Exploring the Factors that Support Learning with Digitally-Delivered Activities and Testing in Community College Algebra

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Abstract. A variety of computerized interactive learning platforms exist. Most include instructional supports in the form of problem sets. Feedback to users ranges from "Correct!" to offers of hints and partially to fully worked examples. Behind-the-scenes design of such systems varies as well – from static dictionaries of problems to "intelligent" and responsive programming that adapts assignments to users' demonstrated skills, timing, and an array of other learning theory-informed data collection within the computerized environment. This poster presents background on digital learning contexts and invites lively conversation with attendees on the research design of a study aimed at assessing the factors that influence teaching and learning with such systems in community college elementary algebra classes.

Research Questions. Funded by the U.S. Department of Education, we are conducting a large-scale mixed methods study in over 40 community colleges to address:

RQ1: What student, instructor, or community college factors are associated with more effective learning from the implemented digital learning platform?

RQ2: What challenges to use-as-intended (by developers) are faculty encountering and how are they responding to the challenges as they implement the learning tool?

Background and Conceptual Framing. First, there are distinctions among cognitive, dynamic, and static learning environments (see table).

Summary Table		Static	Dynamic
A particular model of learning is explicit in design and implementation (structure and processes)	No	Text and tasks with instructional adaptation external to the materials	Adaptive tutoring systems (Khan Academy, ALEKS, ActiveMath)
	Yes	Textbook design and use driven by fidelity to an explicit theory of learning	"Intelligent" tutoring systems (Cognitive Tutor)

Learning environments can vary along at least two dimensions: (1) the extent to which they adaptively respond to student behavior and (2) the extent to which they are based on a careful cognitive model. Static learning environments are those that are non-adaptive and devoid of a cognitive model – they deliver content in a fixed order and contain scaffolds/feedback that are identical for all users and have a design based on intuition, convenience, or aesthetic appeal. An example of this type of environment might be online problem sets from a textbook that give immediate feedback to students (e.g., "Correct" or "Incorrect"). Dynamic learning environments keep track of student behavior (e.g., error rates or time-on-problem) and use this information in a programmed decision tree that selects problem sets and/or feedback based on students' estimated mastery of specific skills. An example of a dynamic environment might be a system such as ALEKS or the "mastery challenge" approach now used at the online Khan Academy. For example, at khanacadmy.org a behind-the-scenes data analyzer captures student performance on a "mastery challenge" set of items. If a student gets all six items correct, the next level set of items in a programmed target learning trajectory is offered. Depending on the number and type of items the particular user answers incorrectly (on the path to six items in a row done correctly), the analyzer program identifies target content and assembles the next "mastery challenge" set of items. In addition to such responsive assignment generation, programming in a *cognitive* learning environment is informed by a theoretical model that asserts the cognitive processing necessary for acquiring skills (Anderson et al. 1995; Koedinger & Corbett, 2006). For example, instead of specifying only that graphing is an important skill necessary for mastery of elementary algebra, a cognitively-based environment will also specify the student thinking and skills needed to comprehend graphing (e.g., connecting spatial and verbal information), and provide feedback and scaffolds that support these cognitive processes (e.g., visuo-spatial feedback and graphics that are integrated with text). In cognitive environments, scaffolds themselves can also be adaptive (e.g., more scaffolding through examples can be provided early in learning and scaffolding can be faded as a student acquires expertise; Ritter et al. 2007). Systems can also provide summaries of student progress, which better enable teachers to support struggling students. Some studies have shown preliminary support of their promise in post-secondary mathematics (Koedinger & Sueker, 1996).

Method. The study is a multi-site cluster randomized trial. Half of instructors at each community college site are assigned to use an adaptive web-based system in their instruction, the other half teach as they usually would. The primary outcome measure for students' performance is an assessment from the Mathematics Diagnostic Testing Program (MDTP), which is a valid and reliable assessment of students' algebra knowledge (Gerachis & Manaster, 1995). In the stratified sampling approach we first did a cluster analysis on all community college sites eligible to participate in the study based on college-level characteristics that may be related to student learning (e.g., average age of students at the college, the proportion of adjunct faculty). This analysis led to five clusters of colleges. Our recruitment efforts then aim to include a proportionate number of colleges within each group. The primary value of this approach is that is allows more appropriate generalization of study findings to the target population (Tipton, 2014).

Quantitative Analysis. The primary aim of the quantitative analysis is to address RQ1, how and for whom the tools are effective. To this end, we employ Hierarchical Linear Modeling (HLM). Models include interaction terms between instructors' treatment assignment and covariates at different levels (e.g., students history of course-taking, self-concept of ability), to explore the moderating impact of tool use on student learning.

Qualitative Analysis. To address RQ2, a great deal of textual, observational, and interview data are being gathered. These data allow careful analysis of the intended and actual use of the learning environment and the classroom contexts in which it is enacted – an examination of implementation structures and processes. Indices of specific and generic fidelity derived from this work also play a role in HLM generation and interpretation.

Results. Fall 2015 is the first full semester of data gathering for the project. It is our "practice" semester in that researchers are refining instruments and participant communication processes while instructors are trying out the web-based learning tool with their classes for the first time. The "efficacy study" semester in Spring 2016. By the time of the conference we will have early results from the practice semester. We are eager to share these and to gather feedback from RUME attendees on (1) design and how to best explain it to stakeholder audiences and (2) strengthening connections between the cognitive science research community and the RUME community.

References

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