Toward more accurate measurements and a better understanding of students' transfer ability in solving physics problems online

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Two earlier studies demonstrated that students’ behavior data from a sequence of online learning modules can be analyzed to measure their ability to transfer their knowledge on solving one physics problem to a similar new one. In addition, adding an on-ramp module that develops basic skills improved students’ transfer ability. In the current study, we improved the accuracy of the transfer measurement by identifying and excluding students who interacted with the learning modules differently from what was expected and examined two possible mechanisms by which the on-ramp module could improve student transfer. Based on a two by two framework of self-regulated learning, we hypothesized that students with a performance-avoidance oriented goal are more likely to consistently guess on their initial attempts, leaving a distinctive pattern in the log data and resulting in an underestimation of students’ actual transfer ability. We divided the remaining student sample according to whether they passed the on-ramp module before or after accessing the instructional materials and compared their performance to a propensity score-matched sample from a previous semester. Improvement in transfer ability was found to primarily occur among students who passed the on-ramp module before learning. A possible explanation is that the on-ramp module served as an effective reminder for students who already possess the essential skills, but may be insufficient to develop those skills for other students. Our results suggest that online learning modules can be an accurate and flexible tool in assessing students’ transfer ability. Further, our results demonstrate that the analysis of online learning data can produce more accurate and insightful results when taking into account details of student learning behavior and learning strategy.
I. INTRODUCTION

In addition to learning physics concepts, a key objective of physics instruction is to facilitate students’ development of robust problem solving skills and the ability to transfer those skills to novel contexts [1–3]. How instructional methods can be developed and evaluated to enhance students’ transfer ability is a highly valuable research question for STEM education. However, most existing instruments that assess students’ conceptual understanding [4, 5] or problem solving skills at scale [6, 7] are not designed to directly measure their ability to transfer, since the tests do not explicitly provide students the opportunity or the resources to learn during the test. Therefore, developing new methods that are not only able to accurately measure students’ ability to transfer, but also shed light on the effectiveness of learning materials and instructional practices is a valuable initial step in the effort to improve students’ transfer ability.

In an earlier paper [8] we proposed a new method for measuring students’ ability to transfer their learning from online problem solving tutorials to new problem contexts with different surface features by analyzing the log of clickstream data of students interacting with a sequence of online learning modules (OLMs). Each module contains both learning materials and assessment problems, as explained in more detail in sections IA and II A. We found that while introductory-level college physics students are highly capable of learning to solve specific problems from online tutorials, they struggled to transfer their learning to a slightly modified problem given immediately afterward on the next module. In a follow-up study [9], we tested two different methods to enhance students’ ability to transfer in an OLM sequence and found evidence suggesting that the addition of an “on-ramp” module (a scaffolding module designed to solidify essential basic skills and concepts [10, 11]) prior to the tutorial resulted in significant improvement in students’ ability to transfer their knowledge in the rotational kinematics sequence.

Those early results raised two important questions that the current study tries to answer. First, since the OLMs are assigned for students to complete on their own, what fraction of students interacted with the modules as we had intended? For those who did not, to what extent did their behavior, as described in section IB, affect the validity of our measurement of students’ transfer ability, and how can we mitigate those impacts for a more accurate measurement? Second, while earlier analyses suggested that the “on-ramp” modules may be effective, what is the mechanism by which those modules enhance students’ ability to transfer? Are the benefits of those modules exclusive only to students who interacted with them in a certain way, as explained in section IC?

A. Measuring transfer in an OLM sequence

As will be explained in more detail in section II, each OLM consists of an instructional component (IC) and an assessment component (AC) which contains one or two problems, as demonstrated in Fig. 2 adapted from [8]. Students are required to complete at least one attempt on the AC before being allowed to study the IC, a design that was inspired by the frameworks of preparation for future learning [1] and productive failure [12]. Students who failed their first attempt can learn to solve the specific type of problem from the IC. When students complete a sequence of two or more OLMs in sequence on the same topic involving similar assessment problems, their required first attempt on the subsequent module serves as an assessment of their ability to transfer their learning from the IC of the previous module. When more than two modules are involved, students’ performance on later modules could be attributed to indirect transfer due to a preparation for future learning effect; that is, completing the first module better prepares students to learn from the second module, which in turn increases performance on the third and subsequent modules.

Data from OLMs can be visualized in a “zigzag” plot (Fig. 1, adapted from Ref. [9]), developed in earlier studies and explained in detail in section IID. Every two points represent the total assessment passing percentage of the student population on attempts before and after learning from the IC of each module. Students’ ability to learn to solve a specific problem is reflected by an increase in passing percentage from Pre to Post on the same module. The odd-numbered points in Fig. 1 (i.e., those labeled “Pre” as well as “Quiz”) show passing rates on initial attempts prior to learning from the IC of each module, and an increase from one point to the next reflects students’ ability to transfer their learning from the previous module(s).

B. Students’ different learning strategies and possible impact on assessment

Measuring students’ transfer ability from their performance on OLM assessment attempts requires that the majority of students either seriously took the required first attempt of each module, or made a quick guess only when they feel that they cannot solve the problem. However, research on students’ self-regulated learning (SRL) processes suggests that learners may choose to guess regardless of their ability or confidence to solve an assessment problem according to their motivational goal orientation. Using a $2 \times 2$ achievement goal framework [13, 14], learners’ goals can be
C. Distinguishing between two different mechanisms of the on-ramp module

In our earlier study [9], we found that the addition of an “on-ramp” module at the beginning of the OLM sequence resulted in better performance on the required first attempts for subsequent modules compared to students from the previous semester. The “on-ramp” modules contain practice problems designed to develop and enhance students’ proficiency of essential skills necessary for problem solving. However, students who passed the AC of the on-ramp module on their required first attempt (or on attempts before accessing the IC) can choose to directly move on to the next module without interacting with the IC of the on-ramp module. Therefore, if the on-ramp module enhances students’ transfer ability by improving their proficiency on essential skills, then the improvement will be less significant or nonexistent among those who passed on the first attempt, and only observed among those who failed their initial attempt and accessed the IC. Alternatively, if the on-ramp module mainly serves as a “reminder” for students to activate existing knowledge of essential skills, then the benefit should be more significant among those who passed on the first attempt, and less so for those who studied the IC. Distinguishing between those two mechanisms can better guide the future development of instructional materials to enhance students’ ability to transfer.
D. Research questions

To summarize, in this study we will answer the following three research questions:

RQ1 What fraction of students adopted a performance-avoidance strategy when interacting with OLM sequences?

RQ2 To what extent did the results from previous studies change after students with performance-avoidance strategies were removed from the sample?

RQ3 Did the on-ramp module enhance students’ ability to transfer by improving students’ proficiency in essential skills or by serving as a “reminder” for those who are already proficient?

The first two research questions are important for the accuracy of the measurements, and lay the groundwork for answering RQ3. In sections II A to II C, we will explain in detail the structure and implementation of OLM sequence, as well as the data collection process. In section II D, we present our operational definition of key concepts such as assessment passing percentage and performance-avoidance strategy in the context of OLMs and outline our analysis procedure for measuring transfer and answering the research questions. In section III, we present the results of our analysis, which are interpreted in section IV A, and their implications are discussed in the rest of IV.

II. METHODS

A. OLM Sequence Structure

The study was conducted using online learning modules (OLMs) [8, 9, 19, 20] implemented on the open source Obojobo platform [21] developed by the Center for Distributed Learning at the University of Central Florida (UCF). Each OLM contains an assessment component (AC) and an instructional component (IC) (see Fig. 2). Students have 5 attempts on the AC, which contains 1-2 multiple-choice problems, and must make at least one attempt before being allowed to access the IC. The IC contains instructional text, figures, and/or practice questions in general. Specific contents of the IC used in each of the modules in the current study will be detailed in the next section. In an OLM sequence, a student must either pass or use up all five attempts on the AC before being allowed to access the next module. Students’ interaction with each OLM can be divided into three stages: The pre-study (Pre) stage in which a student makes one or more attempts on the AC, the study stage in which those who failed in the Pre stage study the IC, and the post-study (Post) stage in which students make additional attempts on the AC. A small fraction of students have also been observed to choose to skip the study stage after multiple failed attempts in the Pre stage. A student is counted as passing an AC if the student correctly answers all problems in the AC within their first 3 attempts, including both Pre and Post stage attempts. In other words, students who either failed on all 5 attempts or passed on their 4th or 5th attempts are considered as failing the module in the current study.

B. Study Setup

In Fall 2017, two sequences each containing 3 OLMs (specifically, OLMs 2, 3, and 5 in Fig. 2) were assigned as homework to 235 students enrolled in a calculus-based introductory physics class at UCF [8]. The 6 modules were worth 3% of the total course credit. The first OLM sequence teaches students to solve Atwood machine type problems with blocks hanging from massive pulleys using knowledge of rotational kinematics (RK). The second sequence
teaches students to solve angular collision problems such as a girl jumping onto a merry-go-round using knowledge of conservation of angular momentum (AM). Both sequences are designed to develop and measure students’ ability to transfer problem solving skills to slightly different contexts. The modules used in this study are free and available to the public at Ref. [22].

The AC of each OLM contains one problem that can be solved using the same physics principles as other ACs in the OLM sequence. The IC of OLM 2 (Fig. 2) contains an online tutorial developed by DeVore and Singh [23, 24], in the form of a sequence of practice questions. The IC of OLM 3 contains a worked solution to the AC problem, and the IC of OLM 5 is empty since it is intended to serve the role of a quiz.

In Fall 2018, the two OLM sequences were each modified by adding two additional OLMs (shown in Fig. 2) and implemented again in the same course taught by the same instructor as homework to 241 students. Both sequences were assigned as homework that was worth 3% of the total course credit. The first new module in each sequence is the “on-ramp” module (OLM 1 in Fig. 2), which contains an AC focusing on one or more basic procedural skills necessary for solving the subsequent ACs in the OLM sequence. For the RK sequence, the on-ramp module presents students with two Atwood machine problems of the simplest form, involving one or two blocks hanging at the same radius from a single massive pulley. For the AM sequence, the on-ramp module addressed the common student difficulty of calculating both the magnitude and sign of the angular momentum of an object traveling in a straight line about a fixed point in space. The second new module in each sequence is the “Example 2” module (OLM 4 in Fig. 2), which contains in its AC a new problem that shares the same deep structure as the one in the previous module, but differs in surface features. The IC of the module was designed in two formats: a compare-contrast format in which students were given questions that prompted them to compare the similarity and difficulty of the solutions to the problems in AC3 and AC4, and a guided tutorial format consisting of a series of tutorial-style scaffolding questions guiding them through the solution of the problem in AC4. Each form was provided to half of the student population at random. We found no difference between the two cohorts in terms of students’ behavior and performance on the subsequent module 5 [9].

C. Data Collection and Selection

Anonymized clickstream data were collected from the Obojobo platform for all students who interacted with the OLM sequences. The following types of information were extracted from the log data following the same procedure explained in detail in Ref. [25]: the number of attempts on the AC of each module, the outcome of each attempt (pass/fail), the start time and duration of each attempt, and the start times of interaction with the IC. The duration of interaction with the IC was also extracted but was not used in the current analysis.

In addition, students’ exam scores and overall course grades, each on a 0-100 scale, were also collected, anonymized, and linked to each students’ log data. The exam scores consist of two midterm exams, each counting for 12% of the final course grade, and a final exam counting for 16% of the final course grade. The final course grade also contains scores from homework, lab, and classroom participation.

In order to maintain a consistent sample across our analyses, only data from students who attempted every module in a sequence at least once are included. Data from seven students for the 2017 RK sequence were removed because of this reason, and two or fewer students were removed for all other OLM sequences. Data from 202 students were retained for the RK sequence in 2017, 198 students in the RK sequence for 2018, 198 students for the AM sequence in 2017, and 189 students for the AM sequence in 2018.

In the Fall 2017 implementation, half of the students were given the option to skip the initial AC attempt of OLM 2 (the first OLM in that implementation) and proceed directly to the tutorial in the IC. However, we found in an earlier study [8] that very few students chose to exercise this option and among those who did there was no detectable impact on subsequent problem solving behavior and outcome. Therefore, in the current analysis, we combined those two groups into one. Similarly, for the Fall 2018 semester, we combined data from students encountering the two different versions of IC in module 4, since no difference in their behavior and outcome on module 5 could be detected [9].

D. Data Analysis

To identify and estimate the size of students adopting a performance-avoidance strategy (RQ1), we will analyze the frequency of students making a very brief first attempt on each module. As explained in section IB, students who adopt this strategy are more likely to consistently guess on their first attempts and gain access to the instructional material.

In the current analysis, we categorize each student’s first attempt as a “Brief Attempt” (BA) if the duration of the attempt is less than 35 seconds. This cutoff time is inherited from a careful analysis of similar OLMs in an earlier
study [25], and chosen as a conservative estimate for the minimum amount of time needed to read and attempt a given question. Students are categorized into three “BA groups” based on the number of BAs on the first four modules: 0-1 BAs, 2-3 BAs, and 4 BAs. Table 1 shows the number of students in each BA group for each OLM sequence. BAs on the quiz module were not considered since there was no IC for the students to access. Due to the conservative BA duration estimation, we believe that the 0-1 BA group is the one with the least performance-avoidance focused students, and are most likely to make valid first attempts on the AC.

To examine the extent to which the behavior of performance-avoidance focused students affect the measurement of transfer (RQ2), we will compare the Pre and Post stage passing rates of the three BA groups on all modules in the two sequences, and plot the outcomes in Fig. 3. Following the convention established in two previous studies [8, 9], the pass rates are defined as follows. On each OLM module except for module 5, the pass rates (P) of students was calculated for both the Pre-study (P_{pre}) and Post-study attempts (P_{post}). The Pre-study pass rate on each module is calculated as

\[ P_{pre} = \frac{N_{pre}}{N_{total}}, \]  

with \( N_{pre} \) being the number of students who passed Pre-study and \( N_{total} \) being the total number of students who attempted the module. Similarly, the Post-study pass rate on each module is calculated as

\[ P_{post} = \frac{N_{pre} + N_{post}}{N_{total}}, \]  

with \( N_{post} \) being the number of students who passed Post-study. By including both \( N_{pre} \) and \( N_{post} \), the Post passing rate reflects the total number of students able to pass the assessment after being given the access to the IC, assuming that students who passed in the Pre stage can also pass in the Post stage if re-tested. This definition is similar to the Post test score in a Pre-test/Post-test setting. For module 5, the passing rate does not distinguish between Pre and Post stage because the IC of the module contains no instructional resources. The \( P_{pre} \) on modules 2-4 and \( P \) on module 5 measures students’ ability to transfer their learning from modules 1-4. We hypothesized that the 0-1 BA group would have significantly better performance than the other two BA groups on their Pre stage attempts on modules 2, 3, and 4 because the other two BA groups are more likely to forfeit the first attempt opportunity regardless of their ability to solve the problem. We further hypothesized that the Post-study pass rates for each BA group will be very similar, because \( P_{post} \) reflects students ability to learn from the modules and solve the specific problem (if they are not already proficient), and the dominant factor separating the three groups is students’ engagement strategy, not their ability to learn from the modules.

Finally, to examine the mechanism by which the on-ramp module improves transfer of knowledge (RQ3), we first separate the student sample from Fall 2018 into three “on-ramp cohorts”:

- **Pass On-Ramp Pre**: students who passed the on-ramp AC before accessing the IC,
- **Pass On-Ramp Post**: students who passed the on-ramp AC only after accessing the IC, and
- **Fail**: students who did not pass the on-ramp AC within 3 attempts.

Based on the analysis outcome for RQ1 and RQ2, we only retained data from the 0-1 BA group for this analysis, since our analysis indicates that data from the other two BA groups could result in an underestimation of students’ ability to transfer.

Next, we identified three comparable cohorts of students from the 2017 sample. We first retained students who only made 0-1 BA on modules in the 2017 sequence, then identified comparable cohorts using propensity score matching, since the general ability of the 0-1 BA group could be different from the rest of the student population. Propensity scores were constructed using a combination of standardized scores from two mid-term exams and one final exam in

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### Table 1: The number of students in each OLM sequence by their number of Brief Attempts. The Brief Attempt groups consist of those who had 0-1, 2-3, or 4 Brief Attempts throughout the first four modules.

| OLM Sequence | # of Brief Attempts |
|--------------|---------------------|
|              | 0-1 | 2-3 | 4 |
| RK           | 100 | 82  | 16 |
| AM           | 91  | 71  | 27 |
FIG. 3. Students are grouped by their number of Brief Attempts throughout the OLM sequences for (a) Rotational Kinematics and (b) Angular Momentum. The pass rates of these groups in each module are plotted along with their standard error.

FIG. 4. Using propensity score matching on course exam scores, a subset of 2017 students are matched to 2018 students with 0-1 Brief Attempts. The pass rates of these two samples are then plotted separately for (a) Rotational Kinematics (RK) and (b) Angular Momentum (AM).

both semesters. Each exam is largely identical across the two semesters, with one or two questions being replaced or modified.

Pass rates on all modules in both sequences are compared between the three 2018 cohorts and the three propensity score matched 2017 cohorts in order to distinguish between the two possible mechanisms for of the on-ramp module. If the “improve proficiency” effect was dominant, then the performance differences should be observed mostly among the Pass On-Ramp Post cohort and its matched cohort in 2017. If the “reminder” effect was dominant, then the differences will be observed for the Pass On-Ramp Pre cohort and its counterparts.

Propensity score matching was performed using R [26] and the MatchIt package [27]. The MatchIt algorithm retains all treated data and attempts to find either an exact one-to-one match or balance the overall covariant distribution for the control data.

Data analysis, statistical testing, and visual analysis were conducted using R [26] and the tidyverse package [28].
III. RESULTS

First, we estimate the fraction of students that adopted a performance-avoidance strategy (RQ1) by listing the number of students with 0-1, 2-3, or 4 BAs on the first four modules of each sequence in Table I. The result shows that, even with relatively conservative criteria for classifying brief attempts, we still identified 10-15% of the students who made a brief attempt on each of the four modules. On the other hand, around 50% of the students belong to the 0-1 BA group. Within the 0-1 BA group, the number of students in each on-ramp cohort is listed in Table II for each OLM Sequence.

Figure 3 shows the Pre and Post stage pass rates of students on modules 2-5, separated by the number of BAs on the first four modules. Pass rates from the two sequences are plotted separately: the RK sequence in Fig. 3a and the AM sequence in Fig. 3b. In both Fig. 3a and Fig. 3b, the most prominent difference between the three BA groups is that students in the 0-1 BA group significantly outperformed the other two groups in Pre stage attempts for the Example 1 module (OLM 2, Fig 2) (Fisher’s exact test on $2 \times 3$ contingency tables, $p < 0.001$ for the RK sequence and $p = 0.001$ for the AM sequence). Students in the 0-1 BA group also outperformed the 2-3 BA group on RK Tutorial Post Stage attempts ($p = 0.028$) and RK Example 1 Post stage attempts ($p = 0.018$), but the difference with the 4 BA group is either statistically insignificant or the direction of the difference is reversed.

The observation of a significant performance difference between the three BA groups on the Pre stage attempts on the Example 1 module partly confirmed our hypothesis (RQ2) that students adopting a performance-avoidance strategy could have a measurable impact on the estimation of the transfer ability of the student population using performance data from Obojobo. Therefore, to mitigate this impact, we limit ourselves to studying the 0-1 BA group for both 2017 and 2018 student samples in the following analysis.

We compared the pass rates of the 0-1 BA group from 2018 on modules 2-5 with a propensity score matched subsample in 2017 who also had 0-1 BAs on the first two modules. The pass-rates for both sequences are shown in Fig. 4, while the $p$-values from Fisher’s exact test comparing each pair of data points on the figures is listed in the first two rows of Table III. All $p$-values are adjusted for Type I error due to conducting multiple tests using the Benjamini-Hochberg method [29]. The data shows that there are significant performance differences in the success rate between the two student populations on Tutorial Pre and Example 1 Pre attempts in the RK sequence, whereas the difference in the AM sequence is less prominent, possibly due to the success rate being very high in both samples. The differences are similar in nature but larger in magnitude compared to what was observed in our earlier study that did not consider alternative learning strategies [9], suggesting that the earlier study could have underestimated the transfer ability of the student population.

To examine the mechanism by which the on-ramp module improves the transfer of knowledge (RQ3), we divided the 2018 0-1 BA population into three cohorts. Since the Fail cohort is much smaller than the other two cohorts and too small for reliable propensity score matching, we will only analyze the Pass On-Ramp Pre and Pass On-Ramp Post cohorts (see Table II). In Fig. 5, we compare the performance of those two cohorts to their propensity score matched counterparts in the Fall 2017 semester. The pass rates of the two cohorts on the same module sequence are shown side by side. Data from the RK sequence is shown on the top row (Fig. 5a and Fig. 5b) and the AM sequence in the bottom row (Fig. 5c and Fig. 5d). The adjusted $p$-values of Fisher’s exact test between each pair of points are listed in the last four rows of Table III.

It can be seen from Fig. 5 that the Pass On-Ramp Pre cohort is responsible for the majority of the differences on Pre-study attempts between the 2017 and 2018 samples. For the RK sequence, the differences are not statistically significant for the Pass On-Ramp Post cohort after ($p$-value adjustment [29]). For the AM sequence, none of the differences were statistically significant after $p$-value adjustment for either the Pass On-Ramp Pre or Pass On-Ramp Post cohorts.

| OLM Sequence | Pass On-Ramp Pre | Pass On-Ramp Post | Fail |
|--------------|------------------|-------------------|------|
| RK           | 32               | 57                | 11   |
| AM           | 32               | 47                | 12   |

TABLE II. The number of students in each OLM sequence that fall into each on-ramp cohort among those with 0-1 Brief Attempts. The cohorts consist of those who passed during on-ramp Pre-study attempts (“Pass On-Ramp Pre”), those who passed during on-ramp Post-study attempts (“Pass On-Ramp Post”), and those that failed the on-ramp assessment (“Fail”). Since the on-ramp module was only included in Fall 2018, only students from 2018 are included here.
IV. DISCUSSION

A. Interpretation of results

We found that roughly half of the students frequently or consistently adopted a learning strategy that is likely motivated by a performance-avoidance goal: making abnormally short attempts on their required first attempts on some or all of the first four modules. These brief attempts could have been generated by students who were either guessing or copying the answer from a peer. While an occasional brief attempt may indicate a lack of confidence in one’s knowledge, continuous brief attempts on multiple modules are more likely a strategic choice to save time on the task, since the performance differences on attempts after studying the learning material are much smaller. This strategy fits well with Boekaerts’s description of students being in a “coping mode,” in which their goal is to pass the module while saving time and “unnecessary” possible failures [18].

For students who adopted the performance-avoidance strategy, their transfer ability can no longer be measured using OLMs, as their brief Pre-study attempts on the following modules do not always reflect their true ability to transfer their learning from the current module. Our analysis suggests that including data from those students resulted in an underestimation of students’ ability to transfer knowledge from the Tutorial module (module 2) to the Example 1 module (module 3) in our earlier study, although most of the qualitative conclusions remain the same. However, it must be clarified that the current analysis is also not an accurate measurement of the transfer ability for the entire student population. Instead, it is an accurate measurement for the subpopulation who did not frequently guess on their initial attempts.

An alternative explanation of our observation is that students who frequently adopt the strategy have a lower level of overall mastery on the subject (and possibly a higher level of self-awareness of their lack of knowledge). Therefore, they would not have been able to pass the required Pre stage attempt even if they had tried, and thus including those students would not result in an underestimation of students’ transfer ability. However, while this may be true for some students, we do not think that this explanation applies to the majority of students in the 2-3 BA and 4 BA groups. This is because their performance on modules 2, 4, and 5, as well as on the Post stage of the Example 1 module are either similar to that of the 0-1 BA group or only slightly worse, which suggests that their overall physics abilities are similar and therefore the difference observed in the Pre stage attempts on the Example 1 module are mostly due to difference in strategical choice.

Another major finding of the current analysis is that the benefit of the on-ramp module in facilitating transfer (as measured by Pre stage attempts of subsequent modules) predominantly occurs among students who can pass the on-ramp module before accessing the instructional component. The difference is much more prominent for the more challenging RK sequence, and less so for the easier AM sequence. This unexpected observation holds true even after we used propensity score matching between the two semesters to control for the fact that the Pass On-Ramp Pre cohort likely includes students with better physics knowledge or higher motivation than students in the Pass On-Ramp Post cohort.

A possible explanation could come from the basic principles of information processing theory [30, 31]. For students who already possess the essential skills or procedures, attempting the on-ramp module assessment prompted them to retrieve those skills from long-term memory and retain them in working memory. All or part of those skills remained either in the working memory or in a more active state when the students moved on to the subsequent modules, thereby freeing up cognitive capacity for those students to better comprehend the additional complexity of the Tutorial and Example 1 modules. On the other hand, for those who had not yet mastered those essential skills, the IC of the on-ramp module was sufficient for them to pass the assessment, but not enough for them to achieve a higher level of

| Fig. | Tutorial Pre | Tutorial Post | Example 1 Pre | Example 1 Post | Quiz |
|------|--------------|---------------|---------------|----------------|------|
| 4a   | 0.003        | 0.330         | < 0.001       | < 0.001        | 0.054|
| 4b   | 0.333        | 0.265         | 0.166         | 0.306          | 0.166|
| 5a   | 0.001        | 1.000         | 0.001         | 0.395          | 0.438|
| 5b   | 0.498        | 1.000         | 0.008         | 0.028          | 0.028|
| 5c   | 0.764        | 0.766         | 0.267         | 1.000          | 0.766|
| 5d   | 0.835        | 0.835         | 0.835         | 0.835          | 0.835|

TABLE III. A list of p-values from Fisher’s exact test comparing the performance of 2018 students and matched 2017 students on each common assessment in the listed figure. The p-values have been adjusted using the Benjamini-Hochberg method [29].
FIG. 5. Using propensity score matching on course exam scores, a subset of 2017 students are matched to 2018 students with 0-1 Brief Attempts in either the (a) and (c) Pass On-Ramp Pre or (b) and (d) Pass On-Ramp Post cohorts. The pass rates of these two cohorts are plotted separately for (a) and (b) Rotational Kinematics (RK) and (c) and (d) Angular Momentum (AM).

proficiency. Therefore, activating those skills on the subsequent modules required a higher amount of cognitive load, limiting students’ abilities to process the additional complexities.

A straightforward and testable implication of this explanation is that providing students with more practice problems on those essential skills will increase their ability to learn and transfer on subsequent modules. In addition, it may be beneficial to distribute those practices rather than clustering them immediately prior to the tutorial sequence, as distributed practice has been shown to be beneficial for skill acquisition and recall [32, 33], and practices of distributed retrieval of factual knowledge have been shown improved students’ physics exam scores [34].

It must be pointed out that our use of propensity score matching to control for the fact that our selected student populations likely have different knowledge and motivation than the rest of the population is far from perfect, since overall exam scores may not fully reflect knowledge on the specific topic involved. A more accurate propensity score could be constructed in the future, when additional modules on the same topic are created and assigned to students prior to the tutorial sequence. Such modules have been created and administered in the Fall 2019 semester, enabling
more accurate analysis to be conducted in the future.

B. Implications for Online Education Research

Our analysis shows that students’ behaviors in a self-regulated online learning environment frequently deviate from what was intended or expected by the instructor. Those unexpected behaviors, such as frequently guessing (or cheating in some cases) on problems, can have a substantial impact on the outcomes of data analysis if not properly accounted for. Excluding students with unexpected behavior improves the accuracy of the measurement, but also limits the measurement to only those who interacted with online learning resources as expected. However, this should not be seen as a limitation that is unique to online education research, since students completing not for credit paper-and-pencil assessments can also adopt avoidance goal oriented strategies. In fact, the ability to detect the presence of diverse student behavior, and correct for their impact in data analysis is a unique strength of online educational research. It can also motivate and facilitate future development of instructional strategies to reduce procedure-avoidance strategies among students in an online environment.

Furthermore, in our earlier analysis [9] on the same module sequences, we found that instructional resources designed based on well-documented learning science principles may not always generate expected outcomes due to variations in the actual implementation. The current analysis further reveals that even when the instructional resource did result in the expected outcome improvement, the underlying mechanism may be different from what was expected. In this case, modules that were designed to train the proficiency of essential skills among students actually benefited those who were already proficient and did not go through the training by serving as a reminder for them to activate the skills. Those results demonstrate the high level of complexity and unpredictability involved in designing and creating effective instructional resources. Moreover, they highlight the importance of discipline-based education researchers’ role as “Education Engineers” who try to bridge the gap between learning theories and actual instructional practices.

Last but not least, the current study is an exploratory attempt at evaluating the effectiveness of instructional materials by comparing the outcomes of students enrolled in two consecutive semesters and controlling for the extrinsic variances using propensity score matching. Compared to the more common method of conducting randomized AB experiments [35, 36], the current method is significantly easier to implement in actual classroom settings and introduces fewer disruptions for students compared to randomized control experiments. In addition, this method allows for a larger sample size since each group consists of an entire class rather than a fraction of the class. While it introduces more variances due to the treatment and control groups coming from different semesters, we demonstrated that the impact from those variances could be controlled to some extent by methods such as propensity score matching. This less disruptive study setup can be particularly valuable under certain situations, such as during the current COVID-19 outbreak which presents students with many obstacles as institutions shift to fully remote instruction, and instructors are reluctant to introduce more potential sources of confusion.

ACKNOWLEDGMENTS

The authors would like to thank the Learning Systems and Technology team at UCF for developing the Obojobo platform. Dr. Michelle Taub provided critical and insightful comments on students’ self-regulated learning. This research is partly supported by NSF Grants DUE-1845436 and DUE-1524575 and the Alfred P. Sloan Foundation Grant G-2018-11183.

[1] J. D. Bransford and D. L. Schwartz, “Rethinking transfer: A simple proposal with multiple implications,” Review of Research in Education 24, 61–100 (1999).
[2] H. S. Broudy, “Types of knowledge and purposes of education,” in Schooling and the Acquisition of Knowledge, edited by Richard C. Anderson, Rand J. Spiro, and William E. Montague (Routledge, 1977) pp. 1–17.
[3] Douglas K. Detterman, “The case for the prosecution: Transfer as an epiphenomenon,” in Transfer on Trial: Intelligence, Cognition, and Instruction, edited by D. K. Detterman and R. J. Sternberg (Ablex Publishing, 1993) pp. 1–24.
[4] David Hestenes, Malcolm Wells, and Gregg Swackhamer, “Force concept inventory,” The Physics Teacher 30, 141–158 (1992).
[5] Ronald K. Thornton and David R. Sokoloff, “Assessing student learning of newton’s laws: The force and motion conceptual evaluation and the evaluation of active learning laboratory and lecture curricula,” American Journal of Physics 66, 338–352 (1998).
[35] Zhongzhou Chen and Gary Gladding, “How to make a good animation: A grounded cognition model of how visual representation design affects the construction of abstract physics knowledge,” Phys. Rev. ST Phys. Educ. Res. 10, 010111 (2014).

[36] Zhongzhou Chen, Christopher Chudzicki, Daniel Palumbo, Giora Alexandron, Youn-Jeng Choi, Qian Zhou, and David E. Pritchard, “Researching for better instructional methods using AB experiments in MOOCs: results and challenges,” Research and Practice in Technology Enhanced Learning 11 (2016).