Differential Responses to Personalized Learning Recommendations Revealed by Event-Related Analysis

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ABSTRACT
Educators are increasingly embracing personalization in online and blended learning programs as a means of focusing students' investment of time and energy into learning plans that are best tailored to their individual needs. When personalized learning tools are deployed into structured learning environments like schools, however, educators and students must consider program provided recommendations alongside potentially immutable factors like set daily schedules, mandated curricula, and student needs in other content areas. These on-the-ground factors make researching the impacts of personalized learning challenging because they are difficult to measure directly, especially for digital programs deployed at scale. Inspired by a widely influential methodology in brain imaging, we tackled this challenge by employing an *event-related* approach that emphasizes changes in student behavior that are time-locked to changes in program provided usage recommendations. Our analysis reveals that while student usage time can often be quite far from the amount recommended, students nevertheless respond to changes in program recommendations by adjusting usage in a corresponding manner. We further extend this general approach to demonstrate that students more often stayed on track toward their end of year goals following a week where they met or exceeded their program provided recommendation. Through these examples, we demonstrate the value of an event-related approach towards understanding how personalized paths can positively influence student learning.

Keywords
Personalized learning, event-related analysis, time management, K-12 schools, personalized recommendations.

1. INTRODUCTION
As schools and communities embrace a rapidly changing world, a growing emphasis on the personalization of learning has emerged [10]. Learning is considered personalized if it is tailored to each learner's strengths, needs, and interests, encouraging flexibility in a student's pursuit of mastery and enabling learners to take an active role in what, when, where, and how they learn [22]. In the competition for instructional time, personalized learning approaches also hold the promise of helping students achieve mastery as efficiently as possible [10], and can facilitate educators' work in guiding students' learning efforts towards educational activities that best match their current needs.

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Online and blended learning programs are uniquely positioned to enable personalized learning because they can support student agency through independent pacing, delivery of differentiated content and support, and the ability to engage with learning anytime and anywhere [22]. However, the double-edged sword of personalized learning is that "the process of personalization puts enormous pedagogical and procedural burden on the students—as well as teachers—to make critical instructional decisions" [4; also see 5]. This includes decisions about how much time students should spend on specific programs and components of programs to maximize learning. While studies often find that students fail to spend as much time in educational technology programs as recommended by the program or researchers [23], students can also over-use, spending time on one set of activities that might be better spent in other areas.

One response from the designers of learning technologies has been the inclusion of embedded recommendations and self-monitoring tools to scaffold student and teacher support for self-regulation. Recommendations are tailored to help students and teachers make good decisions within a personalized learning environment without enforcing rigid requirements that may reduce student agency and be unrealistic for particular educational contexts. Individualized usage time recommendations do not appear to be common in most learning technologies; many continue to provide one-size-fits-all usage recommendations [9]. However, they hold the promise of facilitating self-pacing by helping students who are at different levels and progressing at different speeds to stay on track toward reaching their goals.

Despite the recognition of learning scaffolds as critical and effective for self-regulation in general [15] and in computer-based learning environments in particular [27, 28], relatively little research has been done into the impacts of recommendations. While the desire to enact personalization grows, the reality is that many educational institutions, particularly K-12 schools, continue to look much as they have for the past century, with set daily schedules and highly-regulated or mandated paths through content material [10]. When individualized learning tools are deployed into schools with structured learning environments, educators and students must consider program provided recommendations alongside these potentially immutable factors. While a program may recommend a different usage time to individual students within the same class or to the same student in different months, they may be unable to follow those recommendations with fidelity because of set schedules of technology access [25], challenges associated with implementing flexible learning time [20], or teacher and parent beliefs about learning technologies and screen time [6, 18]. Furthermore, researchers often have data on the usage recommendations a student received and their time spent using the program, but lack direct insight into the specific contexts in which the program is implemented [26].

We addressed this research challenge by examining how students respond to personalized usage time recommendations within *Lexia® Core5® Reading* (hereafter "Core5") - a blended learning literacy program that provides instruction in foundational literacy skills for students in grades preK-5. To isolate the impacts of program provided recommendations from the largely unknown aspects of school context, we model an analytic approach after one widely used in the field of brain imaging - *event-related design* [for a general overview see 12, 13; for a widely-cited early example see 11]. The key aspect of this methodology with respect to our present application is that we focus on *changes* in actual student usage time that occur time-locked to *changes* in personalized recommendations. That is, we ask how student behavior *responds* to changes in program suggestions rather than whether it is *aligned* to recommendations, as consistent student responses to changed program recommendations could be observed even if baseline student usage is widely variable across diverse school contexts. Utilizing this approach, we find that students indeed adjust the amount of time per week that they spend using Core5 in a manner that differentially relates to the direction and magnitude of the recommended change. We also extend our analysis to examine events defined directly by student behavior and find that the act of meeting one's recommendation in a given week is associated with more frequently staying on track toward end-of-year goals in future weeks. Together, these examples highlight the power of an *event-related* approach, and reveal positive associations between the personalization of learning and student progress within school contexts.

2. DATA

2.1 Usage time recommendations in Core5

To personalize the learning path for each individual student, Core5 recommends a number of minutes per week that the student should use the online portion of the program, promoting regular, right-sized use and proactive time management throughout the school year to enable student success [7]. Each student's usage recommendation reflects the estimated amount of time needed to reach their end of year "benchmark" - that is, to complete all program content for their grade level by the end of the school year. It is based on a predictive model that takes into account a student's current place in the program, the amount of material left for them to reach their benchmark, and their time spent and progress made in the prior month [16]. These recommendations are shared prominently with educators in the program's online data portal, and are visible to students while logged in to Core5.

Critically, student usage recommendations are not fixed throughout the school year, but are recalculated at the start of each month to reflect student progress and pace (see Figure 1). At the start of the year, before enough data has been collected to personalize recommendations, all students are set to a default recommendation of 40 minutes per week. At the start of the next calendar month (first Monday), a student's recommendation changes to 20, 30, 50, or 60 minutes per week. With the beginning of each new month, a student's usage recommendation is recalculated, resulting in either an additional change or a static recommendation. This cadence was chosen to allow regular revisions that reflect student's usage and progress, while still remaining implementable for teachers. The goal in personalizing and updating these recommendations is that students use the program enough to stay on pace to end the year at their grade level benchmark, without spending more time than necessary that could be invested in other learning activities. Previous research has shown that students who consistently meet recommended usage in Core5 make more progress and more often reach their grade-level benchmark than those students who infrequently or never meet their usage recommendation [17].

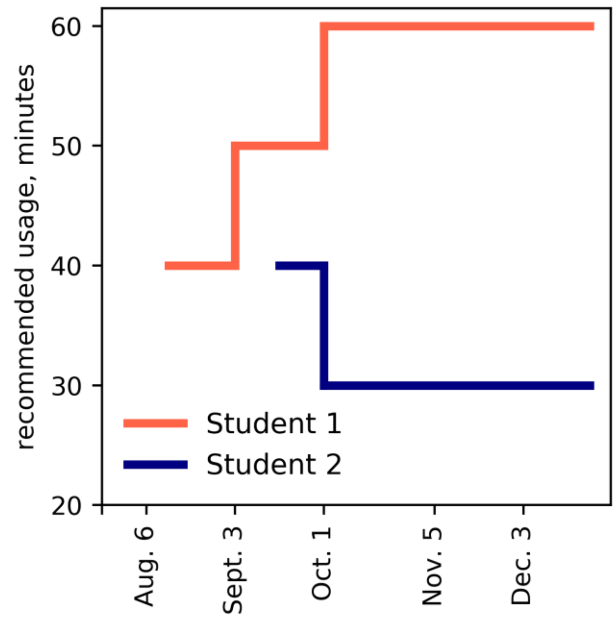

Figure 1: Usage recommendation profiles for two example students. Each line illustrates how usage recommendations for an individual student change across the time frame under study. Student 1 began the school year in early August, and like all students was initially recommended 40 minutes per week. On the first Monday of September, Student 1's recommendation changed to 50 minutes per week, and at the start of October it was adjusted again to 60 minutes per week. Student 2 was also initially set at 40 minutes per week, but began the school year later (in mid-September). Following the same rules, however, Student 2's recommendation was adjusted at the start of the next calendar month (October) to 30 minutes per week. For this student, the recommendation remained there for the duration of this time frame.

2.2 Sample Details

Weekly usage records for Core5 students in Kindergarten through 3rd grade were used for the analyses presented in this paper. Although Core5 also provides usage recommendations for pre-K, 4th, and 5th grade students, the specific time values differ for these grade levels. We therefore restricted our sample to K-3 students for clarity of interpretation, though we anticipate that results would be similar for students in other grades.

To obtain the records, schools were chosen at random from among those who had at least one student using Core5 in the fall of 2018 (total of 168 schools chosen). These schools were geographically diverse, located across 39 US states and 4 Canadian Provinces. Student-level demographic data is unavailable for this dataset. All weekly Core5 usage records between August 6, 2018 and December 31, 2018 were obtained for all students at these schools. To be included in the final sample, students must have used Core5 for at least 7 weeks within this date range, and had their usage recommendation change at least once (as described in Section 1, the goal of the event-related approach is to focus on these changes). In addition, students who met their end of year benchmark (completed all grade level material) within this timeframe were excluded (this sets ones' usage recommendation to 0 minutes per week). Furthermore, students must have had a usage target of 40 minutes in their first week of program use within this timeframe. As previously described, Core5 assigns a default recommendation of 40 minutes per week during a student's first month of use in a school year, and any other value at that time point is an indication that there was a manual override (this is rare - 0.9% of students in our sample - but an available option for educators). The final sample contained 10,851 students (2,838 in Kindergarten; 3,213 in 1st grade; 2,836 in 2nd grade; 1,964 in 3rd grade). To ensure that these exclusion criteria did not produce non-representative results, we ran robustness checks using different cutoffs for minimum weeks of program use (6 or 8) and repeated our analyses with two additional samples of students based on new random selections of schools. We found that all results were qualitatively consistent with our reported findings.

The weekly Core5 records obtained contain aggregated usage data for each week that a student logged into the program. The metrics collected that are relevant to the presented analyses include the total time of Core5 use during that week, the recommended use time for that week, whether or not a student met their recommendation (total time greater than or equal to recommended time), and the Monday date of the week reported.

3. RESULTS

3.1 Alignment to usage recommendations

Our primary research aim is to assess whether students' usage time is responsive to Core5's personalized recommendations. Before presenting our results, however, it is critical that we distinguish this question of students' *responsiveness* to personalized recommendations from a related question about *alignment* between recommended and actual usage time. Specifically, we could observe changes in actual Core5 usage following a change in the program provided recommendation (i.e. a personalized *response*) without necessarily finding that students used the program for a particular number of minutes that is close to their recommended value (i.e. *alignment*). Indeed, because Core5's personalized recommendations serve as only one factor within the school context, it would not be surprising if a student's usage time in a given week was quite far from their personalized recommendation value, and more closely related to unknown (from a researcher's perspective) contextual factors such as the amount of time dedicated in their school's schedule to literacy learning or student-directed after school usage. Critically, even if there is poor *alignment*, we may find that when recommendations are changed that students' time spent using the program systematically adjusts in a manner consistent with those changes - a result indicative of responsiveness to Core5 recommendations.

We indeed find that alignment between Core5's usage recommendations and actual student usage time is weak. Although most students had a mean weekly usage time that fell within the range of Core5 recommendations (Figure 2, top panel; 70.0% of students with weekly mean between 20 and 60 minutes), there was a small negative correlation between actual and recommended program use time in aggregate (Pearson r = -0.117; 95% CIs = -0.137, -0.098). Honing in on a snapshot of one particular week in our dataset (Figure 2, bottom panel), it is evident both that there is poor alignment to recommendations, and that there is widespread individual variability in usage time. While the average within-student mean for actual and recommended usage time were similar (46.2 and 43.3 minutes per week, respectively) the across-student standard deviations for these metrics were widely disparate (SDs = 22.9 and 11.1 minutes, respectively).

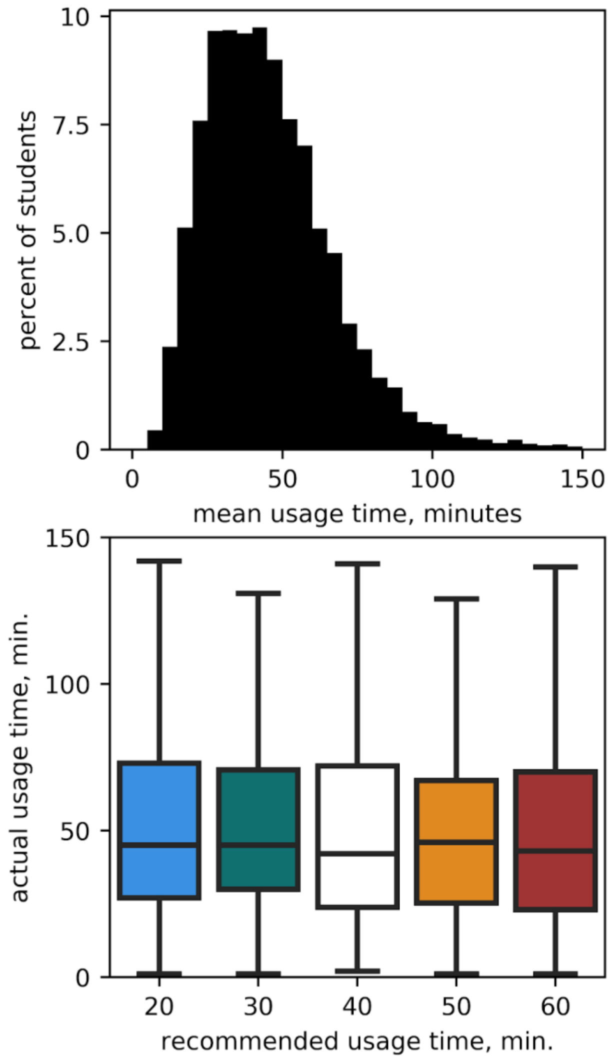

Figure 2: Distributions of students' Core5 usage time. (top) Though mean weekly usage across students was in a range similar to Core5's usage recommendations, there was a notable extent of individual variability. (bottom) A snapshot of the distribution of actual use (y-axis) for students with each unique recommended usage time during a particular week (x-axis) revealed no apparent relationship between the two. The data shown is for one example week that had the largest number of unique students using Core5 (week beginning November 26, 2018; 9,606 students, or 88.5% of full sample, had Core5 use), but other weeks had qualitatively similar relationships. The correlation between recommended and actual usage was similar for this sample week (Pearson *r* = -0.043, 95% CIs = -0.063, -0.023) to that seen for the aggregate results.

3.2 Event-related approach to recommendation changes

In light of these observations indicating a lack of positive alignment (Figure 2), we turned to our key question of whether student usage time in Core5 was nevertheless *responsive* to changes in personalized recommendations. Because of the complex and largely unknown (from a researcher's perspective) context in which these personalized recommendations are implemented, we turned to an *event-related* analytic approach. This methodology allows for context-independent examinations of an event of interest by effectively contrasting responses that occur in temporal coordination with that "event" against a baseline period just before the event occurred [11].

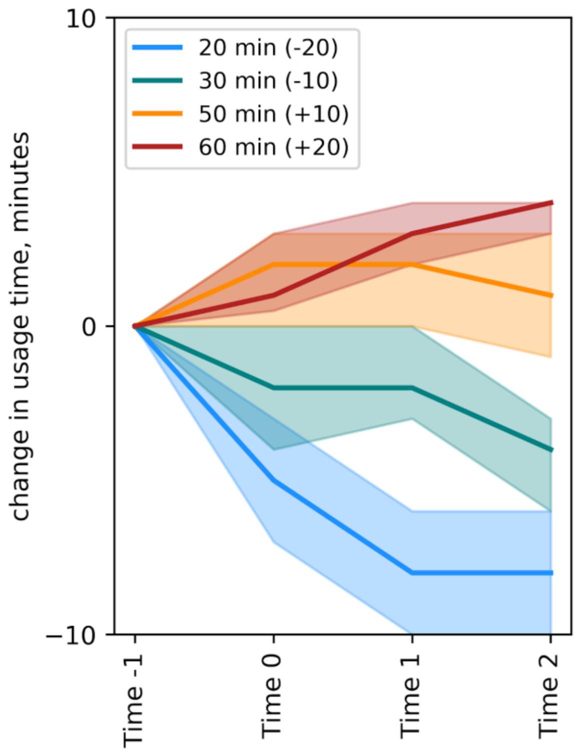

Figure 3: Event-related analysis of usage recommendation changes. When a student's weekly usage recommendation changes from 40 minutes (Time -1) to another duration (Time 0-2) early in a new school year, student usage tends to change in the direction of (and with magnitude correlated to) the change in recommendation. Each bold line represents the median change in actual weekly usage time across students, with all usage times in the analysis expressed as a difference from Time -1 (this is why all lines converge to 0 at Time -1). Shaded areas around each line represent 95% confidence intervals on the median generated via a bootstrap resampling procedure.

The first step in conducting this analysis is to define the event of interest - here, we focused on how each student's first change in recommendation influenced their usage time within Core5. Note that because all students began the school year with a recommendation of 40 minutes, this event reflects a change from 40 minutes (at Time -1 in Figure 3) to one of the other four possible usage recommendations (20, 30, 50, or 60 minutes at Time 0-2 in Figure 3). We next aligned all student data to a temporal reference frame defined by this event. In other words for each student, we defined Time -1 as their last week of program use prior to the recommendation change, Time 0 as the week when the new recommendation first appeared, and Times 1 and 2 as the next two weeks during which that same recommendation remained. Note that these weeks are ordered but are not necessarily consecutive, as students do not always use the program every week. This means it was possible for a student's recommendation to change *again* at Time 1 or 2 if it fell in the next calendar month. To ensure that the time-course analyzed in Figure 3 reflects the response to the initial target change, we excluded 363 students (3.3%) for whom this occurred, leaving a sample of 10,488. Finally, we subtracted out each student's actual usage time at Time -1 from all 4 time points to yield a difference metric (this is why all lines converge at 0 for Time -1).

Figure 3 shows the median event-related change in actual student usage time when a recommendation changes from 40 minutes per week at the start of the school year to another value. A two-factor ANOVA (factors of recommendation and time from 0 to 2 in Figure 3, the latter as a repeated measure) revealed significant main effects of both recommendation and time ($F_{3, 10484}$=93.564, $p <$ 0.0001, partial η^2 = 0.0260; $F_{2, 20968}$ = 5.71, $p < 0.0001$, partial η^2 = 0.0005, respectively), as well as a significant interaction between time and recommendation ($F_{6, 20968}$ = 10.10, $p < 0.0001$, partial η^2 = 0.0030). Repeating this statistical test with a sample that excluded outliers (353 students, or 3.4%, with a change at any time point more than 3 SDs from the mean) produced the same pattern of results. These findings clearly indicate differential responses to Core5 usage recommendations, with decreases in recommended usage (from 40 to 20 or 30 minutes per week) tending to result in decreases in program use, and increases in recommended usage (from 40 to 50 or 60 minutes per week) tending to result in increases. Interestingly, the response to a recommendation change appears to unfold in time, with students continuing to adjust usage time in the direction that their recommendation changed over the next few weeks. This finding further emphasizes the limitations of using snapshot analyses like those in Figure 2 to tease apart effects with unknown temporal dynamics.

It is notable that the median change in program use was smaller in magnitude than the recommended change, especially when one's Core5 recommendation increased. This observation is consistent with the explanation that contextual factors specific to each student's school and situation are weighed alongside the program's personalized recommendations. We also found that despite the visible responses to recommendation changes (Figure 3), that average usage time for all recommendation categories tended to hover around 40 minutes per week (e.g. means in Figure 2, bottom). Such a result suggests a continued reliance on the initially recommended value of 40 minutes per week for all students (see Section 4).

3.3 Event-related approach to student fidelity of program use

As we have demonstrated, taking an event-related approach to studying learning paths in Core5 can clearly reveal differentiated student responses to personalization. While the analysis illustrated in Figure 3 represents one application of this approach to events defined directly by program-driven occurrences (changes made by Core5 at specific points in time), a key advantage of event-related designs is their flexibility to define new events based on the nature of student actions as well [c.f. 8, 13]. To exemplify this type of approach and to gain more insight into how personalized recommendations influence students' program use, we next define new events based on whether or not a student met or exceeded their recommended usage time in a given week.

Using this definition, we can now ask whether the "event" of a student meeting or exceeding Core5's usage recommendation in a given week is associated with a lasting impact on a student's fidelity of program use, relative to weeks when that same student did not meet her Core5 usage recommendation. In other words, are these helpful recommendations that encourage students to set achievable targets, appropriately pace themselves, and use with fidelity throughout the year [19]? Because it is critical that this analysis be conducted in a within-student fashion (i.e. comparing how the same student responds to both event types), we included only students who had at least one instance of both meeting and not meeting their usage recommendation within the timeframe under study (N=8,911; 82.1% of full sample).

Results indicated that students more often met or exceeded their Core5 usage recommendation if they had also met or exceeded their recommendation during their prior week of program use (56.0%, vs. 50.5% when they did not meet or exceed their recommendation during the prior week; odds ratio = 1.248). We also found that while it was very likely overall for students to use Core5 in consecutive weeks, that this was even more frequent following a week of meeting than not meeting one's usage recommendation (88.0% vs. 83.6%, odds ratio = 1.438). Together, these results suggest that following personalized usage recommendations is associated with staying on track toward end of year goals and maintaining regular program use.

4. DISCUSSION

While measuring the impacts of personalized learning in school settings carries significant challenges, we demonstrate the power of an event-related analytic approach toward revealing how student behavior responds to program provided recommendations. Clearly, educators and students must make decisions about personalized recommendations within the context of their school environment and alongside myriad other considerations. The apparent lack of alignment between actual program use and Core5 recommendations (Figure 2), then, is a manifestation of these important but competing priorities. Using an event-related design, we were able to reveal that even within this complex ecosystem, students' Core5 usage time does change in a manner that directly corresponds (and is time-locked) to changes in their personalized recommendations. Furthermore, our results demonstrated that students more often stayed on track toward their end-of-year target following weeks in which they met, versus lagged behind, their suggested pace.

Although usage recommendations are visible to students in the Core5 program, given our sample's age group (K-3) we expect that teachers and school administrators are primarily responsible for monitoring Core5 usage time, responding to recommendations, and weighing program time against other educational priorities. This balancing act likely explains why students' usage time adjustments were typically smaller than was recommended (Figure 3). Together with our other findings, this pattern is consistent with program provided recommendations influencing but not determining student usage time when they are considered alongside additional factors in each unique school context. In future work it will be interesting to investigate whether responsivity and/or alignment to usage recommendations changes with student age, perhaps reflecting increasing self-regulation and autonomy as they advance in school.

While the ability to isolate one factor of interest from within a complex, dynamical system is a key strength of an event-related approach, it is also a limitation in that it does not afford the ability to quantify influences of other factors or to provide insight as to their relative importance. From the perspective of those designing and improving personalized learning tools, however, an event-related approach is powerful for exactly that reason - it allows for isolated study of a personalized feature that is directly within the designer's control, thus facilitating improvement of the program's design and iteration on these enhancements [c.f. 14]. For example, we noted an interesting finding that even as student usage times changed in response to program provided recommendations, they seemed to remain tied to the initial, impersonal value of 40 minutes per week (e.g. Figure 2, bottom). This pattern may reflect a well-studied cognitive bias known as anchoring, which typically manifests as a continued reliance on an initially given value when making numerical judgments [24]. It may also be that educators have more flexibility to adjust student schedules early in the year than they do as school progresses. In either event, this result suggests that personalizing a student's usage recommendation earlier in the school year could yield larger impacts.

By extending our event-related approach, we found that weeks in which a student met or exceeded their personalized recommendation were more often followed by continued on-track behavior and more regular program use, which have previously been shown to be positive predictors of student performance in online courses [c.f. 7, 21]. Such an effect may stem from integration of Core5's personalized recommendations within educators' learning plans and/or with students' emerging self-regulation [1, 2, 19]. As previously described, our event-related approach limits our ability to quantify effects beyond those owing to program provided recommendations by intentionally filtering them out to isolate only a single factor. That said, these findings motivate further study of the mechanisms through which usage recommendations facilitate students' ability to stay on track for success throughout the school year.

We also note that while our approach is inspired by one developed for the analysis of brain imaging data, it differs in important ways. First and foremost, event-related designs in brain imaging research are typically used in the context of randomized studies, where an experimenter controls many aspects of the timing and context of "events" (although note that the ability to flexibly define events post-hoc is a key methodological advantage, c.f. 8). In contrast, Core5 students are assigned usage recommendations based on their pace through content material and the amount they have left to finish that year. By definition, then, students who are farther behind in class will tend to receive higher Core5 usage recommendations. Although the analyses we present highlight within-student usage changes in response to time-locked events, it is important to note that the groups of students at each recommendation level (e.g. at Times 0-2 in Figure 3) likely differ in other key ways. For example, we may speculate that one reason why usage time increases were typically of smaller magnitude than usage time decreases (Figure 3) could be that students who are farther behind tend to receive offline interventions at school rather than additional time in the online program.

Analytic applications in the field of brain imaging also suggest extensions of this work that could yield continued insights into the impact of personalization in learning. For example, once well characterized, event-related time courses serve as a template for identifying structural brain regions with particular functional properties [8, 13]. Analogously, having defined the typical time course of how student usage responds to recommendation changes (Figure 3), we could now use these expected functions as regressors to identify schools where recommendations are or are not strongly implemented. This in turn could help guide vendors to better help schools resolve issues and successfully implement digital learning tools. It could also motivate additional research studies that compare student outcomes in school contexts where personalized recommendations either were or were not implemented with fidelity. Such investigations will yield a deeper understanding of the value of personalized recommendations within schools, and in turn provide examples that enable educators to operationalize personalization in their classrooms.

5. ACKNOWLEDGMENTS

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