-mortar students attending their course and student activity among virtual students, the positive correlation between student activity and performance in the two environments is relatively similar (Dickson, 2005).

Some researchers, however, have found that the level of activity in the LMS had a negative or intermediate relationship with student performance (Cavanaugh et al., 2016; Colthorpe et al., 2015). Liu and Cavanaugh (2012) examined fully online Algebra courses for K-12 students and found that those who logged into the LMS less frequently achieved higher scores, while students who spent more time in the LMS performed better. Carver, Mukherjee, and Lucio (2017) found that time spent in various components of nine online undergraduate courses did not predict what specific final grade the student would obtain, but that the time spent in synchronous sessions predicted whether or not a student would achieve a final grade of A. Dickinson (2005) encouraged consumers of LMS activity data to consider that the quality of student activity may reflect more efficient learning than the quantity of student activity. These findings along with the current body of research confirm that having additional information about student behavior and level of interaction with the LMS can provide valuable insights for educators and administrators alike.

Chronotype

One factor that has been shown to impact student performance is student chronotype (or inner biological clock), which has been found to relate to the time of day that a student is most productive (Enright & Refinetti, 2017; Horzum et al., 2014; Luo et al., 2018; Rahafar et al., 2016; Zerbini & Merrow, 2017). Chronotype can be assessed using students' self-reported preferences for the time of day they prefer to do their schoolwork, and these preferences have been shown to impact levels of activity and performance; Morningness is often associated with higher performance than eveningness (Enright & Refinetti, 2017; Preckel et al., 2013; Zerbini & Merrow, 2017). Specifically, students who prefer to work in the morning are also more active (Luo et al., 2018) and outperform students who work in the evening (Enright & Refinetti, 2017).

Researchers have extended this work to online courses to determine if the flexibility of online learning is a solution to the impact chronotype has on synchronous student performance. However, this work has been limited primarily to higher education. Dvorak and Jia (2016) examined whether the level of undergraduate student activity, time of day, and proactive work on assignments in the course management system were associated with higher performance. They found that students who received the lowest scores in the course (or those who ended up withdrawing) visited the online course far less than their peers, and when they did it was mostly late at night. Conversely, students with higher course scores tended to visit the course most frequently and in the early afternoon. These findings mirror the current study's aim and suggest that both level and time of activity may impact student course performance despite the flexibility of the course. Luo et al. (2018) found that students who preferred to work in the morning had more hits in the LMS during their preferred time than in the evening, and similarly, students who preferred to work in the evening had more hits in the evening than in the morning. While the student's preferred time to work in the LMS did not predict course performance, their level of activity did.

Horzum, Önder, and Beşoluk (2014) captured student chronotype and motivation toward learning via survey. They found that among the undergraduate online learning students, there was no significant difference in performance based on chronotype. Instead, there was a significant difference among the chronotypes, with morning-type students exhibiting the highest levels of motivation. Similarly, Roeser, Schlarb, and Kubler (2013) found that motivation had a mediating effect between chronotype and student performance in adolescent brick-and-mortar students. Morning-type students had a positive association with motivation, and hence, performance. These findings suggest that the flexibility of online learning could enhance evening-type student performance by alleviating the effect chronotype can have on student motivation and by association, performance.

RESEARCH QUESTIONS

Given that higher activity in the LMS is related to higher academic performance (Luo et al., 2018), the current study sought to explore how the time of day students work within online courses relates both to activity level and performance. Prior research with online higher education and brick-and-mortar settings suggests an important relationship between time of day a student prefers to work, activity level, and academic performance. However, there is a gap in research available for K-12 students, and the question is particularly relevant given the inherent flexibility of the virtual K-12 online classrooms. Thus, we first analyzed how course performance varied with the time of day students were most active based on LMS activity data. Next, we examined the effect of total activity level on course performance after controlling for the time of day they were most active. Late enrollment was a covariate in both analyses as that is a known confound in education research. Highly mobile students, or students who change schools more than the normal rate, end up enrolling late and consequently performing below their typically enrolled peers (Welsh, 2017).

RQ 1: Did performance among eleventh-grade English students enrolled in full-time virtual schools differ based on the time of day they were most active in the online course after controlling for late enrollment?

RQ 2: Did total activity (# of student hits) throughout the course impact student performance in eleventh-grade English after controlling for the time of day they were most active and late enrollment?

METHODS

Participants and Study Design

The sample included 414 students enrolled in an eleventh-grade English course in two full-time virtual schools. The school principals and student caretakers provided their consent to have their data used for this analysis via electronic form in the LMS. All students completed the course with a final grade. An Analysis of Covariance (ANCOVA) and hierarchical linear regression were used to analyze the differences in the English 11 A course scores as a function of the time of day that students were most active in the course. We also investigated how the total number of hits students produced in the course throughout the semester impacted their course score after controlling for the time of day they were most active.

Data Collection

Analyses were based on Google page tracker and proprietary LMS data for an English 11 A course taken by students in the fall of 2018 at two Midwestern full-time virtual K-12 schools. These locations utilize the same proprietary LMS, curriculum, and course materials. Google page tracker captures the clicks a student makes within the virtual English 11 A course. When students click on a resource that directs them to a third-party site or otherwise external destination to the LMS, Google page tracker stops tracking clicks until they re-enter the LMS. For the current analysis, the data consisted of student enrollment status, English 11 A course score recorded at the end of the semester in the LMS, and the time of day that the student was most active based on Google page tracker.

Mode of Student Activity

Student clickstream data captured within the LMS were used to obtain both student activity levels in the online course and the time of day the student was most active (a proxy for Chronotype). The time of day a student most frequently worked in the virtual classroom (mode) was used to determine what time of day they were most active, notwithstanding their preference or biological predisposition. This method is similar to the one used by Luo et al. (2018) in which mouse-clicks (i.e. hits) in the LMS were used to approximate student activity.

Mouse clicks, or hits, a student made within their English 11 A course were captured by Google Page Tracker. These were subsequently recorded, totaled, and categorized into one of four times of day: morning (5 AM-11 AM), afternoon (12 PM-4 PM), evening (5 PM-11 PM) and overnight (12

AM-4 AM). The time of day a student was most active was calculated by taking the mode of these categories for each student. All 414 students were classified into one of the four times of the day (chronotype) when they are most active given the mode of their click activity.

Academic Performance and Enrollment

English 11 A course score was recorded at the end of the semester in the LMS. Final grades ranged from 1% to 98% with a mean of 71.5%. Also, in the data were students' enrollment statuses; that is, whether the student was enrolled on the first day of the fall semester or late. There were 309 (74.6%) students enrolled on time, and 105 (25.4%) students enrolled late.

RESULTS

The analyses proceeded in two steps. First, a one-way ANCOVA was used to explore the relationship between English course performance among eleventh-grade full-time virtual students and the time of day that they were most active in the course after controlling for the effect of late enrollment. Second, hierarchical regression was employed to assess whether total activity within the online course had an impact on student performance after controlling for the time of day they were most active and late enrollment.

Descriptive Statistics

As shown in Table 1, students who were most active in the morning earned, on average, the highest final score in the course (76%), while students who were most active overnight had the lowest performance of the chronotype classifications (62%). The group of overnight chronotype students was the smallest. Table 2 displays the average total number of hits made in the course based on chronotype classification. Students who were most active in the LMS in the morning were also the most active users overall based on the average total amount of hits made. This suggests the importance of investigating student chronotype in the context of their overall activity level in the course.

Table 1
Course Score and Late Enrollment by Chronotype

Chronotype	*N*	Avg. course score	*SD*	Enrolled late
Morning	94	76.4%	17.3	22.3%
Afternoon	237	71.2%	20.2	27.2%
Evening	72	67.6%	20.1	28.8%
Overnight	11	62.1%	26.6	28.3%

Table 2
Average Total Hits by Chronotype

Chronotype	*N*	Avg. total hits	*SD*
Morning	94	1156	574
Afternoon	237	974	389
Evening	72	932	272
Overnight	11	980	332

One-Way ANCOVA

A one-way ANCOVA was run to determine the effect of student chronotype on final English course scores after controlling for late student enrollment. Although the covariate of late enrollment was binary, the homogeneity of slopes assumption was tested. The relationship between late enrollment and English score was found to be consistent among the majority of chronotype categories (afternoon, evening, and overnight). However, the relationship between the covariate and English scores differed (changed direction) for morning students. Standardized residuals were abnormally distributed, as assessed by Shapiro-Wilk's test ($p < .001$). However, ANCOVA is known to be robust against this minor violation (Rutherford, 2011). There were homoscedasticity and homogeneity of variances, as assessed by visual inspection of a scatterplot and Levene's test for homogeneity of variance ($p = .54$), respectively. Independence of residuals was assessed by the Durbin-Watson statistic of 1.77 and fell within the appropriate range of 1.5 and 2.5 (Field, 2011). The interaction of chronotype and the covariate was not significant. There was no multicollinearity as the tolerance value was not smaller than 0.1, and variance inflation factor (VIF) value was not larger than 10. There were no outliers in the data as assessed by the absence of cases with standardized residuals greater than ±3 standard deviations. With all assumption tested, the results of the analysis can still be interpreted.

The results revealed that after adjustment for student's late enrollment status, there was a statistically significant difference in English course scores between the chronotype categories, F (4, 414) = 6.46, $p < .001$, partial $\eta2 = .06$. However, the overall adjusted $R^2 = .050$, was a small effect size. The covariate of late enrollment was significantly related to the course score, F (1, 409) = 14.33, $p < .001$, partial $\eta2 = .04$, with a small effect size. There was also a significant effect for student chronotype on the course score after controlling for late enrollment, F (3, 409) = 3.44, $p < .05$, partial $\eta2 = .03$. Again, a small effect size was found.

Table 3
ANCOVA for English Course Score Differences among Times of Day and On-Time Enrollment

	Type III sum of squares	*df*	Mean square	*F*	*p*	Partial η^2	Observed power [b]
Corrected Model	.98[a]	4	.25	6.46	.00***	.06	.99
Intercept	61.39	1	61.39	1622.30	.00***	.80	1.00
Enrollment	.54	1	.54	14.33	.00***	.04	.97
Chronotype	.39	3	.13	3.44	.02*	.03	.77
Error	15.48	409	.04				
Total	228.30	414					
Corrected Total	16.46	413					

Note: a. R^2 = .059 (Adjusted R^2 = .050), b. Computed using alpha = .05
a < .05, ** a < .01, * a < .001*

Post hoc analyses were performed using bootstrap pairwise comparisons of the estimated marginal means and were adjusted due to the presence of a covariate using Bonferroni adjustment (See Table 4). All popular post hoc methods (Fisher's LSD, Bonferroni, and Sidak) indicated similar significant differences. Only the results of the Bonferroni post hoc are displayed. There was a significant difference in the English 11 A course score between morning students and afternoon students M_{diff} = .048, 95% CI [-.001, .092], $p < .05$. There was also a significant difference in the course score between morning students and evening students, M_{diff} = .083, 95% CI [.022, .141], $p < .01$.

Table 4
Bootstrap for Pairwise Comparisons (Bonferroni Adjustment)

Chronotype (I)	Chronotype (J)	Mean diff (I-J)	Bias	Std. error	*p*
Morning	Afternoon	.048	-.001	.022	.039*
	Evening	.083	-.001	.029	.009**
	Overnight	.138	-.002	.076	.057
Afternoon	Morning	-.048	.001	.022	.039*
	Evening	.035	.001	.026	.185
	Overnight	.091	.000	.074	.193
Evening	Morning	-.083	.001	.029	.009**
	Afternoon	-.035	-.001	.026	.185
	Overnight	.055	-.001	.077	.442
Overnight	Morning	-.138	.002	.076	.057
	Afternoon	-.091	.000	.074	.193
	Evening	-.055	.001	.077	.442

**a < .05, ** a < .01*

Hierarchical Regression

A hierarchical multiple regression was used to determine whether the addition of total student activity level (hits) improved the prediction of English 11 A course score over and above late enrollment and chronotype (See Tables 5 and 6). Analyses of the assumptions for hierarchical linear regression revealed a violation of homoscedasticity as assessed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. The assumption of normality was also slightly violated. For this reason, a square transformation was performed on the dependent variable (English 11 A course score) (Field, 2017). The assumptions of homoscedasticity and normality were then met via non-significant Breusch-Pagan test statistic and P-P plot, respectively. There was evidence of linearity as assessed by partial regression plots and a plot of studentized residuals against the predicted values. Independence of residuals was assessed by the Durbin-Watson statistic of 1.78 and fell within the appropriate range of 1.5 and 2.5 (Field, 2011). There was also no clear violation when standardized residuals were plotted on an autocorrelation function (ACF) plot. There was no evidence of multicollinearity, as assessed by tolerance values greater than 0.1. There was 1 student with standardized residual greater than ±3 standard deviations (which was removed as an outlier), although there were no leverage values greater than 0.2, and no values for Cook›s distance above 1. With the square transformation of student course scores, all assumptions were met, and the results of the hierarchical multiple regression can be considered valid.

The full model of late enrollment, chronotype, and total activity (block 2) was statistically significant, $R^2 = .26$, $F\ (1, 406) = 108.02$, $p < .001$; adjusted $R^2 = .25$. Late enrollment and chronotype (block 1) had a statistically significant relationship to English course scores, $R^2 = .06$, $F\ (2, 407) = 12.64$, $p < .001$. The addition of total activity also related to a statistically significant increase in the amount of variance the model accounted for, $\Delta R^2 = .20$.

According to the model displayed in Table 5, chronotype and late enrollment explained 5.8% of the variance in student final course scores (block 1). The addition of total hits the student produced in the course in block 2 of the model explained an additional 19.8% variance in course score, the largest impact on the English course score. The time of day a student is most active (chronotype), and late enrollment, may simply provide context to the more impactful variable of a student's total activity throughout the course. This could indicate that the time of day when a student is most active still matters. Students who start their work in the morning may have more time in the day to keep clicking and higher levels of overall click activity. Students who begin to be active in the evening may simply have less time left in the day to generate high levels of activity.

Table 5
Hierarchical Regression Model and ANOVA Summary

Model Summary									ANOVA		
Block	*R*	R^2	Adj. R^2	Std. error	ΔR^2	ΔF	*df*(1,2)	*p*	*F*	*df*(1,2)	*p*
1	.24a	.06	.05	.23	.06	12.64	2, 407	.00	12.64	2, 407	.00
2	.51b	.26	.25	.20	.20	108.02	1, 406	.00	46.65	3, 406	.00

Note: a. Constant, Chronotype and Enrollment,
b. Constant, Total hits, Covariates: Chronotype and Enrollment
Dependent Variable: English Course Score (squared)

Table 6
Hierarchical Regression Coefficients

Block		B	β	*p*	*VIF*
1	Late	-.09	-.17	.00	1.00
	Chronotype	-.05	-.16	.00	1.00
2	Late	-.06	-.12	.01	1.02
	Chronotype	-.04	-.11	.01	1.02
	Total Hits	.00	.45	.00	1.03

Note: Dependent Variable: English Course Score (squared)

DISCUSSION

This study used a novel way to approximate chronotype with student activity data to shed light on a previously under-researched population of online students. Unlike previous studies that have relied on student surveys, student activity data captured by the LMS were used to determine the time of day eleventh-grade students at full-time virtual schools were most active in their English course. Ultimately, students who were most active in the morning performed significantly better than students who were most active in the afternoon and evening. It's also likely that morning students do significantly better than overnight students, yet our tests failed to detect any significant effects due to the small number of students who were most active overnight. These findings mirror current research that focused on brick and mortar settings and higher education (Enright & Refinetti, 2017; Zerbini

& Merrow, 2017). However, like Luo et al. (2018), students in the current study who worked most frequently in the morning were also the most active overall based on their total number of hits in the LMS throughout the course. This suggests that while course performance is related to the time of day a student is working, the amount of activity they exhibit may have an even greater impact. Future research should continue to explore the relative influence of these two factors.

As full-time, virtual K - 12 programs become an increasingly desirable option for students who seek a more flexible learning model, researchers will need to continue to explore how this flexibility impacts student outcomes. The findings from this study were able to show that with the flexibility of an online environment, student choices about time of day that they work (chronotype) and student activity levels play a part in student outcomes. Online learning programs offer students the opportunity to adapt their education to their preferred learning style and environment and optimizing this experience for students is vital to the future of online education. The findings from the current study suggest more information is needed surrounding the time of day K-12 students are able, or choose to, complete their online coursework. Future K-12 research could use surveys to better contextualize the LMS chronotype method used here to determine if students are working in the evening by choice, or by circumstance. Virtual educators rarely have insight into these student factors.

More broadly, while the findings from this study begin to illuminate the relationships between the time and amount of click activity, more can be learned about full-time K-12 students based on LMS activity such as effective patterns of activity and evidence of engagement or other affective states (such as boredom or frustration) that may be reflected in the data. Ultimately, as more information is gathered, student activity data could be used as a non-invasive proxy for an array of student attitudes and behaviors that can inform online instructional practices and enable more individualized learning experiences for students.

Declaration of Conflicting Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) declared no financial support for the research, authorship, and/or publication of this article.

Acknowledgments

The authors would like to thank Michael K. Barbour for his insight into the topics related to this study and the feedback he provided on the article's content.

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