Making Connections

An analysis of student engagement patterns and online course outcomes in Wisconsin

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Key findings

This study used data from the fall 2014 semester at Wisconsin Virtual School to examine whether patterns of student engagement in online courses (the amount of time a student was logged in to the online course each week and how this varied over time) were associated with course outcomes (the percentage of possible points earned in the course and the percentage of course activities completed). Key findings include:

- Student enrollments in online courses followed one of six engagement patterns, with average engagement ranging from 1.5 hours to 6 or more hours per week.
- Most students (77 percent) steadily engaged in their online course for 1.5 or 2.5 hours per week.
- Students who engaged in their online course for at least 1.5 hours per week typically earned a high enough percentage of possible points to pass the course.
- Students who engaged in their online course for two or more hours per week had better course outcomes than students who engaged for fewer than two hours per week.

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Summary

Student enrollment in online courses has increased in the past 15 years and continues to grow (Watson, Pape, Murin, Gemin, & Vashaw, 2014). However, little is known about students' education experiences or online course outcomes. These are areas of particular interest to the Midwest Virtual Education Research Alliance, whose goal is to understand how to support student success in online courses. Members of the alliance partnered with Regional Educational Laboratory Midwest to develop and conduct this study on how students engage in online learning and how student engagement patterns are associated with online course outcomes. Findings from this study may help inform policymakers, state and local education agencies, and online learning providers as they seek ways to support student success in online courses.

This study analyzed learning management system data and student information system data for all core, elective, and Advanced Placement online high school course enrollments during the fall 2014 semester. The data were collected by Wisconsin Virtual School, a state-level online learning program that partnered with 194 Wisconsin districts to serve 5,511 student enrollments in 256 supplemental online courses during the 2014/15 school year.

Analyses looked for student engagement patterns in online courses and the percentage of student enrollments that followed each pattern; differences among student engagement groups (groups of student enrollments that followed a given pattern) in course type taken, gender, or grade level; and associations between student engagement in online learning and online course outcomes. Engagement refers to behavioral engagement and was defined as the amount of time a student was logged in to the online course each week. Course outcomes were measured by the percentage of possible points earned in the course (which students' home schools use to assign a letter grade based on the local grading scale) and the percentage of course activities completed.

Analyses revealed six engagement patterns among student enrollments in Wisconsin Virtual School online courses. Each pattern represents an average of the total time a student spent logged in to the online course each week,[1] as well as how that amount varied across the semester (for example, increasing, decreasing, or remaining steady). The six student engagement patterns and the percentage of student enrollments in each were as follows:
- *Initial 1.5 hours with decrease (8 percent).* Engagement of approximately 1.5 hours per week at the beginning of the semester that drops off to near 0 hours midway through the semester.
- *Steady 1.5 hours (39 percent).* Steady engagement of approximately 1.5 hours per week, with a slight increase toward the end of the semester.
- *Initial 2 hours with spike (4 percent).* Engagement of approximately 2 hours per week at the beginning of the semester that increases steadily after the midpoint of the semester to nearly 12 hours per week in the final week.
- *Steady 2.5 hours (38 percent).* Steady engagement of approximately 2.5 hours per week across the semester.
- *Steady 4+ hours (8 percent).* Consistent engagement of approximately 4 hours or more per week across the semester.
- *Variable 6+ hours (2 percent).* High but variable engagement ranging from approximately 6 hours per week at the beginning, middle, and end of the semester and peaking to near 10 hours between those points (during weeks 3 and 17).

Students who engaged in their online course for at least 1.5 hours per week (all groups but the initial 1.5 hours with decrease group) typically earned a high enough percentage of possible points to pass the course even though they varied in total time logged in each week initially and across the semester. However, the steady 1.5 hours group performed significantly worse than the initial 2 hours with spike, steady 2.5 hours, steady 4+ hours, and variable 6+ hours groups in percentage of possible points earned in the course and percentage of course activities completed.

Although this study is not designed to determine whether the relationship between student engagement patterns and course outcomes is causal, educators may want to use the findings to identify students who need additional support to succeed—for example, the initial 1.5 hours with decrease and steady 1.5 hours engagement groups, which had poorer course outcomes. In addition, online learning programs across the country may be able to use the findings as a framework for investigating the data available in their learning management systems and student information systems.

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Why this study?

Student enrollment in online courses has increased in the past 15 years and continues to grow (Watson et al., 2014). Districts and public high schools enroll students in online courses for a variety of reasons, such as to provide students with opportunities to take courses not otherwise available to them or to take college-level courses, as well as to personalize student learning or to provide students with an alternative learning environment (Means, Bakia, & Murphy, 2014; Queen & Lewis, 2011). In addition, five states (Alabama, Arkansas, Florida, Michigan, and Virginia) require that students take at least one online or blended online and face-to-face course to graduate high school (Watson et al., 2014). Specific requirements vary across states, with one state (Alabama) requiring that the online course be in a core subject area and all but one state (Virginia) requiring that the online course be credit bearing. In all cases the requirement is intended to broaden students' educational experiences to prepare them for college and the workplace. Definitions of online courses and other key terms used in this report are provided in box 1.

This study examines how students engage in online learning and how student engagement patterns are associated with online course outcomes

However, little is known about students' educational experiences or online course outcomes. Student failure to complete online courses is a substantial problem for some online learning programs (Angelino, Williams, & Natvig, 2007). And although providing students the opportunity to personalize their learning is often stated as a potential benefit of online learning (International Association for K–12 Online Learning, 2011a), little is known about whether or how students take advantage of the opportunity. A recent study conducted in collaboration with Regional Educational Laboratory Midwest's Virtual Education Research Alliance found that two of the greatest challenges for online teachers at Wisconsin Virtual School—a state-level online learning program that partners with districts in the state to offer supplemental online courses for middle and high school students (see box 2 for a description of Wisconsin Virtual School)—were keeping students engaged throughout the course and getting students to complete the course (Zweig, Stafford, Clements, & Pazzaglia, 2015).

The current study examines how students engage in online learning and how student engagement patterns are associated with online course outcomes. Such information may help inform policymakers, state and local education agencies, and online course providers in developing or refining online programs and promoting student success in online courses. Although this study is not designed to determine whether the relationship between student engagement patterns and course outcomes is causal, educators may want to use the findings to identify students who need additional support to succeed. In addition, the study provides a framework for how other online learning programs can use the data available in their learning management systems and student information systems to examine student engagement and online course outcomes.

Types of student engagement

In response to concerns that schools are not adequately preparing students for success in college and beyond, some researchers and policymakers have placed a spotlight on how factors such as student engagement may play an important role in academic success (Farrington et al., 2012; Lawson & Lawson, 2013; Rosen, Glennie, Dalton, Lennon, & Bozick, 2010). Although research on student engagement includes many definitions and conceptualizations, one recent literature review identified three types of engagement—affective,

Box 1. Key terms

Advanced Placement. A program offered by the College Board that gives high school students the opportunity to take college-level courses for college credit.

Core course. A course required for high school graduation. In Wisconsin core courses are English language arts (four credits), social studies (three credits), math (three credits), science (three credits), and physical education (1.5 credits; Wisconsin Statutes and Annotations, 2014).

Course outcome. The percentage of possible points earned in the course or the percentage of course activities completed.

Credit recovery course. A course that allows students to obtain credit for classes they have failed.

Elective course. A course other than an Advanced Placement, core, or credit recovery course.

Learning management system. The technology platform through which students access online courses. It generally includes software for creating and editing course content, communication tools, assessment tools, and other features for managing the course (International Association for K–12 Online Learning, 2011b).

Online course. Any course offered over the Internet (International Association for K–12 Online Learning, 2011b).

Online learning. Education in which instruction and content are delivered primarily over the Internet (that is, electronically). The term does not include print correspondence courses; courses delivered by broadcast television or radio, CD, or videocassette; or standalone educational software programs that do not have a substantial Internet-based instructional component (International Association for K–12 Online Learning, 2011b).

Online learning program. An organized offering of courses delivered primarily over the Internet (International Association for K–12 Online Learning, 2011b).

Online teacher. A staff member of the online learning program who teaches students in online courses.

Onsite facilitator. A staff member at a brick-and-mortar school responsible for monitoring and supporting students in the school who are taking online courses. The staff member filling this role can range from a classroom teacher to a guidance counselor to an aide.

Student engagement. Researchers have identified several types of engagement. This study focuses on behavioral engagement and defines student engagement as the amount of time that a student is logged in to the online course.

Student engagement group. A group of students who follow a given student engagement pattern.

Student engagement pattern. A pattern of student engagement measured and modeled over time, such as throughout the duration of a course.

Student information system. A system for storing and managing student data, including contact information; demographic characteristics such as gender, grade level, age, race/ethnicity, special education status, and English learner student status; and previous academic performance.

Box 2. Wisconsin Virtual School

Wisconsin Virtual School is a state-level online learning program that partners with districts throughout Wisconsin to offer 256 supplemental online courses for middle and high school students. In operation since 2000, Wisconsin Virtual School served 5,511 student enrollments in 194 Wisconsin districts during the 2014/15 school year. The online learning program employs 54 Wisconsin-certified online teachers, who are expected to be actively involved in planning instruction, assessing learning, and communicating with students. Wisconsin Virtual School also requires that partnering districts have an onsite facilitator (called a "local education guide") to monitor progress and provide face-to-face support for students enrolled in online courses.

The online courses are asynchronous, which means that students and teachers typically do not log in to the online course at the same time. Students are expected to log in to the learning management system daily to check email and course announcements and are encouraged to communicate with their teacher at least once a week. While logged in, students review course content (including interactive audio and video clips), complete practice activities, post on discussion boards, attend real-time online chat sessions with the teacher and other students, and complete assignments for each unit sequentially before taking quizzes or exams. All coursework must be submitted through the learning management system, but some courses include assignments that require reading, writing, or other work that occurs outside the learning management system. As such, the act of logging in to an online course is conceptually similar to spending time in a class in a brick-and-mortar school and possibly some time doing homework, depending on the nature of the particular course and assignment.

Wisconsin Virtual School provides certificates of completion for all students who complete 95–100 percent of the possible course points and reports the percentage of points earned to students' schools. The home district then determines whether 95–100 percent course activity completion with a passing grade, which is determined locally, provides an earned credit or advancement.

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cognitive, and behavioral—and found that all three are positively associated with student success in traditional face-to-face schooling (Lawson & Lawson, 2013). The current study focuses on behavioral engagement, which includes the amount of time students spend on coursework. For online courses, engagement can be partially measured by the amount of time a student is logged in to the online course each week, which is collected by learning management systems (the online platforms that deliver online courses).

Student engagement in online courses

Although research and recommendations exist for promoting student engagement in face-to-face school settings, it is unclear whether those recommendations translate to the online environment, because online settings involve unique considerations and challenges. The challenges include physical distance, lack of interaction, and psychological distance (Moore, 1993; Murphy & Rodriguez-Manzanares, 2008; Rovai, 2002). Furthermore, investigating engagement in online learning may be particularly important in light of research suggesting that student attrition and course failure are problems for some online programs (Carr, 2000; Freidhoff, 2015; Freidhoff, DeBruler, & Kennedy, 2014; Roblyer, 2006; Roblyer & Davis, 2008; Rovai & Wighting, 2005; Simpson, 2004). Understanding whether and how students' engagement in online learning is associated with course outcomes may provide a foundation for future research on how to support student engagement and success.

It is unclear whether research and recommendations for promoting student engagement in face-to-face school settings translate to the online environment, because online settings involve unique considerations and challenges, including physical distance, lack of interaction, and psychological distance

This study builds on recent research using learning management system data and student information system data to identify factors that predict student success in online courses. Hung, Hsu, and Rice (2012) found that students with higher engagement (as measured by the total number of learning management system activities across the span of the course, including frequency of login, frequency of modules accessed, frequency of clicks, and frequency of discussion board posts) tended to have higher final grades. Liu and Cavanaugh (2011) found that the number of times a student logged in to the learning management system throughout the course and the total number of minutes a student was logged in throughout the course were associated with students' final scores in two online biology courses offered through a Midwestern state virtual school. They also found that the total number of minutes that a student was logged in throughout the course was the strongest predictor of final scores in a model that accounted for student demographics and the number of teacher comments throughout the course. Because these studies were correlational in nature, it is not possible to determine the direction or extent of causality between engagement and course outcomes. It is possible that factors such as motivation or academic ability cause both student engagement and course outcomes.

The total amount of time a student was logged in to the online course each week was used to investigate student engagement patterns in online courses

The current study builds on these earlier studies by identifying distinct patterns of student engagement within online courses over time and exploring whether the patterns are associated with online course outcomes.

What the study examined

This study used data collected by Wisconsin Virtual School's learning management system and student information system (see box 2 for a description of Wisconsin Virtual School). In particular, the total amount of time a student was logged in to the online course each week was used to investigate student engagement patterns in online courses.

Three research questions guided the study:
- How many student engagement patterns are evident in online courses, and what percentage of student enrollments follow each pattern?
- Do student engagement groups differ in course type taken, gender, or grade level?
- How are student engagement patterns associated with the percentage of possible points earned in the course and the percentage of course activities completed?

The research questions were addressed by first identifying patterns of student engagement with online courses and then examining the relationship between the patterns and course outcomes (see box 3 for a summary of the study's data and methodology and appendix A for more detail).

What the study found

Student enrollments followed one of six engagement patterns in Wisconsin Virtual School online courses. In five of the six engagement groups students typically earned a high enough percentage of possible points to pass their course, and students who engaged for two or more hours per week had better course outcomes than students who engaged for fewer than two hours per week.

Data

Wisconsin Virtual School provided student information system data and learning management system data. The student information system data included course characteristics, student demographic characteristics, and course outcomes (percentage of possible points earned in the course and percentage of course activities completed). The learning management system data included the amount of time each week that each student was logged in from August 1, 2014, to February 28, 2015. The two data files were merged using Wisconsin Virtual School's student IDs to link the files.

This study included 1,512 student enrollments from 109 Wisconsin Virtual School Advanced Placement (15 percent of student enrollments), core (36 percent), and elective (49 percent) high school courses from the fall 2014 semester. The study did not analyze credit recovery courses because those courses have a shortened timeline. The sample included 1,179 unique students, 170 of whom took more than one online course. Sixty percent of student enrollments were female students, and 40 percent were male students. The majority of student enrollments were in grades 9–12: 11 percent were in grade 9, 25 percent were in grade 10, 28 percent were in grade 11, and 32 percent were in grade 12. Three percent of student enrollments were in grades 5–8.

Methodology

To answer the research question on student engagement patterns, the study team used group-based trajectory modeling, which first identifies patterns of behavior across time and then assigns individuals to pattern-based groups. To answer the research question on differences in course type taken, gender, and grade level across student engagement patterns, descriptive statistics of those characteristics were calculated for each engagement group, and tests of statistical significance were used to compare the characteristics across groups. To answer the research question on the association between student engagement and course outcomes, regression analysis that accounts for how students are similar within online courses was used; it compared the outcomes of students displaying the most common engagement pattern with students displaying each of the other engagement patterns, while statistically adjusting for student and course characteristics.

Student enrollments in online courses followed one of six engagement patterns

The amount of time a student was logged in to the online course each week was best represented by a model with six student engagement patterns (figure 1). The two most common patterns each accounted for almost 40 percent of student enrollments; the least common pattern accounted for just 2 percent. The six patterns and the percentage of student enrollments in each are:

- *Initial 1.5 hours with decrease (8 percent).* Engagement of approximately 1.5 hours per week at the beginning of the semester that drops off to near 0 hours midway through the semester.
- *Steady 1.5 hours (39 percent).* Steady engagement of approximately 1.5 hours per week, with a slight increase toward the end of the semester.
- *Initial 2 hours with spike (4 percent).* Engagement of approximately 2 hours per week at the beginning of the semester that increases steadily after the midpoint of the semester to nearly 12 hours per week in the final week.

- *Steady 2.5 hours (38 percent).* Steady engagement of approximately 2.5 hours per week across the semester.
- *Steady 4+ hours (8 percent).* Consistent engagement of approximately 4 hours or more per week across the semester.
- *Variable 6+ hours (2 percent).* High but variable engagement ranging from approximately 6 hours per week at the beginning, middle, and end of the semester and peaking to near 10 hours between those points (during weeks 3 and 17).

Student enrollments in the six engagement groups differed in course type taken, gender composition, and grade-level composition

Several statistically significant differences in characteristics emerged across student engagement groups:
- The initial 2 hours with spike, steady 2.5 hours, steady 4+ hours, and variable 6+ hours groups each had a higher percentage of student enrollments in Advanced Placement courses (19–31 percent) than the initial 1.5 hours with decrease (7 percent) and steady 1.5 hours groups (9 percent; table 1).
- The initial 2 hours with spike group had a higher percentage of male student enrollments (57 percent) than the steady 1.5 hours, steady 2.5 hours, steady 4+ hours, and variable 6+ hours groups, which had close to the sample average (40 percent).
- The initial 1.5 hours with decrease and variable 6+ hours groups had a higher percentage of student enrollments in grade 9 (20 percent and 17 percent) than the other groups (9–11 percent).

Figure 1. Student enrollments in Wisconsin Virtual School online courses followed one of six engagement patterns, fall 2014
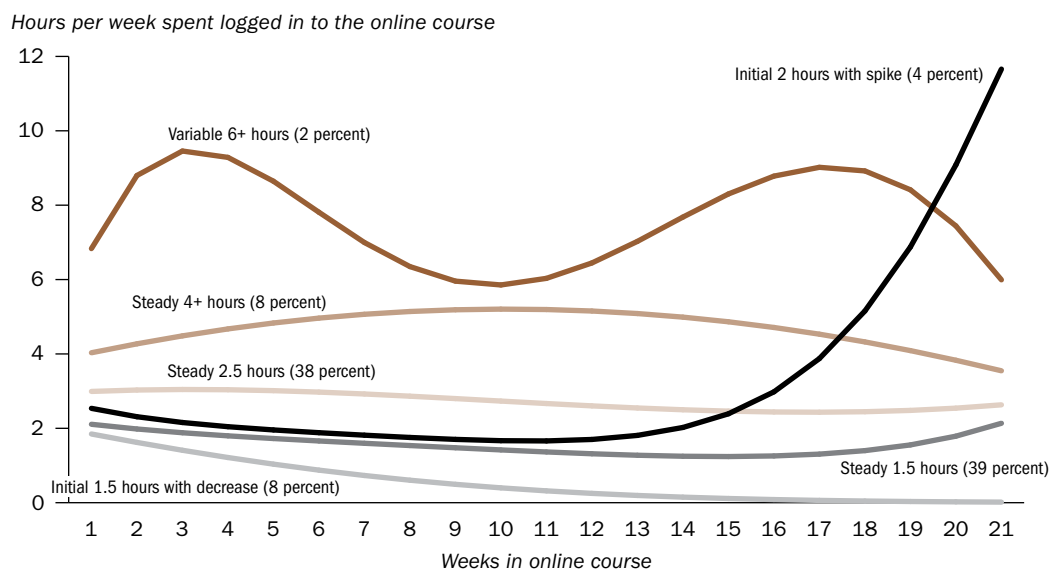
The two most common student engagement patterns each accounted for almost 40 percent of student enrollments; the least common pattern accounted for just 2 percent

Hours per week spent logged in to the online course

Weeks in online course

Note: Analysis is based on 1,512 student enrollments. The maximum number of data points for each student enrollment is 21 weeks, though some students finished their course in fewer than 21 weeks. This approach uses all available data for each week. Values in parentheses are the percentage of the sample that followed each engagement pattern; percentages do not sum to 100 because of rounding. The student engagement patterns depicted were stylized using the predicted values for each week. See figure B1 in appendix B for confidence bands around the predicted patterns and estimates of population percentages for each pattern.

Source: Authors' analysis of Wisconsin Virtual School data (fall 2014 semester).

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Table 1. Engagement groups differed in course type taken, gender, and grade level, fall 2014

Percent of student enrollments

Characteristic	Initial 1.5 hours with decrease (*n* = 122)	Steady 1.5 hours (*n* = 592)	Initial 2 hours with spike (*n* = 68)	Steady 2.5 hours (*n* = 572)	Steady 4+ hours (*n* = 122)	Variable 6+ hours (*n* = 36)	Full sample
Course type taken (*n* = 1,512)							
Advanced Placement	7	9	25	19	31	25	15
Core	48	34	34	35	32	44	36
Elective	46	57	41	46	37	31	49
Gender (*n* = 1,501[a])							
Female	57	61	43	60	60	66	60
Male	43	39	57	40	40	34	40
Grade level (*n* = 1,501[a])							
5–8	4	3	1	2	6	3	3
9	20	10	9	11	9	17	11
10	18	27	25	25	27	26	25
11	20	30	38	28	24	34	28
12	38	30	26	35	34	20	32

a. 11 student enrollments (less than 1 percent of the total) were missing information on gender or grade level. Percentages exclude missing values.

Note: Percentages may not sum to 100 because of rounding

Source: Authors' analysis of Wisconsin Virtual School data (fall 2014 semester).

Table B1 in appendix B provides additional descriptive statistics, and table B2 in appendix B provides tests of statistical significance.

Most students in five of the six engagement groups earned a high enough percentage of possible points to pass their online course

Most students in the five engagement groups with average engagement of at least 1.5 hours per week (which includes all groups except the initial 1.5 hours with decrease group) earned a high enough percentage of possible points to pass their online course, though average total time logged in each week and the change in that average over time varied across groups (figure 2).

Students with low but steady engagement in their online course had better outcomes than students with low initial engagement that diminished throughout the course

The steady 1.5 hours engagement group had better course outcomes than the initial 1.5 hours with decrease group after student and course characteristics were controlled for (table 2). The average percentage of possible points earned in the online course was 35 percentage points higher for the steady 1.5 hours group than for the initial 1.5 hours group, and the average percentage of course activities completed was 63 percentage points higher for the steady 1.5 hours group than for the initial 1.5 hours with decrease group.

The steady 1.5 hours a week engagement group had better course outcomes than the initial 1.5 hours with decrease group after student and course characteristics were controlled for; the average percentage of course activities completed was 63 percentage points higher for the steady 1.5 hours group than for the initial 1.5 hours with decrease group

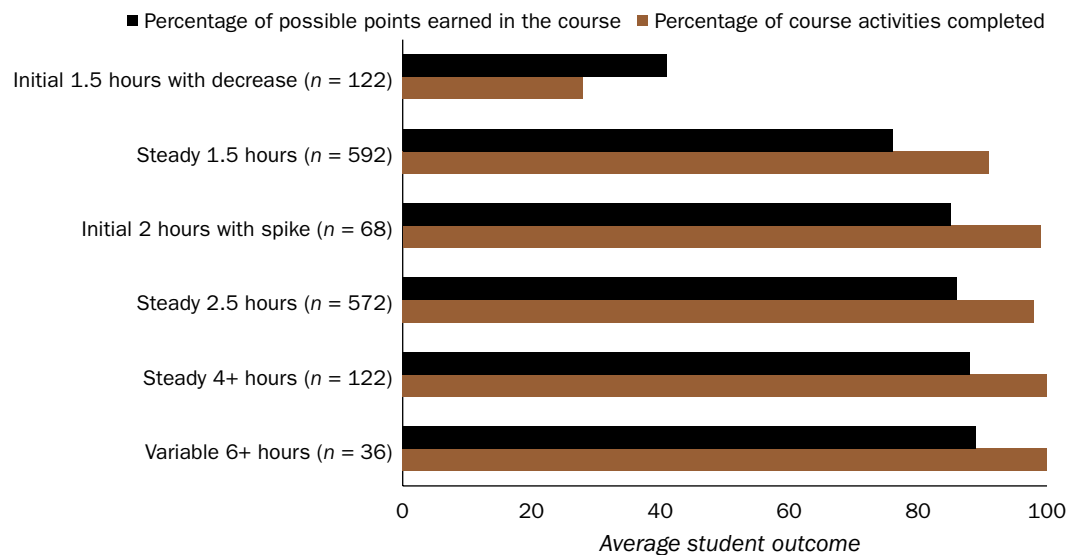**Figure 2. Most students in five of the six engagement groups earned a high enough percentage of possible points to pass their online course, though their engagement patterns differed, fall 2014**

■ Percentage of possible points earned in the course   ■ Percentage of course activities completed

Initial 1.5 hours with decrease (*n* = 122)

Steady 1.5 hours (*n* = 592)

Initial 2 hours with spike (*n* = 68)

Steady 2.5 hours (*n* = 572)

Steady 4+ hours (*n* = 122)

Variable 6+ hours (*n* = 36)

0   20   40   60   80   100

Average student outcome

Note: Data were statistically adjusted for student demographic characteristics and course type taken (Advanced Placement, core, or elective). Wisconsin Virtual School provides the percentage of possible points earned in the course to students' home schools, which then assign a letter grade based on the local grading scale, so benchmarks for passing grades can vary across schools or districts. For Wisconsin Virtual School, students must complete 95–100 percent of the possible course activities to obtain a certificate of completion. The home district then determines whether 95–100 percent course activity completion with a passing grade, which is determined locally, provides an earned credit or advancement.

Source: Authors' analysis of Wisconsin Virtual School data (fall 2014 semester).

Students who engaged in their online course for two or more hours per week had better outcomes than students who engaged for fewer than two hours per week

After student and course characteristics were controlled for, students who engaged for 2 hours or more per week (the initial 2 hours with spike, steady 2.5 hours, steady 4+ hours, and variable 6+ hours groups) had better course outcomes than students who engaged consistently during the semester with less time each week (the steady 1.5 hours group).

Of particular interest is the comparison between the steady 1.5 hours and steady 2.5 hours groups, which account for a large majority of the sample and had similar engagement patterns, with the exception that the steady 2.5 hours group was logged in an average of approximately one additional hour per week. The average percentage of possible points earned in the course was 10 percentage points higher for the steady 2.5 hours a week engagement group than for the steady 1.5 hours group, and the average percentage of course activities completed was 7 percentage points higher for the steady 2.5 hours group than for the steady 1.5 hours group (see table 2). The differences were statistically significant.

Despite their unique engagement patterns, students who engaged in their online course for two or more hours per week had similar course outcomes

Four engagement groups (initial 2 hours with spike, steady 2.5 hours, steady 4+ hours, and variable 6+ hours) had similar course outcomes on average (see table 2). This indicates

The average percentage of possible points earned in the course was 10 percentage points higher for the steady 2.5 hours a week engagement group than for the steady 1.5 hours group, and the average percentage of course activities completed was 7 percentage points higher for the steady 2.5 hours group than for the steady 1.5 hours group

Table 2. Students who engaged for two or more hours per week outperformed students who engaged for fewer than two hours per week, and students who engaged 1.5 hours per week steadily across the semester outperformed students whose engagement decreased over the semester, fall 2014

Engagement group	Percentage of possible points earned in the course		Percentage of course activities completed	
	Mean[a]	Standard deviation	Mean[a]	Standard deviation
Initial 1.5 hours with decrease	41***	35	28***	27
Steady 1.5 hours	76	21	91	18
Initial 2 hours with spike	85***	14	99**	10
Steady 2.5 hours	86***	13	98***	7
Steady 4+ hours	88**	14	100**	10
Variable 6+ hours	89*	8	100*	0.5

* is statistically significantly different from the mean for the steady 1.5 hours group at $p < .05$; ** is statistically significantly different from the mean for the steady 1.5 hours group at $p < .01$; *** is statistically significantly different from the mean for the steady 1.5 hours group at $p < .001$.

a. Statistically adjusted for student demographic characteristics and course type taken (Advanced Placement, core, or elective). See table B3 in appendix B for regression coefficients.

Source: Authors' analysis of Wisconsin Virtual School learning management system data (fall 2014 semester).

that students (all of whom were allowed to engage in their online course at their own pace) were likely to succeed in terms of the percentage of possible points earned in the course and the percentage of possible course activities completed as long as they were logged in to their online course for at least two hours per week on average.

Implications of the study findings and directions for future research

This study provides state policymakers, state and local education agencies, and online learning providers with information about student engagement in online courses and how patterns of engagement are associated with course outcomes.

Because the findings are based on correlational data, they cannot be used to make causal connections between student engagement and online course outcomes. Although patterns of high engagement appear to be associated with better course outcomes, it is possible that a third unmeasured variable is associated with course outcomes beyond student engagement (such as student interest in content, motivation, or access to technology).

Wisconsin Virtual School directors and directors of other online learning programs may be able to use information from this study as they seek ways to support student success in online courses, especially students in the initial 1.5 hours with decrease and steady 1.5 hours engagement groups, which had poorer course outcomes. Supports might include having online teachers and onsite facilitators target students who log in for fewer than two hours per week to see whether they are struggling with course content or need assistance with skills such as time management. Online teachers might also consider contacting the student, parents, or the brick-and-mortar school to provide notice that the student is at risk of failing the course based on his or her limited participation.

Other online learning programs across the country may be able to use the findings as a framework for investigating the data available in their learning management systems and student information systems. In combination with future studies investigating how much

Although patterns of high engagement appear to be associated with better course outcomes, it is possible that a third unmeasured variable is associated with course outcomes beyond student engagement (such as student interest in content, motivation, or access to technology)

these findings can be generalized to students in other online learning programs, the results may be able to inform the provision of support to students who demonstrate engagement patterns that are associated with poor course outcomes.

In addition to informing policies and practices for supporting students in online courses, the current study could inform a future comprehensive study investigating associations among student engagement, online teacher and onsite facilitator support, and online course outcomes. Researchers could collect data related to teacher and facilitator support by, for example, administering a survey about support practices or encouraging educators to communicate with students using the messaging capabilities in the learning management system so that communications are stored for later analysis.[2] Such a study might confirm the relationship between student engagement and course outcomes found by the current study and extend the model to account for teachers' and facilitators' support. Future research might also explore whether certain teaching activities or course requirements lead to different engagement patterns.

Limitations of the study

This study has three main limitations.

First, the findings may not extend to other types of online courses or other online learning programs. The study sampled student enrollments in Advanced Placement courses, core courses, and elective courses because these courses represent the majority of Wisconsin Virtual School enrollments. The findings are not generalizable to credit recovery courses because they were excluded from the sampling plan due to their shortened, 12 week timeline. It also is possible that the findings do not represent the engagement patterns or relationships between engagement and course outcomes evident in other online learning programs.

Second, the amount of time a student is logged in to a learning management system is an imperfect measure of student engagement. Students are not necessarily actively working while logged in, and some courses may require engagement in academic activities outside the system, such as writing reports or reading books. However, the learning management system logs students out after five minutes of inactivity, which should reduce some of the error associated with these measures. The study team was unable to capture other measures of engagement such as communications among students, onsite facilitators, and online teachers, as nearly all course communications occur outside the learning management system, through school email or phone calls, and are therefore not captured in any existing datasets.

Third, the analysis methods did not fully account for the complex structure of online course data. It is possible that students with the same facilitator, school, or online teacher have more similar outcomes than students who do not share these relationships. The analyses accounted for the relationships among students only within online course sections, which does not capture all possible relationships in the data. As typically implemented, online courses involve a complex structure, with students assigned to particular onsite facilitators, brick-and-mortar schools, online courses, and online teachers. Further complications arise when considering that students in the same brick-and-mortar school might be enrolled in sections of the same course with different online teachers or in different courses with the same online teacher. Because the analysis did not capture all these possible relationships, it is possible that the results do not accurately estimate the associations between engagement group membership and course outcomes.

In addition to informing policies and practices for supporting students in online courses, the current study could inform a future, comprehensive study investigating associations among student engagement, online teacher and onsite facilitator support, and online course outcomes

Appendix A. Study methodology

This appendix describes the sampling strategy; data sources, instruments, and collection methods; and data processing and analysis in general and for each research question.

Sampling strategy

The sample included all Wisconsin Virtual School high school course enrollments from the fall 2014 semester for which the student logged in to the learning management system for the first time between August 1 and September 30, 2014. This sampling strategy excluded enrollments in credit recovery courses, because the duration of those courses is shorter than Advanced Placement, core, and elective courses.[3] Students who dropped their course during Wisconsin Virtual School's 14 day grace period were also excluded. The study sample included 1,512 student enrollments in 109 courses (19 Advanced Placement courses, 44 core courses, and 46 elective courses). Students could enroll in more than one online course, so the sample represents 1,179 unique students, 170 of whom took more than one online course during the fall 2014 semester. Each student enrollment in an online course represented a single "case" in the analysis.

Because Wisconsin Virtual School uses a rolling enrollment system, students could have enrolled in a course at any time and could have had up to five months to complete a semester course. Wisconsin Virtual School directors reported that most students taking courses during fall 2014 would have enrolled by the end of September and completed their course by the end of February 2015. As a result, the study used data for students who enrolled in the sampled courses between August 1 and September 30, 2014, including students who completed the course and students who dropped the course any time prior to February 28, 2015. Any student who enrolled in the course after September 30 was not included in the sample because his or her outcome data were not available in time to be included in the current study, and the analysis approach required that all included students have course outcome data.

Data sources, instruments, and collection methods

The research questions were addressed using data from Wisconsin Virtual School's learning management system and student information system. The data included the following elements: students' online course activity (the date, time, and duration of logins in hours), students' demographic characteristics, online course characteristics, and students' scores on quizzes and exams.

General data processing and analysis

Prior to conducting the planned analyses, several steps were taken to prepare the data for analysis. First, the learning management system reports zero values when students do not log in during a particular week, regardless of their status in the course, and some of the values needed to be deleted. The raw data contained three types of zero values: zeros indicating that a student did not log in to the learning management system during a particular week but logged in during subsequent weeks, zeros indicating that a student was no longer attempting to complete the course but had not formally dropped the course, and zeros indicating that a student was not logging in because he or she had successfully completed the

course. An enrollment status variable was used to determine which students were actively enrolled and which had successfully completed the course. For students who had not completed the course but were still attempting to do so and students who did not intend to complete the course but had not formally dropped the course, all values were retained, as the values represent cases in which the student could still log in to the course. For students who completed the course, all zeros after the last nonzero login value were deleted, because a student who had successfully completed the course was not expected to log in.

Because the analysis approach described later is sensitive to spikes or fluctuations in values across repeated measurements such that the model would not converge using the raw data, the data were top-coded at the global 99th percentile of 14 hours per week (all values greater than 14 were replaced with 14). This procedure should not influence the results because these extreme values were rarely observed (only 1 percent of values were replaced), and top-coding allows all available cases to be included in the analysis.

Finally, the time variable was recoded from weeks in the online course (1–21) to percentage of the course (week/21). The data were recoded in this way to reduce the range and avoid the propagation of extreme values in the estimation process.

Analysis for the research question on student engagement patterns

To answer the first research question (How many student engagement patterns are evident in online courses, and what percentage of student enrollments follow each pattern?), the study team used a group-based trajectory modeling approach (Nagin, 2005) to examine patterns of student engagement across the duration of the online course and to classify the patterns into unique groups. Group-based trajectory modeling is an extension of traditional growth curve modeling; both model individual-level variation in developmental trajectories. Group-based trajectory modeling differs from standard growth curve modeling because group-based trajectory modeling assumes that there may be an unknown distribution within the population of individual differences within groups, making it a nonparametric method for examining growth, rather than assuming that the distribution of trajectories in the population follows a multivariate normal distribution (Nagin, 2005). As output from the group-based trajectory modeling analyses, each case receives an estimate of assignment probability to each latent group and can subsequently be classified into qualitatively distinct trajectory groups. This approach is particularly useful for applications such as the current study, in which there is no theoretical basis for assuming qualitatively similar patterns of change across individuals (Andruff, Carraro, Thompson, Gaudreau, & Louvet, 2009); in other words, engagement might increase for some students and decrease for others across the duration of the course.

Student engagement was measured by the amount of time each student was logged in to the learning management system. Weekly aggregate measures were created by summing the login amounts for each week (Monday through Sunday), beginning with the week the student first logged in to the learning management system and ending when the student completed the course or the five-month course period elapsed. Students therefore had different numbers of engagement scores depending on the rate at which they finished the course. Group-based trajectory modeling allows for different timing and frequencies of measurement occasions across cases (Nagin, 2005), so this approach naturally accommodates this issue. Because students were given a maximum of five months to complete their

course, approximately 21 data points were available for each student. Students who completed their course more quickly had fewer than 21 data points.

After the data were prepared for analysis, a group-based trajectory modeling procedure was conducted using STATA. After loading a trajectory estimation software package,[4] three general steps of statistical modeling were conducted: model selection, model estimation, and model interpretation.

Step 1: Model selection. Selecting a group-based trajectory model involves two stages: model enumeration and model specification. Model enumeration involves determining the number of latent groups with unique growth trajectories. Model specification involves parameterizing the multigroup models by including the order of the growth trajectories (such as linear, quadratic, or cubic forms) for each group. First, a baseline, single-group trajectory model was generated using a censored normal (Tobit) model.[5] Subsequent models were then fit with increasing numbers of latent growth engagement groups (in other words, a two-group solution was fit, followed by a three-group solution, then a four-group solution, and so on).

To specify each model's optimal solution, higher order slope terms were assessed for each group's trajectory by fitting a series of models. First, a fully specified model with quintic trajectories for each group was fit. In the next run the highest order nonsignificant parameter for each group was trimmed. After parameters were trimmed, the more parsimonious model was re-run. Modeling followed this iterative trimming process until each of the remaining highest order parameters achieved significance for each group. This trimming process resulted in an estimation of the most parsimonious solutions for two groups, three groups, four groups, five groups, and six groups. Modeling was ceased at six groups because additional groups resulted in redundant trajectory groups.

As latent groups are added, the Bayesian information criterion estimates (Schwarz, 1978) change. By examining the two Bayesian information criterion statistics, one using the number of student enrollments to estimate degrees of freedom (n = 1,512) and another using the number of student engagement data points (n = 29,109), the best-fitting model can be selected using guidelines outlined in Andruff et al. (2009), Kreuter and Muthén (2008), and Nagin (1999, 2005), with higher Bayesian information criterion values (closer to zero) indicating better model fit. Bayesian information criterion fit statistics favor parsimonious models, ensuring that the increase in explanatory power that results from the complexity associated with adding parameters is statistically warranted. Although the Bayesian information criterion necessarily gets larger as parameters are added, the fit statistic also assesses a penalty for adding to the model's complexity. The goal of this process is to identify distinctive features in the data that result in a set of groups with unique engagement patterns; both Bayesian information criterion statistics support a six-group solution for the trajectory analysis (table A1).

Step 2: Model estimation. After identifying the number of unique student engagement trajectory groups and the best-fitting trajectory forms, the study team estimated the resulting six group trajectory parameters in STATA, obtaining posterior probabilities of group membership for each student enrollment along with each student's estimated group assignment using the maximum probability assignment rule. Among students who were assigned to each group, the average of the estimated probability of membership in that group was

Table A1. Fit statistics for model enumeration process, fall 2014

	Bayesian information criterion fit statistics	
Model	With number of student enrollments used to estimate degrees of freedom (*n* = 1,512)	With number of student engagement data points used to estimate degrees of freedom (*n* = 29,109)
Two group	−62,357	−62,373
Three group	−61,376	−61,404
Four group	−60,918	−60,948
Five group	−60,551	−60,591
Six group	−60,338	−60,384

Note: Larger values (closer to zero) indicate better model fits.

Source: Authors' analysis of Wisconsin Virtual School data (fall 2014 semester).

calculated to provide a measure of internal reliability for each group, with all average probabilities greater than .70 indicating acceptable reliability (Andruff et al., 2009; average predicted probabilities of group membership are provided in table A2).

Step 3: Model interpretation. A figure was created to depict the estimated shapes of the resulting group patterns throughout the duration of the online course for each group. The engagement trajectories were stylized by connecting the predicted values for each week. Groups were named based on the resulting average weekly login durations and variability in login durations across the semester.

Analysis for the research question on differences in student engagement patterns by course and student characteristics

To answer the second research question (Do student engagement groups differ in course type taken, gender, or grade level?), group profiles were assembled for each engagement group. Indicators of group membership were created using the group assignment probabilities for each student determined through the group-based trajectory modeling analysis.

Table A2. Average group assignment probabilities for student engagement groups, fall 2014

	Number assigned	Model identified group						Range[a]
Assigned group		1	2	3	4	5	6	
Initial 1.5 hours with decrease (group 1)	122	.961	.038	.000	.001	.000	.000	.50–1.00
Steady 1.5 hours (group 2)	592	.007	.890	.011	.011	.000	.000	.44–1.00
Initial 2 hours with spike (group 3)	68	.000	.043	.914	.003	.000	.000	.47–1.00
Steady 2.5 hours (group 4)	572	.000	.010	.015	.859	.026	.000	.42–1.00
Steady 4+ hours (group 5)	122	.000	.000	.004	.004	.915	.008	.42–1.00
Variable 6+ hours (group 6)	36	.080	.000	.000	.000	.046	.953	.52–1.00

Note: The model assigns each student a probability that he or she belongs in each group. Under perfect conditions the probability of actual group assignment would be 1 for one group and 0 for all others. The model-identified group column heads refer to the six groups identified by the model. The assigned group row labels represent the groups to which students were actually assigned based on the maximum probability rule. The estimates in the table represent the average model assignment probabilities across students in each assigned group.

a. Reports the highest and lowest model assignment probabilities across students for the group to which they were assigned.

Source: Authors' analysis of Wisconsin Virtual School data (fall 2014 semester).

Descriptive statistics were calculated, including means, standard deviations, and percentages for each group. A series of chi-squared analyses were conducted to determine whether differences across groups in course type taken, gender, and grade level were statistically significant.

Analysis for the research question on associations between student engagement patterns and course outcomes

To answer the third research question (How are student engagement patterns associated with the percentage of possible points earned in the course and the percentage of course activities completed?), the study team statistically assessed the relationships between engagement group membership and performance in the online course while controlling for course type taken, student gender, and grade level. The study team conducted a series of two-level regression analyses with students nested within online courses using hierarchical linear modeling (Raudenbush & Bryk, 2002).

The two measures of student learning outcomes, percentage of possible points earned in the course and percentage of course activities completed, were included as dependent variables in two separate models (y_{ij}). Five dummy-coded indicators of engagement group membership were included as independent variables (ENG_{mij}). To examine engagement group effects, it was necessary to select a reference group for comparison. The steady 1.5 hours engagement group was chosen because it was the largest group and because the average percentage of possible points earned in the course and percentage of course activities completed were closest to the whole sample's averages. Gender and grade level were included as covariates (ST_{qij}), with gender dummy-coded such that zero values were male students and values of 1 were female students. Grade level was grand mean–centered at grade 11. Since the majority of enrollments were in grades 10, 11, and 12, this approach allowed the study team to estimate the intercept for a grade that is at the center of the distribution of grade levels. Online course–type variables, elective and Advanced Placement, were added as dummy-coded indicators at level 2 to control for potential differences in the outcomes based on course type taken (OC_{fj}), with core courses as the reference group. Cross-level interactions were included for online course type taken and engagement group ($ENG_{mij}*OC_{fj}$). All effects were modeled as fixed. The general form of the model was as follows:

$$y_{ij} = \gamma_{00} + \sum_{m=1}^{5} \gamma_{m0} ENG_{mij} + \sum_{q=6}^{V} \gamma_{q0} ST_{qij} + \sum_{f=1}^{2} \gamma_{0f} OC_{fj} + \sum_{m=1}^{5} \sum_{f=1}^{2} \gamma_{mf} ENG_{mij} * OC_{fj} + u_{0j} + r_{ij}.$$

Appendix B. Supplemental findings

This appendix provides supplemental statistical results for each research question.

Table B1. Relationships between course type taken, gender, and grade level and course outcomes, fall 2014

Characteristic	Number of student enrollments	Percentage of possible points earned in the course		Percentage of course activities completed	
		Mean	Standard deviation	Mean	Standard deviation
Course type taken					
Advanced Placement	229	81.45	19.37	93.05	19.15
Core	539	76.61	23.19	87.92	25.97
Elective	744	80.06	21.54	90.13	23.38
Gender[a]					
Female	897	79.75	21.76	90.36	23.14
Male	604	77.73	22.18	88.75	24.95
Grade level[a]					
5–8	43	76.92	16.67	90.51	22.36
9	170	76.38	24.22	84.98	27.52
10	381	79.49	21.67	90.36	23.24
11	421	78.98	20.60	91.05	21.15
12	486	79.54	22.84	89.62	25.25

a. 11 student enrollments (less than 1 percent of the total) were missing information on gender or grade level. Percentages exclude missing values.

Source: Authors' analysis of Wisconsin Virtual School data (fall 2014 semester).

Table B2. Relationships between course type taken, gender, and grade level and engagement groups, fall 2014 (chi-squared statistic)

Characteristic and engagement group	Steady 1.5 hours	Initial 2 hours with spike	Steady 2.5 hours	Steady 4+ hours	Variable 6+ hours
Course type taken (Advanced Placement, core, elective)[a]					
Initial 1.5 hours with decrease	8.09*	13.44**	12.79**	24.49***	10.39**
Steady 1.5 hours		18.79***	28.50***	49.24***	15.00**
Initial 2 hours with spike			1.69	0.83	1.42
Steady 2.5 hours				9.98**	3.36
Steady 4+ hours					1.91
Gender (male, female)[b]					
Initial 1.5 hours with decrease	0.64	3.80	0.38	0.15	0.78
Steady 1.5 hours		8.75**	0.09	0.09	0.28
Initial 2 hours with spike			7.87**	5.19*	4.92*
Steady 2.5 hours				0.01	0.39
Steady 4+ hours					0.40
Grade (5–8, 9, 10, 11, 12)[c]					
Initial 1.5 hours with decrease	17.52**	12.98*	16.56**	8.63	9.45
Steady 1.5 hours		2.63	11.04	4.38	9.94
Initial 2 hours with spike			5.07	5.99	3.99
Steady 2.5 hours				8.43	4.32
Steady 4+ hours					8.42

* is significant at $p < .05$; ** is significant at $p < .01$; *** is significant at $p < .001$.

a. Assessed using chi-squared ratio with two degrees of freedom.

b. Assessed using chi-squared ratio with one degree of freedom.

c. Assessed using chi-squared ratio with four degrees of freedom.

Note: p-values are not adjusted for multiple comparisons.

Source: Authors' analysis of Wisconsin Virtual School data (fall 2014 semester).

Figure B1. Engagement patterns with confidence bands, fall 2014

Hours per week spent logged in to the online course
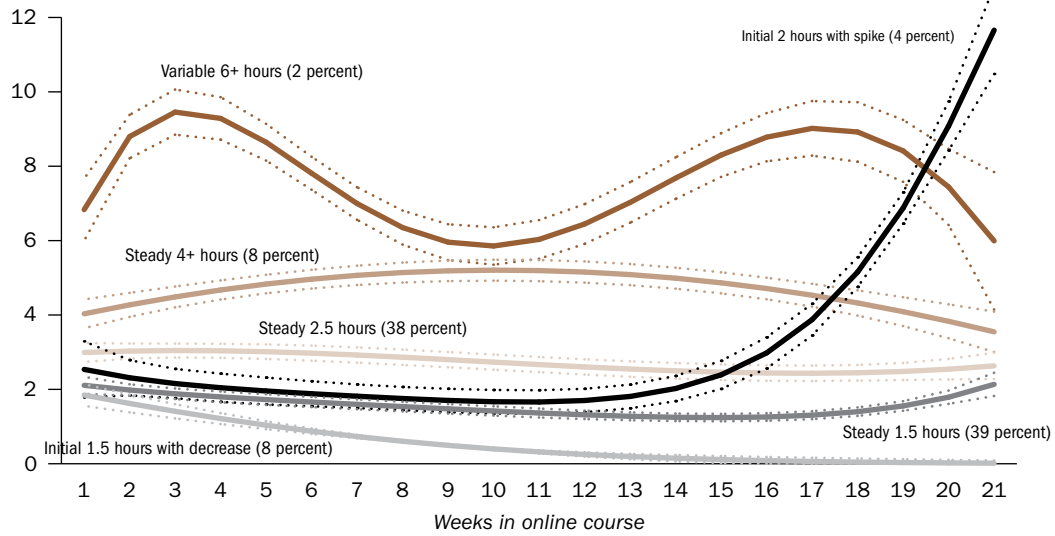
Note: Analysis is based on 1,512 student enrollments. The maximum number of data points for each student enrollment is 21 weeks, though some students finished their course in fewer than 21 weeks. This approach uses all available data for each week. Values in parentheses are the percentage of the sample that followed each engagement pattern; percentages do not sum to 100 because of rounding. The student engagement patterns depicted were stylized using the predicted values for each week. The model also estimates population percentages, which were very similar to the sample percentages: initial 1.5 hours with decrease, 8 percent; steady 1.5 hours, 39 percent; initial 2 hours with spike, 5 percent; steady 2.5 hours, 37 percent; steady 4+ hours, 9 percent; and variable 6+ hours, 2 percent. Dashed lines depict 95 percent confidence intervals around the estimated trajectories.

Source: Authors' analysis of Wisconsin Virtual School data (fall 2014 semester).

Table B3. Regression coefficients for course outcome analyses, fall 2014 (percentage points)

Fixed effect	Percentage of possible points earned in the course	Percentage of course activities completed
Intercept	72.52***	89.65***
Elective	5.39*	1.85
Advanced Placement	−3.73	−3.62
Gender	1.38	0.68
Grade level	−0.04	−0.01
Initial 1.5 hours with decrease	−29.98***	−62.62***
Elective	0.08	4.64
Advanced Placement	1.10	1.99
Initial 2 hours with spike	13.73***	10.29**
Elective	−7.88	−4.51
Advanced Placement	2.08	1.99
Steady 2.5 hours	9.91***	7.28***
Elective	−2.30	−1.88
Advanced Placement	8.61*	5.48
Steady 4+ hours	9.91**	7.76**
Elective	1.76	2.03
Advanced Placement	10.19	5.21
Variable 6+ hours	10.27*	10.18*
Elective	6.93	1.34
Advanced Placement	10.72	3.45

* is significant at $p < .05$; ** is significant at $p < .01$; *** is significant at $p < .001$

Note: The steady 1.5 hours group was the reference group for engagement group, and core course was the reference group for course type taken. The intercept coefficient represents the score estimate for the steady 1.5 hours group for male students in core courses. The coefficients next to each group represent the difference in its estimate compared with the reference group (for example, the initial 1.5 hours with decrease group averages 29.98 percentage points less than the steady 1.5 hours group). The coefficients that appear underneath each group (elective, Advanced Placement, gender, and grade level) represent the conditional effects of being in an elective course, a female student, or in a different grade level). The grade level was centered at grade 11.

Source: Authors' analysis of Wisconsin Virtual School data (fall 2014 semester).

Notes

1. Analyses focus on the total amount of time spent logged in each week, but the frequency of logins each week can vary within engagement groups. For example, for two students both logging in a total of two hours in a particular week, one student may have logged in one time for two hours, while the other student may have logged in four times for 30 minutes each.

2. A review of Wisconsin Virtual School's learning management system data revealed that most communications among teachers, facilitators, and students occur through school email rather than through the learning management system, which means that those communications were not accessible for analysis.

3. Credit recovery courses must be completed in 12 weeks, while all other courses must be completed in five months, which would result in necessarily different engagement trajectories.

4. Trajectory estimation software was downloaded from http://www.andrew.cmu.edu/user/bjones/index.htm.

5. The STATA Traj package does not include an option for a standard normal, but the censored minimums (0 hours) and maximums (14 hours) for the current analyses were set such that they encompassed all the data. This model is therefore equivalent to a standard normal model.

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