Impact of a Web-based Activity and Testing System for Supporting Students’ Algebra Learning in Community Colleges

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WestEd

Algebra I plays a critical role in post-secondary educational attainment. In California alone, college admissions to 4-year universities require Algebra (California Department of Education, n.d.). However, many students arrive in college underprepared for Algebra courses (Porter & Polikoff, 2012). For instance, on the 2009 National Assessment of Educational Progress (National Center for Education Statistics, 2010), only 26% of 12th graders scored at or above “Proficient” in mathematics. Given the stark challenges facing preparedness for post-secondary mathematics education, stakeholders are increasingly interested in effective instructional methods to improve post-secondary mathematics outcomes.

A promising solution to this challenge is the use of Web-based Activity and Testing Systems (WATS). WATS are interactive learning platforms whose features include adaptive problem sets, instructional videos, and resources for instructors to monitor and assist student learning. WATS have the potential to address a diverse range of student learning needs and are becoming increasingly common for educational use, in part due to advances in computer technology, as well as increasing availability of technology in classrooms.

In the present study, we investigate the impact of a WATS platform for supporting community college students in remedial algebra courses. The particular WATS platform we investigate contains motivational tokens for completing problem sets, and keeps track of student behavior (e.g., error rates and time-on-problem) so it can use this information in a programmed decision tree that selects problem sets and/or feedback based on students’ estimated mastery of specific skills. The platform also provides summaries of students’ progress for teachers.

Our study reports on the preliminary outcomes of the first year of a multi-year study.

Method

The present study took place in community colleges within a large western U.S. state. Our methodological approach involved randomly assigning community college instructors to either incorporate WATS into their Algebra I curriculum (the treatment condition), or to conduct Algebra I in a business-as-usual fashion (the control condition). The present study reports on outcomes from the second half of the year-long study (in the first half, treatment instructors had the opportunity to practice using the WATS platform in their remedial algebra course). The study sample includes 509 students from 29 instructors across 18 colleges.

The aim of the quantitative analysis was to address the question, what is the impact of WATS use on students’ algebra readiness? To this end, we employed Hierarchical Linear
Modeling (HLM) (Raudenbush & Bryk, 1998) to predict students’ end of semester scores on an assessment from the Mathematics Diagnostic Testing Program (MDTP), which is a valid and reliable assessment of students’ algebra readiness (Gerachis & Manaster, 1995). This study used a multilevel extension of the two-parameter logistic (Birnbaum, 1968) item response theory model to compute student and teacher pre- and post-test scale scores. Response-pattern Expected A Posteriori estimates (EAP scores; Thissen & Orlando, 2001) were computed for each student and teacher to utilize in the analytic model. The analytic model is presented below.

**Model**

\[ \gamma_{ij} = \beta_0 + \beta_{01} T_x_j + \beta_{10} Stu\text{Pre}_{ij} + \beta_{02} Tea\text{Pre}_{j} + \xi_{0j} + \epsilon_{ij} \]

The HLM model includes a random effect of teacher to account for the nesting of students within instructors, and covariates that account for students’ pretest MDTP EAP scores at both student and teacher levels (i.e., teacher level EAPS generated from student scores). Covariates were grand mean centered to achieve the intended covariate adjustment. Importantly, in the model, \( T_x_j \) represents a dichotomous variable (dummy coded) indicating treatment assignment, and the main effect of the intervention is captured by \( \beta_{01} \).

**Results**

The random and fixed effects for the model presented above are displayed in Tables 1 and 2, respectively. Controlling for students’ pretest EAP scores, we found that using WATS corresponds to a 0.35 increase in students’ post-test EAP scores, a statistically significant positive effect \((p < .05)\). The Hedges g value for this effect is 0.32, which is considered a small but noteworthy effect in educational research for studies of this size (Cheung & Slavin, 2015; WWC, 2014). The 95% confidence interval of the Hedges g value is .14 - .50.

Similar results were obtained using number of items correct on the MDTP as the outcome variable and as predictor variables. In particular, with these variables in the model, WATS corresponded to a 2.59 increase in student scores on the post-MDTP relative to the control group, a statistically significant effect \((p = .04)\). Since the post-MDTP is out of 50 items, the improvement corresponded to 5-percentage point increase in student scores (the Hedges g value was also .32).

While these results suggest that WATS has a positive impact on students’ algebra knowledge, it is important to note that this study suffered from high instructor attrition, which may bias the outcome of results.

**Discussion**

To investigate the robustness of the findings above, we are in the process of repeating this study with a second cohort of participants during the current (2016 – 2017) academic year. Pooling the results of these two studies will help to determine the extent to which study results replicate with different populations (Cheung & Slavin, 2015).
In addition, a great deal of textual, observational, and interview data are still being gathered and analyzed. These data allow careful analysis of the intended and actual use of how WATS are enacted in classroom contexts. Indices of specific and generic fidelity derived from this work also will play a role in exploring how and for whom WATS are effective.
References


Table 1. Random effects results of the model.

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<tr>
<th></th>
<th>Variance</th>
<th>St. Dev.</th>
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<tr>
<td>Teacher $\xi_{0j}$</td>
<td>0.16</td>
<td>0.40</td>
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<tr>
<td>Level-1 Error $\epsilon_{ij}$</td>
<td>0.40</td>
<td>0.63</td>
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Table 2. Fixed effect results of the model.

<table>
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<th>Variable</th>
<th>B</th>
<th>St. Error</th>
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<tr>
<td>Intercept</td>
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<tr>
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<td>0.16</td>
<td>.04</td>
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<tr>
<td>StuPre</td>
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<td>TeaPre</td>
<td>0.30</td>
<td>0.19</td>
<td>.13</td>
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