

# Quantifying How Students Use an Online Learning System: A Focus on Transitions and Performance

Erica L. Snow  
Center for Technology in Learning  
SRI International  
333 Ravenswood Ave  
Menlo Park ,CA  
erica.snow@sri.com

Andrew E. Krumm  
Center for Technology in Learning  
SRI International  
333 Ravenswood Ave  
Menlo Park ,CA  
andrew.krmm@sri.com

Timothy Podkul  
Center for Technology in Learning  
SRI International  
333 Ravenswood Ave  
Menlo Park, CA  
timothy.podkul@sri.com

Mingyu Feng  
Center for Technology in Learning  
SRI International  
333 Ravenswood Ave  
Menlo Park, CA  
mingyu.feng@sri.com

Alex J. Bowers  
Teachers College  
Columbia University  
525 West 120th St.  
New York, NY 10027  
bowers@tc.edu

## ABSTRACT

The current study employs transitional probabilities as a way to classify and trace students' interactions within an online learning system. Results revealed that students' interaction patterns within the system varied in relation to their performances on embedded assessments. The results and methodologies presented here are designed to provide practitioners with a starting place for how to extract information concerning how and why their students interact within an online environment.

## Keywords

Blended Learning, Transitional Probabilities, Online Technology

## 1. INTRODUCTION

The use of blended learning techniques has become increasingly prevalent within high school classrooms [1]. One goal of blended learning is that information concerning students' behaviors and performance within various technologies can be used to inform instructional practice [2]. However, trace-level data from most technologies are often inaccessible or unusable for practitioners [3]. The current work aims to better understand what methodologies and tools are useful for helping practitioners make sense of *how* students interact with assessments and resources within online technologies. Using transitional probabilities we examined how 812 middle and high school students interacted with an online learning system (OLS) as part of their regular Math classroom instruction and how these behaviors varied as a function of students' performance within the system.

## 2. METHODS

### 2.1 Participants

The participants included 812 students from a large charter management organization (CMO) in the San Francisco Bay area. Over 60% of students who attend this CMO come from underserved populations (e.g., African American and Hispanic or Latino) and over 40% qualify for free or reduced priced lunches. The participating students regularly interact with the OLS as part of their Math curriculum.

### 2.2 Procedure, Measures, and Data Processing

Students interacted with the Math content on the OLS throughout the 2014-2015 school year. In the work presented here we examined how students interacted in one lesson for their Math curriculum, *Linear Equations*. During this lesson, students could freely choose to engage in a variety of activities at their own pace. These activities can be grouped into three categories that represent a different type of functionality within the system; these functionalities are *Post Assessments* (Linear Equation content gleaned from system resources), *Pre Assessments* (baseline measure of students' Linear Equation knowledge), and *Resources* (unique items –PDFs, videos, images- that provide Linear Equation content). These categories afforded the opportunity to trace students' choice of interactions within the system while also providing a means of surfacing reoccurring patterns of behavior that students exhibit throughout the school year. All interactions are logged within the system and provide valuable insight into *how* students interact with the OLS.

## 3. QUANTITATIVE METHODS

To examine variations in students' behavior patterns within the Linear Equation curriculum of the OLS, transitional probabilities were conducted. This analytical tool provides a means to provide teachers with a visualization of students' learning trajectories. This is particularly useful for practitioners interested in examining how closely students' choices followed the intended system curriculum. The following section provides a brief description and explanation of transitional probabilities and their application to the current data set.

### 3.1 Transitional Probabilities

Transitional probabilities were calculated using a statistical sequencing procedure established in D'Mello, Taylor, and Graesser (2007; [4]). This sequencing procedure is calculated using the formula  $L[I_t \rightarrow X_{t+1}]$ . In this formula,  $L$  is the likelihood function of the student's current choice in the system ( $I$ ) at specific time point  $t$ , and  $X$  is their next interaction choice at the next time point ( $t+1$ ). Thus, this sequencing procedure surfaces the probability of a student's interaction choice given their previous choice. For instance, if Zach chooses to take a Pre

Assessment, the above formula will be used to surface what choice Zach is most likely to choose next (e.g., another Pre Assessment, a Post Assessment, or a Resource). These probabilities were calculated for each of the 812 students, which resulted in a unique pattern of choices for each student. The results reported below address students' interactions with the Pre Assessment, Post Assessment, and Resources associated with Linear Equations content within a 9<sup>th</sup> grade Math course.

#### 4. RESULTS

Overall, 812 students interacted with the Linear Equation content within the OLS system. Teachers recommended that students take the Pre Assessment, interact with system Resources, and then take the Post Assessment to measure changes in learned material. However, as this was a blended learning environment students were free to choose how they would spend their time and what features they would interact with. Using system log data, we classified students' interactions into one of three orthogonal categories (i.e., Post Assessments, Pre Assessments, and Resources). We classified students as passing if they scored at or above 80% and failing if the scored below 80%. To examine how students interacted with the system, we calculated the total frequency of students' interactions with each of these three categories. On average, students made 38 interactions within the system and spent the majority of their time interacting with Pre Assessments (53%), followed by taking Post Assessments (32%) and interacting with Resources (15%).

##### 4.1 Interaction Transitions

The current work aimed to better understand how students' performance in Math 9 influenced their next interaction within the OLS. Figure 1, displays the conditional transition probabilities for students who passed a Post Assessment for Linear Equations. In this figure, there are three possible interactions, retrying a Post Assessment, transitioning to a Pre Assessment, or transitioning to a Resource. Students can also choose to move onto another topic. This analysis revealed that after students' passed a Post Assessment, .01% of the time they tried another Post Assessment, 1% of the time they took a Pre Assessment, and 17% of the time they interacted with a Resource. Most often after passing a Post Assessment, students left that content area to start another (72%).

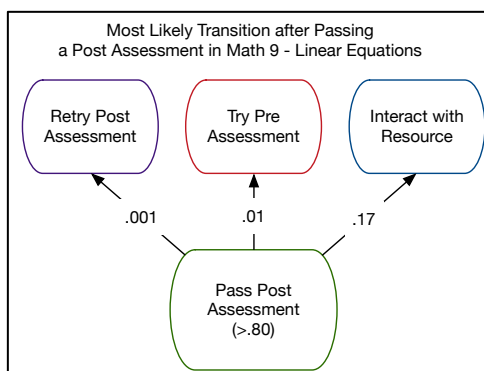


Figure 1. Conditional probabilities after passing Post Assessment.

Figure 2, displays the conditional transition probabilities if a student fails a Post Assessment for Linear Equations. Similar to Figure 2, there are three possible interactions along with students' choice to leave the curriculum. This analysis revealed that after students' failed a Post Assessment, 48% of the time they retook the Post Assessment, 43% of the time they took a Pre Assessment and 7% of the time they interacted with a Resource. Unlike

students who passed a Post assessment (Figure 1), students who failed a Post Assessment were less likely to exit the curriculum (2%) and instead most often interacted with another form of assessment (Pre or Post).

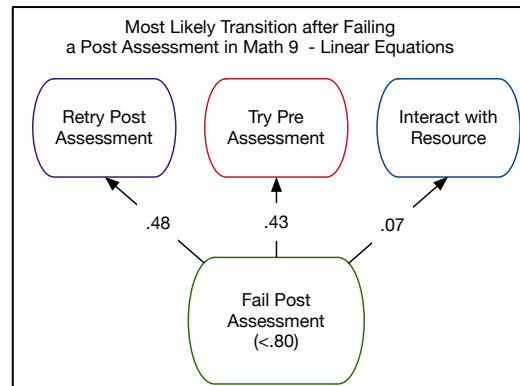


Figure 2. Conditional probabilities after failing a Post Assessment.

#### 5. DISCUSSION

These exploratory findings are promising for both educational researchers and practitioners as they reveal how students' behavior patterns manifest and vary as a function of performance. The current work begins to shed light upon the nuanced ways in which students' interactions can be traced and classified within online environments. In the future, this work will be expanded to examine students' behavior patterns across multiple classrooms and courses. The goal will then be to examine how students' behaviors vary as a function of performance and domain. This information may prove useful to practitioners wishing to better understand how information extracted from technology can be used to inform instructional practices.

#### 6. ACKNOWLEDGEMENTS

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