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Paper Title: What Predicts Successful Use and Completion of an Adaptive Mathematics Software Intervention?

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TITLE: What predicts successful use and completion of an adaptive mathematics software intervention?


ABSTRACT

This study analyzes patterns and predictors in detailed performance data collected internally by adaptive web-based software designed to improve middle school students' structural understanding of and fluency with fractions. Our sample consists of 764 sixth graders in 29 Philadelphia public schools who participated in the first cohort of a larger randomized controlled trial. We use measures of active learning time and initial accuracy with the software to define indicators and norms that teachers can use to actively manage students' use of the software. These types of norms are crucial in helping teachers implement the intended software intervention effectively for children, regardless of their prior knowledge or initial accuracy with the software.


OBJECTIVES

This paper explores patterns in usage and completion of adaptive web-based software designed to improve middle school students' structural understanding of and fluency with fractions. The sample is drawn from the first cohort of a larger randomized control trial of a suite of interactive mathematics learning modules that integrate (1) principles of *perceptual learning*, which accelerate learners' abilities to recognize and discriminate key structures and relations in complex domains, and (2) *adaptive learning* algorithms that use a constant stream of performance data, combined with principles of learning and memory, to improve the effectiveness and efficiency of learning by adapting to individual students as they work toward objective mastery criteria [1, 2].

This investigation analyzes patterns and predictors in detailed performance data collected internally by the learning software with two primary objectives:

(1) To better define indicators and norms that teachers can use to actively manage students' use of the software.

(2) To take a finer-grained look at the degree to which the intended intervention is being implemented in various classes and to devise strategies to enhance the implementation in more classrooms.

Specifically, our research questions are: (1) Is active time spent using the software related to the probability of reaching mastery? (2) Does the association between active time using the software and the probability of mastery vary depending on the student's initial accuracy using the software? (3) What are the features of students who out-performed or under-performed relative to their class? and (4) What are the features of classes who out-performed or under-performed relative to other classes?

## THEORETICAL FRAMEWORK

Although the importance of pattern recognition, problem classification, and structural intuition has been recognized in many learning domains, including mathematics [1, 3, 4, 5, 6, 7, 8], these have seemed to lie beyond the scope of instruction in schools. In contrast, studies of expertise consistently demonstrate large changes in information extraction and processing that go beyond the acquisition of declarative and procedural knowledge [9, 10]. The process by which such changes in information extraction and fluency occur has been termed *perceptual learning* [11; see 12 and 13 for recent reviews], defined by Eleanor Gibson as experience-induced changes in the pick-up of information [11]. Kellman [13] argued that perceptual learning (PL) effects fall into two categories. *Discovery effects* involve learning what features or relations are relevant to a particular concept or task. *Fluency effects* involve improvements in the speed and automaticity of extracting discovered task-relevant information.

Kellman and Massey and their colleagues have demonstrated the effectiveness of incorporating principles of perceptual and adaptive learning into learning software known as perceptual learning modules (PLMs) [e.g. 1, , 6, 7, 8, 14] that exploit natural human abilities to extract invariant structure. Students engage in problems that involve direct interaction with meaningful mathematical structures, relations, and representations. Over the course of a PLM, students interact with a large variety of examples with constant feedback. The software tracks each student's performance across a variety of subcategories until the student reaches specific objective mastery criteria for each type of problem.

This paper focuses on data collected with one of these PLMs: Slice and Clone 1, which is intended to develop the relationships between partitioning quantities into units and iterating units to create new quantities. The goal is for students to achieve a flexible, fluent understanding of fractions as quantities in which a partitioning unit, $1/a$, is multiplicatively iterated (e.g., ¾ is 3 times ¼ unit) [15]. Figure 1 provides a visual representation of the software. The learning set includes 11 subcategories of problems which vary in difficulty from relatively simple integer problems to complex problems involving mixed numbers and improper fractions.

## METHOD AND DATA

### *Analytic Sample*

We recruited sixth grade teachers who taught at least two classes in the Philadelphia public schools to participate as part of a larger RCT. Teachers were instructed to use the software with all students assigned to intervention classes during scheduled math instruction time. We restricted the analytic sample to students who completed more than 10 problems because some students had insufficient time with the module due to poor attendance, mobility in and out of classrooms, and special needs. This restriction resulted in our dropping 57 students from the analysis. The total remaining sample consisted of 764 students in 30 classrooms and 29 schools.

### *Data Collection*

As the students used the web-based software, time-stamped data were automatically collected on a problem-by-problem basis, including what problems each student completed, whether they were correct or incorrect on each, and their current status with respect to meeting mastery criteria for categories in the learning set.

### *Measures*

Our dependent variable is a binary indicator of whether students mastered at least 10 out of 11 categories. To master each learning category, students had to complete at least 4 out of the last 5 presentations of that problem type correctly. Approximately 57% of students (433/764) reached mastery. Figure 2 displays the distribution of the percentage of the 11 learning categories the student mastered.

We measured active time using the software with a measure of the number of problems the student completed. To make this measure more interpretable, we center this variable around the grand mean of total number of problems completed by students in regression models.  Initial accuracy is an ordinal variable representing quartiles of the distribution of average accuracy on the first two problems for each of the 11 learning categories. Problems for each of the 11 learning categories were interspersed, so this accuracy measure represents whether students got questions seen close to the beginning of their software use correct.

*Analysis*

The analytic approach has three parts. First, we examined the relationship between number of problems completed and mastery at the student and classroom levels descriptively. Second, we fit a logistic regression model:

$$\ln\left(\frac{p_i}{1-pi}\right) = \alpha + \beta_1(Active\ Time\ ) + \beta_2\ (Active\ Time\ Squared) + \beta_3\ (Intial\ Accuracy) + \beta_4(Active\ Time\ X\ Initial\ Accuracy) + u_i$$

to predict the probability of achieving mastery as a function of the active time the student spent engaged with the software (measured as the deviation from the grand mean number of problems completed in the sample), active time squared, initial accuracy (measured by the quartile of initial accuracy) and an interaction between active time and the quartile of initial accuracy. We corrected for the clustering of the standard errors within classrooms in these models.

Third, we examined factors related to the underperformance or over-performance of students and classes, including the initial accuracy and total number of completed problems of these students and whether the class consisted of individuals with lower initial accuracy or whether the class spent more time engaged in use of the software than average.

## RESULTS

*Describing the Relationship Between Mastery and Active Time Using the Module*

The total number of problems completed is related to mastery both at the individual and class level. Figure 3 shows the distribution of completed problems by percent mastery for students. The graph has a horizontal reference line at 155, which is the grand mean number of problems completed. Students with lower mastery levels completed fewer problems, as shown by the lower medians for students at 0-36% mastery relative to the medians of students at 55% mastery and higher. The outliers in the top right quadrant of the graph achieved mastery but did so only after completing twice the mean number of problems. Figure 4 shows how the proportion of the class that reached mastery is related to the total number of problems the class completed on average. Classes with lower than average completion of problems also had a lower proportion of students reach mastery and classes with higher than average completion had a higher proportion of students reach mastery.

*Predicted Probability of Reaching Mastery*

The predicted probability of mastery increased with the number of completed problems but differently depending on initial accuracy (see Figure 5). Students with the highest initial accuracy had high predicted probabilities of mastery and required fewer problems to reach mastery. These students likely had prior knowledge of the math and were able to skip over the discovery phase and instead engage in building fluency. By contrast, students with the lowest accuracy still had a low predicted probability of mastery, even after they had completed double the average number of problems completed by all students. These students were likely stuck in the discovery phase and never reached fluency.

*Understanding Factors Related to Mastery for Students Who Out-Performed and Under-Performed*

Mastery was highly dependent on initial accuracy (see Figure 6). Even net of initial accuracy, however, the number of problems completed was significantly associated with the predicted probability of mastery. Among students with low initial accuracy who reached mastery (N=38), the average number of problems completed was 295 but some students required as many as 627 problems to reach mastery. Students with high initial accuracy on average only took 106 problems. (See Figure 7).

The number of problems completed was related to classroom level factors. Some classes had insufficient practice, as gauged by the number of problems they did relative to other classes. In these classes, it was unlikely that students with low initial accuracy could meet mastery. Figure 8 shows the students who were outliers in terms of initial accuracy and mastery. Students who reached mastery despite having the lowest initial accuracy are represented by red dots (N=38) while students who failed to reach mastery despite being in the highest initial accuracy quartile are represented by blue dots (N=27). There are two interesting patterns on this figure. First, almost all of the blue dots fall below the grand mean and their class mean in terms of the number of problems completed. These are students who likely would have reached mastery with more practice but were in classes where conditions were insufficient for successful completion of the intervention. Second, several red dots fall below the line. These dots are the students nested in classes where the average number of problems completed was higher than the grand mean number of problems completed. Indeed, Figure 9 supports the inference that students with low initial accuracy are unlikely to reach mastery unless given above average practice. Figure 9 shows that most classes where students completed fewer than 150 problems on average had 0% of their students with low initial accuracy reach accuracy.

## SIGNIFICANCE

Teachers often have little to go on in deciding how to allocate time to learning software and whether that time is being used effectively. These analyses allow us to identify patterns that teachers can use to monitor and facilitate students' progress with PLM software, with norms for working with students starting at different levels. For example, analyses to date indicate that teachers with a high proportion of students with low initial accuracy should plan sufficient time for students to attempt over 200 problems, so that even their lowest performing students have the chance to master the material. Ongoing analyses will also flag common sticking points and patterns that indicate unproductive use so that teachers can intervene with strategic coaching or modeling as appropriate.

These analyses also contribute to ongoing efforts to build more sophisticated adaptive algorithms that model students' learning in real-time and adapt in more dynamic ways. Ideally, more powerfully adaptive software can manage some aspects of learning that are challenging for students to monitor for themselves and for teachers to track for large numbers of students simultaneously.

More generally, this approach provides a model for developing more sophisticated measures of the quality and sufficiency of use of learning software that go beyond time spent in front of a screen, both in classroom use and in efficacy research. It has generally been difficult to find effects of learning software in large efficacy trials [16, 17, 18], but questions about whether various forms of educational technology “work” are just beginning to move into the more nuanced territory of investigating what, how, why, when, for whom, and under what circumstances. These analyses are intended to advance that effort.

REFERENCES:


[1] Kellman, P.J., Massey, C.M & Son, J. (2010). Perceptual learning modules in mathematics: Enhancing students' pattern recognition, structure extraction, and fluency. *Topics in Cognitive Science*, *Special issue on Perceptual Learning, Vol 2,* Issue 2, 285-305.

[2] Mettler, E., Massey, C.M., & Kellman, P. J. (2011). Improving adaptive learning technology through the use of response times. In L. Carlson, C. Hölscher, & T. Shipley (Eds.), *Proceedings of the 33nd Annual Conference of the Cognitive Science Society*. Boston, MA: Cognitive Science Society.

[3] Bereiter, C. & Scardamalia, M. (1996). Rethinking learning. In D. R. Olson & N. Torrance (Eds.), *The handbook of education and human development: New models of learning, teaching, and schooling*. (pp. 485-513). Cambridge, MA: Basil Blackwell.

[4] Bransford, J.D., Brown, A. L., & Cocking, R.R. (1999). *How people learn: Brain, mind, experience, and school*. Washington, DC: National Academy Press.

[5] Goldstone, R. L., Landy, D., & Son, J. (2008). A well-grounded education: The role of perception in science and mathematics. In A. Glenberg, M. DeVega, & A. Graesser (Eds.) *Proceedings of the Garachico Workshop on Symbols, Embodiment and Meaning*, Universidad de La Laguna, Tenerife.

[6] Kellman, P.J., Massey, C.M., Roth, Z., Burke, T., Zucker, J., Saw, A., Aguero, K. & Wise, J. (2008) Perceptual learning and the technology of expertise: Fraction learning and algebra. *Cognition Pragmatics, Special Issue on Cognition and Technology, 16*(2), 356-405.

[7] Krasne, S., Hillman, J.D., Kellman, P.J. & Drake, T.A. (2013). Applying perceptual and adaptive learning techniques to introductory histopathology for medical students. *Journal of Pathology Informatics*, 4: 34-41.

[8] Massey, C.M., Kellman, P.J., Roth, Z. & Burke, T. (2010). Perceptual learning and adaptive learning technology: Developing new approaches to mathematics learning in the classroom. In N. L. Stein and S. Raudenbush (Eds.), *Developmental and learning sciences go to school*. New York: Taylor & Francis.

[9] Kellman, P.J. & Garrigan, P.B. (2009). Perceptual learning and human expertise. *Physics of Life Reviews*, *Vol. 6*, No. 2, 53-84.

[10] Kellman, P. J. & Massey, C. M. (2013). Perceptual learning, cognition, and expertise. In Brian H. Ross (Ed.). *The Psychology of Learning and Motivation, Vol. 58*. New York: Elsevier.

[11] Gibson, E. J. (1969). *Principles of perceptual learning and development*. New York: Prentice-Hall.

[12] Goldstone, R.L. (1998). Perceptual learning. *Annual Review of Psychology*, *49*, 585-612.

[13] Kellman, P.J. (2002). Perceptual learning. In R. Gallistel (Ed.), *Stevens' Handbook of Experimental Psychology: Vol. 3. Learning, Motivation, and Emotion, Third Edition* (pp. 259 – 299). New York: Wiley.

[14] Bufford, C.A., Mettler, E., Geller, E.H. & Kellman, P.J. (2014). The psychophysics of algebra expertise: Mathematics perceptual learning interventions produce durable encoding changes. In P. Bello, M. Guarini, M. McShane & B. Scassellati, (Eds.), *Proceedings of the 36th Annual Conference of the Cognitive Science Society*. Austin, TX: Cognitive Science Society.

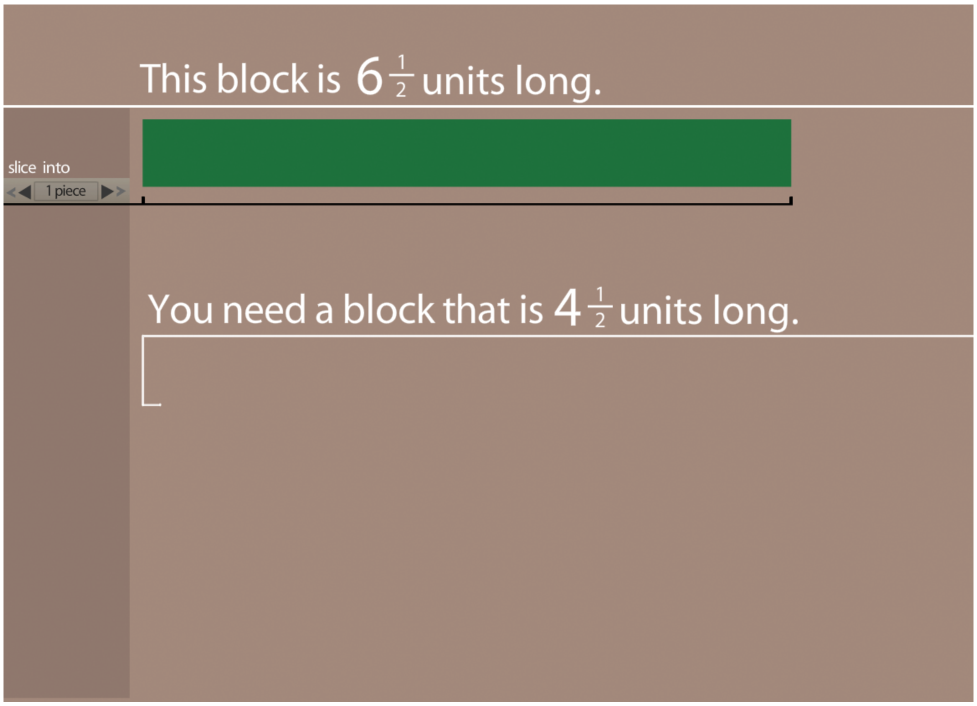
[15] Thompson, P., & Saldanha, L. (2003). Fractions and multiplicative reasoning. In J. Kilpatrick, G. Martin & D. Schifter (Eds.), *Research companion to the principles and standards for school mathematics* (pp. 95-114). Reston, VA: NCTM.

[16] Campuzano, L, Dynarski, M., Agodini, M., & Rall, K. (2009). Effectiveness of reading and mathematics software products: Findings from two student cohorts (NCEE 2009-4041). Washington, DC: National Center for Education Evaluation and Regional Assistance, Institute of Education Sciences, U. S. Department of Education.

[17] U.S. Department of Education (2013). Expanding evidence approaches for learning in a digital world. Washington, DC. Author. Available: http://www.ed.gov/edblogs/technology/files/2013/02/Expanding-Evidence-Approaches.pdf

[18] U.S. Department of Education (2010). Transforming American education: Learning powered by technology. National Educational Technology Plan. Washington, DC: Author. Available: http://www.ed.gov/sites/default/files/netp2010.pdf

Figure 1: The Slice and Clone 1 software environment makes the structure and relations underlying fraction concepts tangible to learners by providing them with interactive on-screen tools that they can manipulate. The students' task is to start with a given quantity and use the slicing and cloning tools to create a new quantity. As shown in the top panel, students operate a "slicer" tool (in the upper left) to cut a continuous extent into a desired number of pieces, thus creating a base unit. As shown in the bottom panel, when they have created a successful unit, it drops down into "cloner" tool (bottom left) that will iterate that unit a desired number of times and output the result. While these screenshots are static, the actual PLM is fully interactive with customized animated feedback at every step.



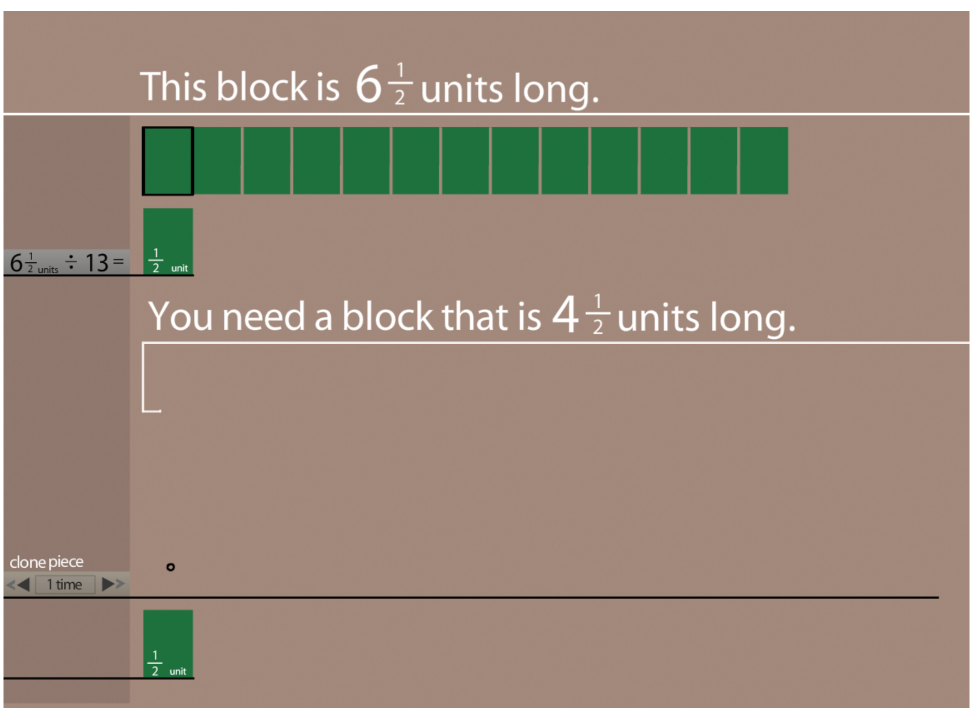



Figure 2: Distribution of Percent Mastery at Student Level

Slice and Clone 1

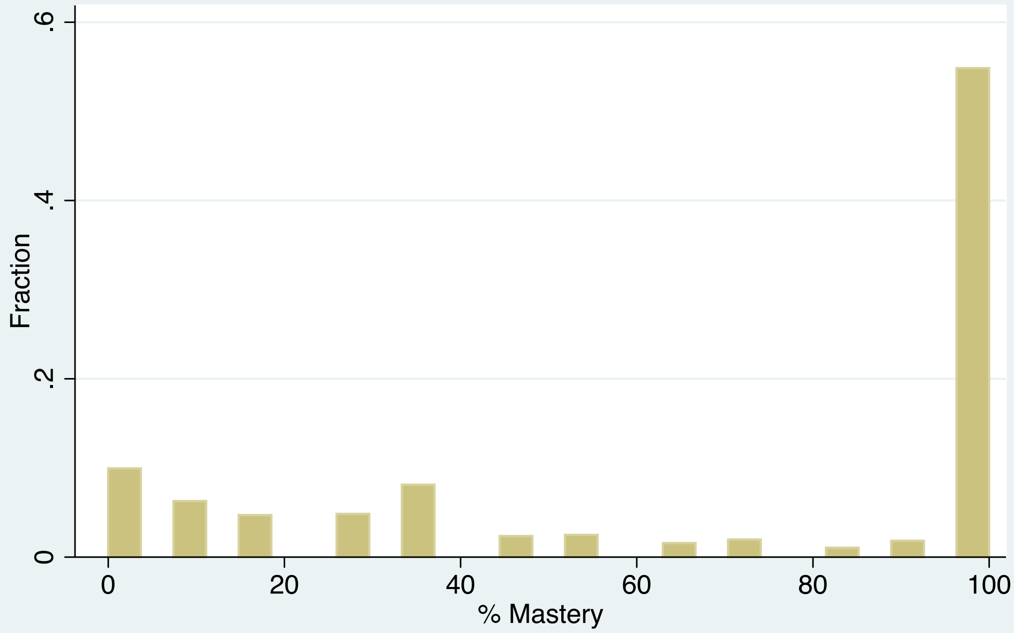
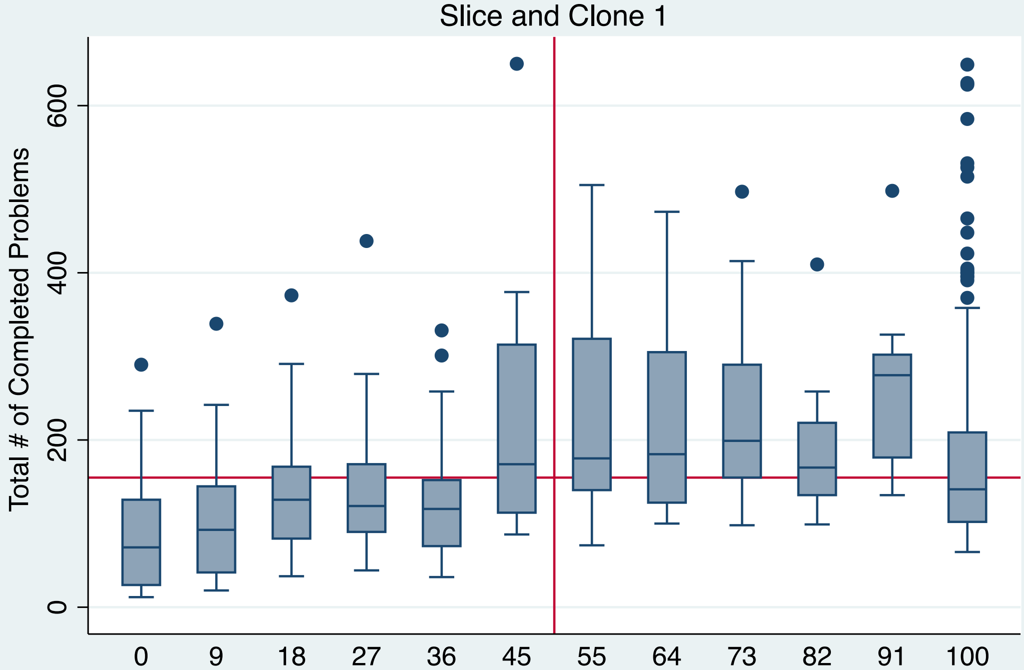



Figure 3: Distribution of Completed Problems by Percent Mastery at Student Level

Slice and Clone 1



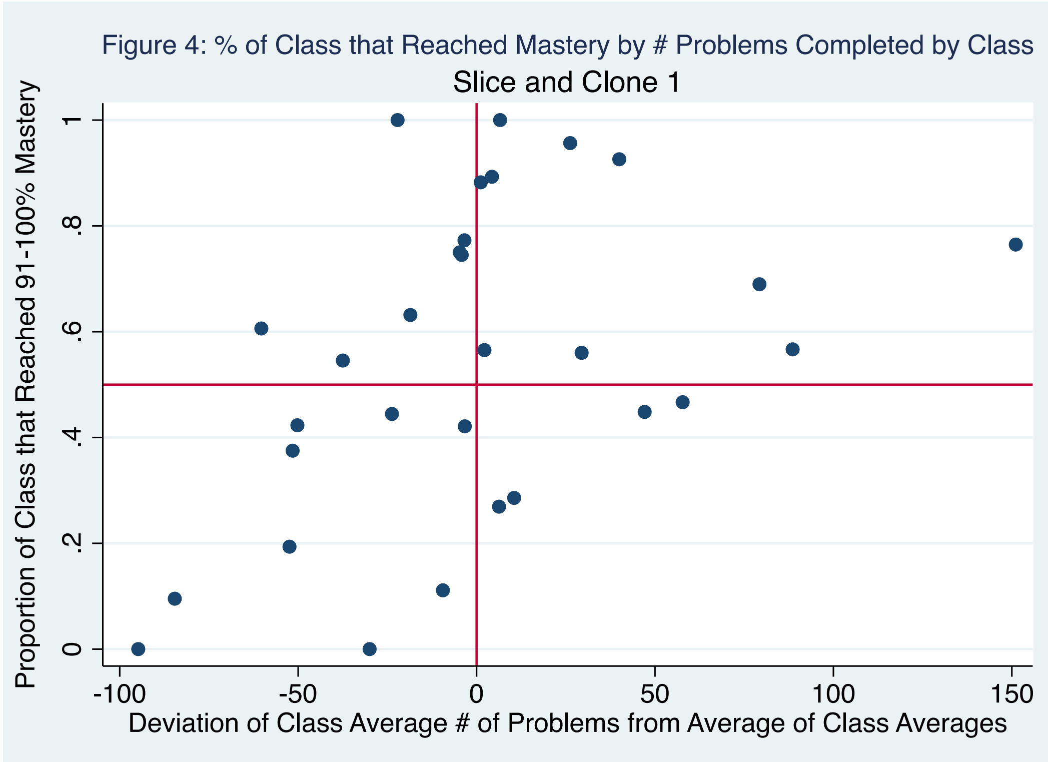


Figure 4: % of Class that Reached Mastery by # Problems Completed by Class
Slice and Clone 1
Proportion of Class that Reached 91-100% Mastery
0
.2
.4
.6
.8
1
-100
-50
0
50
100
150
Deviation of Class Average # of Problems from Average of Class Averages

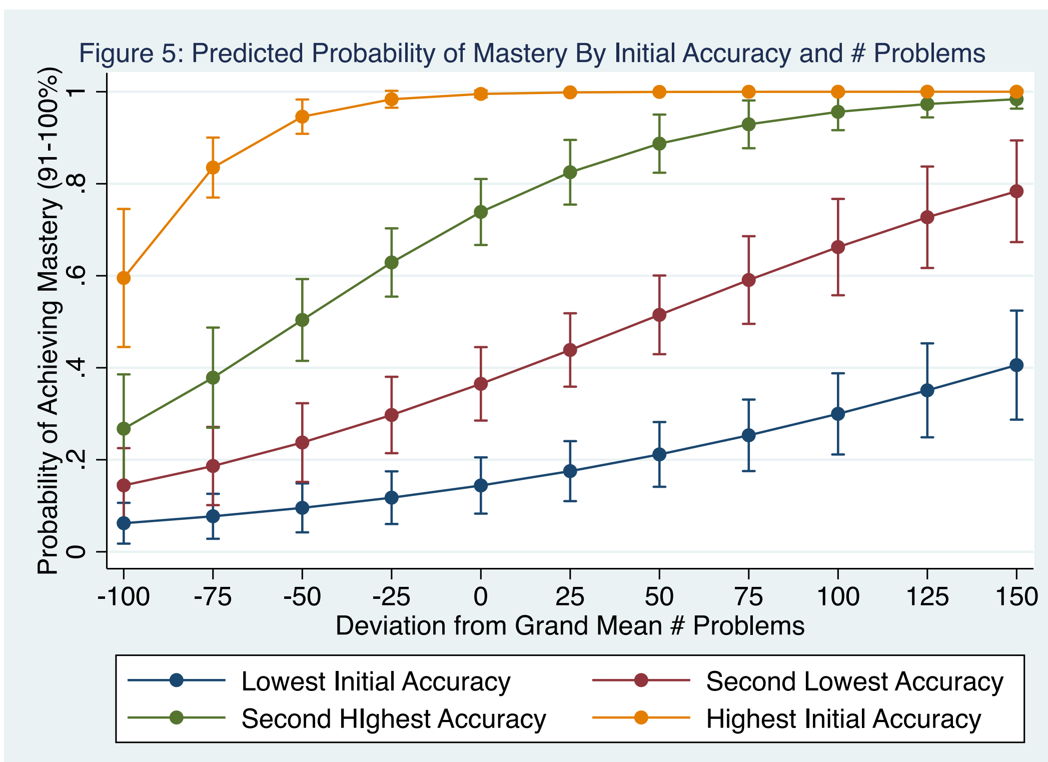


Figure 5: Predicted Probability of Mastery By Initial Accuracy and # Problems
Probability of Achieving Mastery (91-100%)
0
.2
.4
.6
.8
1
-100
-75
-50
-25
0
25
50
75
100
125
150
Deviation from Grand Mean # Problems
Lowest Initial Accuracy
Second Lowest Accuracy
Second HIghest Accuracy
Highest Initial Accuracy

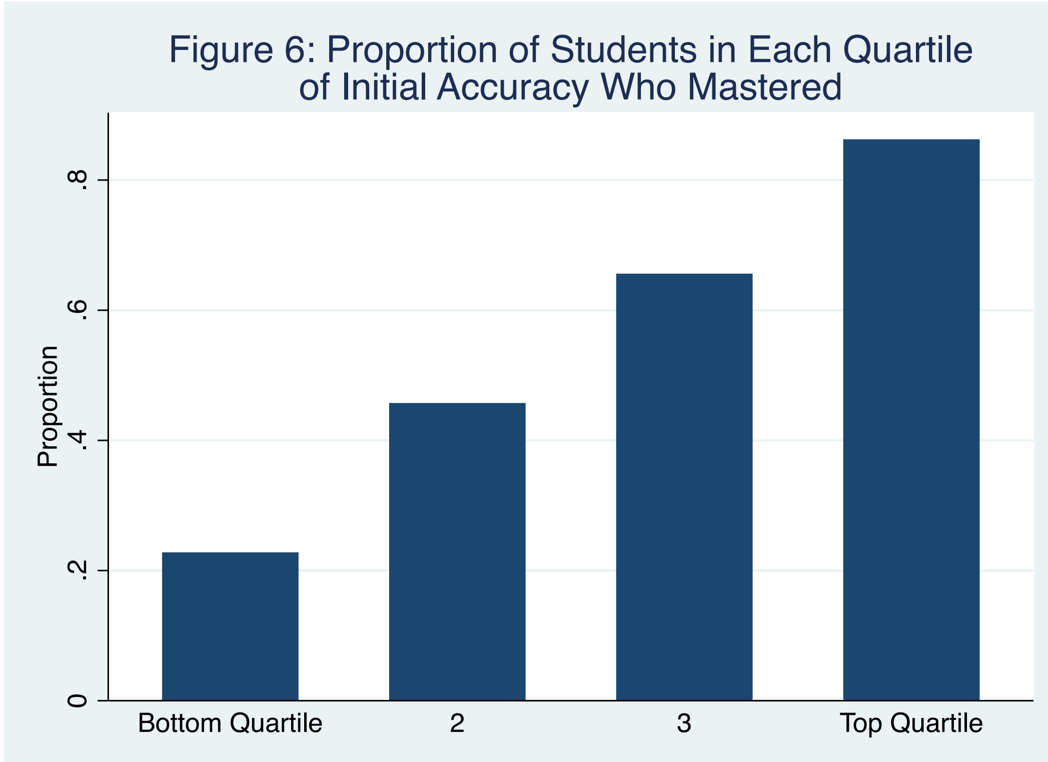


Figure 6: Proportion of Students in Each Quartile of Initial Accuracy Who Mastered
Proportion
0
.2
.4
.6
.8
Bottom Quartile
2
3
Top Quartile

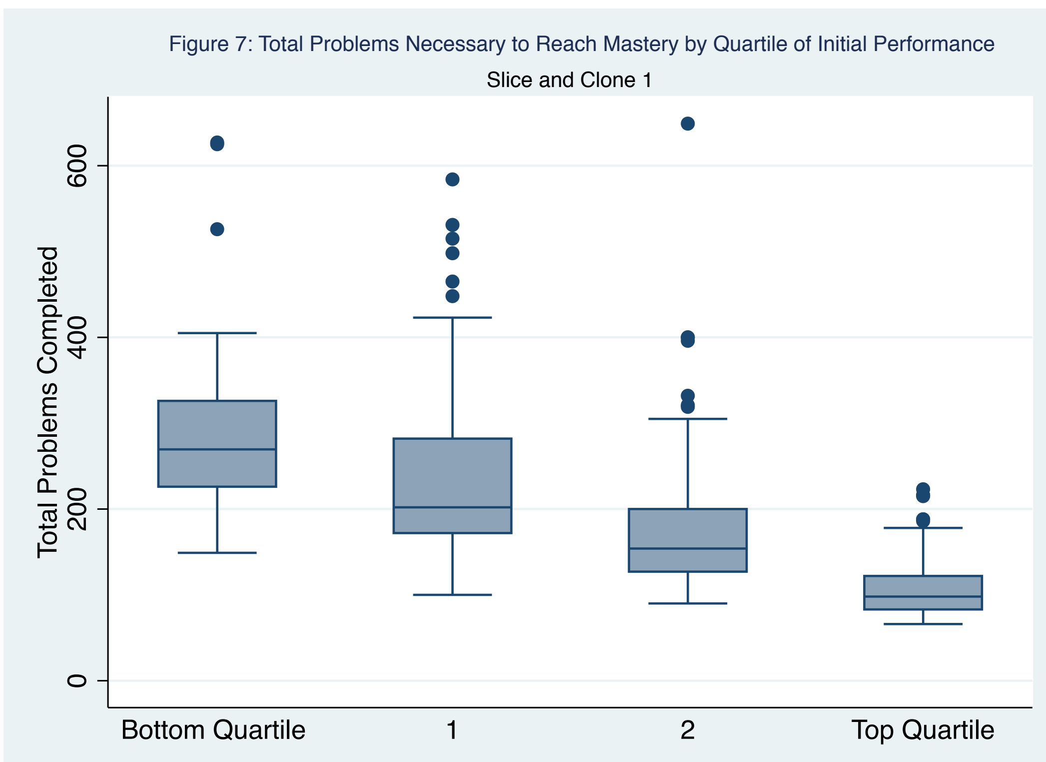


Figure 7: Total Problems Necessary to Reach Mastery by Quartile of Initial Performance
Slice and Clone 1
Total Problems Completed
0
200
400
600
Bottom Quartile
1
2
Top Quartile

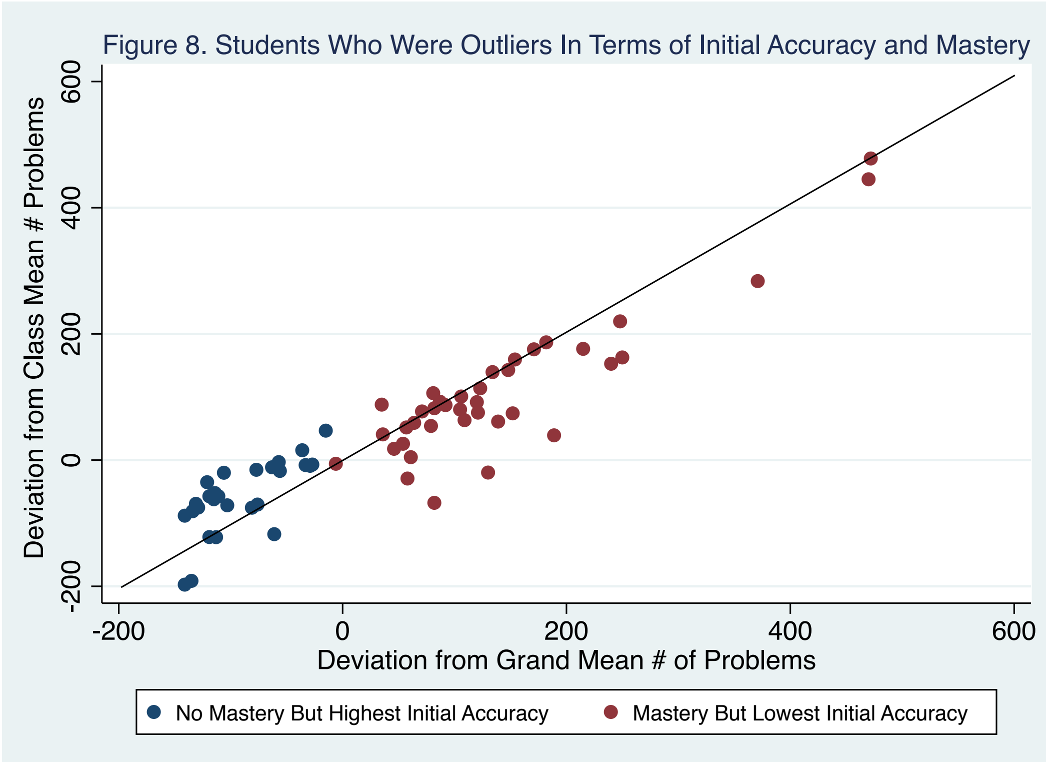


Figure 8. Students Who Were Outliers In Terms of Initial Accuracy and Mastery
Deviation from Class Mean # Problems
-200
0
200
400
600
-200
0
200
400
600
Deviation from Grand Mean # of Problems
No Mastery But Highest Initial Accuracy
Mastery But Lowest Initial Accuracy

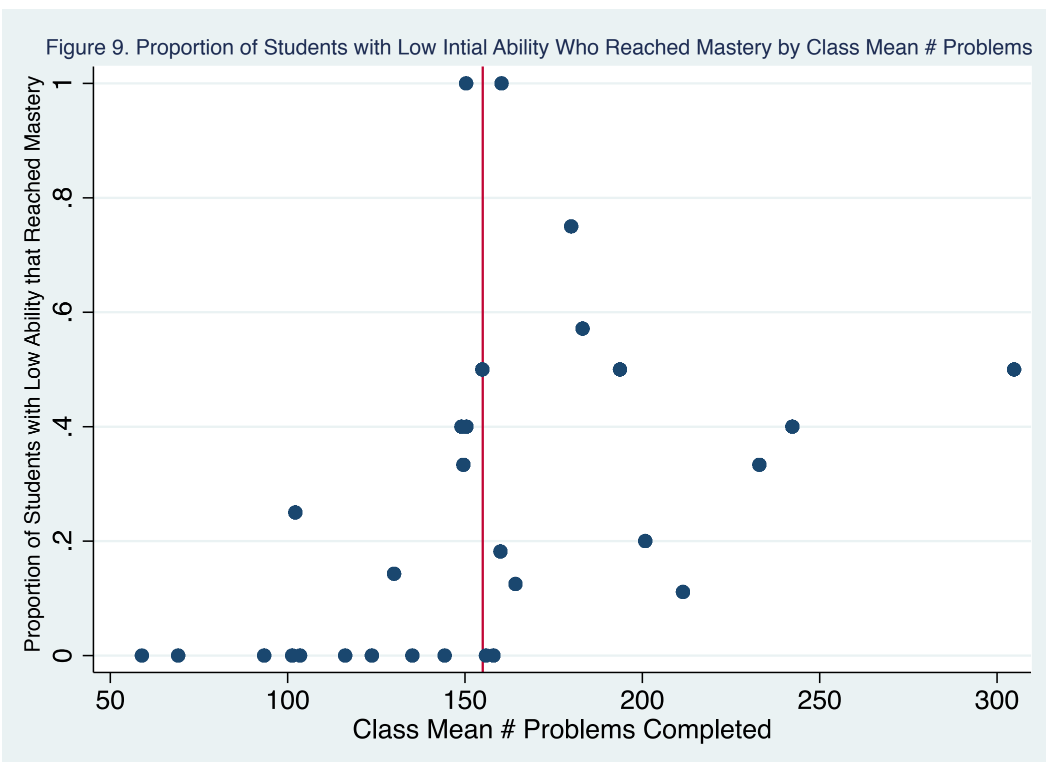


Figure 9. Proportion of Students with Low Intial Ability Who Reached Mastery by Class Mean # Problems
Proportion of Students with Low Ability that Reached Mastery
0
.2
.4
.6
.8
1
50
100
150
200
250
300
Class Mean # Problems Completed