Effect of Personalized Learning Paths on Learning Quadratics in Algebra

by

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A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Approved November 2015 by the
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ARIZONA STATE UNIVERSITY

December 2015

ABSTRACT

This study was conducted to assess the performance of 176 students who received algebra instruction through an online platform presented in one of two experimental conditions to explore the effect of personalized learning paths by comparing it with linearly flowing instruction. The study was designed around eight research questions investigating the effect of personalized learning paths on students' learning, intrinsic motivation and satisfaction with their experience. Quantitative results were analyzed using Analysis of Variance (ANOVA), Analysis of Covariance (ANCOVA) and split-plot ANOVA methods. Additionally, qualitative feedback data were gathered from students and teachers on their experience to better explain the quantitative findings as well as improve understanding of how to effectively design an adaptive personalized learning platform. Quantitative results of the study showed no statistical difference between students assigned to treatments that compared linear and adaptive personalized instructional flows.

The lack of significant differences was explained by two main factors: (a) low usage and (b) platform and content related issues. Low usage may have prevented students from being exposed to the platforms long enough to create a potential for differences between the groups. Additionally, the reasons for low usage may in part be explained by the qualitative findings, which indicated that unmotivated and tired teachers and students were not very enthusiastic about the study because it occurred near the end of school year. Further, computer access was a challenging issue at the school throughout the study. On the other hand, platform and content related issues worked to inhibit the potential beneficial effects of the platforms. The three prominent issues were: (a) the

majority of the students found the content boring or difficult, (b) repeated recommendations from the adaptive platform created frustration, and (c) a barely moving progress bar caused disappointment among participants.

DEDICATION

To my wife, Gozde Bicer, who turned my intention into an achievement with her superhuman support.

ACKNOWLEDGMENTS

First, I would like to express my sincere gratitude to my advisor Dr. Gary Bitter for the continuous support of my Ph.D. study and related research and for his patience, motivation and immense knowledge. His guidance helped me throughout the time of research and writing of this dissertation. I could not have imagined having a better advisor and mentor for my Ph.D study. He was with me seven years ago when I first applied for the ASU Educational Technology Master's program, then he encouraged me for the Ph.D. program and always stayed with me throughout the completion of my long journey.

Besides my advisor, I would like to thank my dissertation committee for their insightful comments and encouragement: Dr. Ray Buss for his constructive feedback and statistical insight; and Dr. Jane Legacy for championing my efforts from the day I interviewed as an applicant to the Educational Technology program to the day I applied for graduation. My sincere thanks also go to Dr. Kurt VanLehn who gave me the perspective for the concept of adaptive personalized learning, to our graduate services supervisor Susan Henderson who was able to solve my all procedural problems every single time instantly and patiently, to Refika Koseler who gave me great ideas with her in-depth knowledge of the intelligent tutoring systems, and to Nedim Yel for his valuable suggestions on my statistical analyses.

I thank my fellow colleagues and all the Sebit family for supporting and sponsoring my education, especially Dr. Mike Brown for proofreading my dissertation and Mr. Jim Bowler and Dr. Mabelle Sonnenschein for their unconditional support. In particular, I am grateful to Mr. Ahmet Eti for encouraging me in the first place and supporting me not only financially, but also mentally, academically and professionally. Without his precious support it would not be possible for me to write these lines here.

Last but not the least; I would like to thank my family: my lovely wife and beautiful girls for motivating me every single day by filling up my soul with their light and energy and keeping me strong, happy and always cheerful.

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Chapter 1

INTRODUCTION AND LITERATURE REVIEW

Finding an effective way to create personalized learning paths for students has always been an important goal for educational researchers. Numerous studies have been conducted on personalized learning paths (Griff & Matter, 2013; Johnson, Phillips, & Chase, 2009; Lee et al, 2011; Pane, Griffin, McCaffrey, & Karam, 2014; Pane, Steiner, Baird, & Hamilton, 2015; Phillips & Johnson, 2011; Yarandi, Jahankhani, & Tawil, 2013). Many school districts across the United States have been considering the use of personalized learning paths and are spending a large amount of resources implementing Technology Enhanced Personalized Learning (TEPL) tools. TEPL tools, as with personalized learning, were based on a constructivist theoretical framework and the ideas of self-directed learning. Utilizing a teacher and/or technology as a More Knowledgeable Other (MKO) has allowed students to achieve new learning. Moreover, students have had a higher level of control in directing their learning, often using a TEPL tool to identify their preferred learning method (Gallagher, 2014).

To understand the evolution of personalized learning paths, it will be instructive to understand the terms "*differentiated instruction*", "*personalized learning*" and "*adaptive learning*". Differentiated instruction is a learner-centered instructional design model that acknowledges students have individual learning styles, motivation, abilities and, therefore, readiness to learn. Moreover, differentiation was planned according to the student's readiness, interests and learning profile (Bush, 2006). In differentiated instruction, there were a number of pre-set categories in which a student can be placed, for instance a gifted class or a remedial class. Personalized learning has operated one level deeper than differentiated instruction. In personalized learning, each student followed an optimal learning path and pace through a mix of instructional methods, including individual and small-group time with teachers, group projects and instructional software (Childress, 2014). Evidence indicated personalized learning may empower and support teachers in meeting students' needs (Hassel & Hassel, 2011). In this type of personalized learning, students' learning paths have usually been rules-based or created by following a decision tree. A common example of rules-based personalized learning would include use of a diagnostic test at the beginning of a unit to determine what the student will learn. On the other hand, a true adaptive system would have been data-driven, it would have learned as the student advanced in the system and improved in real time. These systems employ big data analysis and complex statistical and probabilistic calculations.

Besides the adaptive features, content structure and content quality have also played an important role in personalizing the learning process. Further, the granularity of the recommendable units and the granularity and frequency of the assessment data have given the system the ability to pinpoint the student needs in the best possible ways.

The goal of this dissertation was to conduct a mixed method (both quantitative and qualitative) experimental study to investigate the effect of personalized learning paths, which were continuously generated in real time by a true adaptive system; a system that employed interactive multimedia content that collected granular assessment data and provided granular recommendable units in Quadratics. This study compared this adaptive personalized platform with another platform that had exactly the same interactive multimedia content, but presented them in a pre-defined linear sequence. The "effect" was investigated in terms of learning, motivation, and satisfaction.

The Adaptive Personalization Platform

The platform created a profile for every learner, fed that profile with assessment data as the learner completed new modules on the platform, updated the learner's profile and knowledge state with this data, analyzed the data using item response theory and data from other learners in its repository and instantaneously recommended the next best module specific to the learner. The platform also presented some useful analytics from which both learners and teachers benefitted. For learners, it showed the expected score of the learner for an assignment, mastery level of the learner on a concept or a topic, likelihood that the learner would complete an assignment on time and with the criteria set by the teacher; and for teachers, it showed aggregated data for all these learners.

The content modules recommended by the platform were interactive multimedia activities and multimedia animations; and the assessment modules were either interactive multimedia assessment activities that sent granular assessment data to the platform, or classic multiple choice items. The Introduction to Quadratics section of an Algebra 1 course usually taken by 9^{th} grade students and its immediate prerequisites, all of which corresponded to two weeks of instruction time, were prepared in the platform for the purpose of this study.

Theoretical Framework

The literature review was organized into four sections. It started with a discussion on using interactive multimedia in educational materials, followed by a comparison of Computer Aided Instruction (CAI), Intelligent Tutoring Systems (ITS) and the adaptive personalization platform used in this study. Then, the importance of embedded assessments was presented and finally, the relation between the type of learning material and motivation was discussed.

Using Interactive Multimedia in Educational Materials

The platforms developed for this study used an integration of technology through high-fidelity visuals, visual representations, animations, simulations, skills application interactions and virtual manipulatives. Content was offered through visual and audio paths alone and simultaneously, which activated multiple cognitive paths. Students became more responsive as they learned math by changing variables and observing the results in real time. Real-world simulations encouraged students to practice mathematical concepts through a series of leading questions.

Weiss, Knowlton and Morrison (2002) explained the use of animations for different purposes in educational settings:

- *Animation used for aesthetics.* As pictures may decorate a computer screen, animation has also served a purely cosmetic function by making directions more presentable and attractive to readers.
- *Animation used to focus attention.* Animation has been used to focus students' attention toward certain aspects of a lesson.
- *Animation used for reinforcement.* Animation has been used to deliver feedback after a student provided a correct or incorrect response to a question.
- *Animation used to present instructional content.* Animation has been used to deliver the instructional content of a lesson.

- *Animation used for clarification.* Animation has also been used to clarify information presented through other means, such as text or audio.

The content prepared for this study employed all types of animations listed above. There was some evidence that showed dynamic (animated) visuals were superior to static visuals in instruction (Höffler & Leutner, 2007). Even simply adding animations based on an instructional analysis to a curriculum with existing text and materials improved learning outcomes (Catrambone & Seay, 2002).

In terms of interactive media, research has shown that the power of virtual manipulatives was in the ability to combine multiple dynamic representations of a concept in a single environment, enabling students to derive meaning and form relationships from their own actions (Moyer-Packenham, Salkind, & Bolyard, 2008). A large impact made by the use of manipulatives has been the improvement of students' thinking. Manipulatives helped students create an internal representation of the external concepts being taught (Puchner, Taylor, O'Donnell, Fick, 2008). Virtual manipulatives helped students with their algebraic reasoning and relational thinking (Suh & Moyer, 2007).

CAI vs. ITS vs. Adaptive Personalization Platform Used in This Study

The oldest and most commonly available technology had students enter the final answer to a question or problem and provided feedback and hints based on the answer (Dick & Carey, 1990). For instance, such a system might have assigned an algebra word problem and required the student to solve it on scratch paper and enter a numerical answer. If the answer was correct, the system indicated so; otherwise, it provided a hint. This kind of tutoring system was often called computer-aided instruction (CAI)

(VanLehn, 2005). Perhaps the second largest category of tutoring system had students enter steps leading up to the solution of a problem and the system gave feedback and hints on those steps as well as on the final answer (Corbett, Koedinger, & Anderson, 1997; Rickel, 1989; Shute & Psotka, 1996; VanLehn, 2006). For instance, after assigning an algebra word problem, such a system required the student to enter a sequence of lines, each consisting of a variable definition or an equation. That is, the work that would otherwise have been done on scratch paper was instead done on the computer. The system provided the student feedback and hints on the intermediate steps leading up to the final answer. These systems were called Intelligent Tutoring Systems (ITS) (VanLehn, 2005). The adaptive personalization platform developed for this study used many different "*narrow-focused*" ITS's in its recommendations to students as well as using other content types (animations, text-based modules and assessment items) for the same purpose. This adaptive system consolidated data science, statistics, psychometrics, content graphing, machine learning, tagging and infrastructure in one place to enable personalization on a massive scale. In addition to powerful adaptivity, it also provided concept-level analytics for students and teachers, pinpoint student proficiency measurement, content efficacy measurement and student engagement optimization.

Shaw, Larson and Sibdari (2014) claimed that an asynchronous, personalized learning platform based on atomistic topics would provide for the needs of individual learners, allowing them to learn the topics based on their interests and background, while using information suitable for each person's ability. For example, learners who proved their content mastery and started at the topic of hashing in lecture 9 of the edX 6.00x syllabus, instead of having to re-learn the course's prior topics that they already understood (edX, 2012). Proponents believed Guided Learning Pathways (GLP) would provide this type of “pre-requisite” information (their personalized pathway) using an expert-defined Content Map that could automatically assess which topics a student needed to master to achieve their overall learning goal. Shaw et al. (2014) also stated that GLP would help learners achieve this goal at their own pace, through personalized learning and personalized content—for instance, examples of neural network usage in aerospace could be provided to our example learner. Using data collected from a multitude of learners, GLP would provide targeted learning recommendations to maximize the learner’s understanding and engagement, much like consumer internet services and merchants provide content recommendations to their users (Shaw et al., 2014).

Embedded Assessments

In recent years, “alternative assessment” has been a major topic of interest, debate and examination in nationwide efforts of educational reform (Wilson & Sloane, 2000). Initial hopes that alternative, authentic, or performance assessments of student achievement would drive (or at least facilitate) changes in what and how students were taught have been tempered by the realities of implementation. Efforts to introduce alternative assessments into large-scale, high-stakes state and district testing programs have met with mixed results due to high costs, logistical barriers and political ramifications (e.g., Gipps, 1995; Kettler et al, 2014; Rothman, 1995). For example, the demise of the California Learning Assessment System was due principally to the complications, technical, political and financial of using performance assessments for large-scale assessment (Wilson & Sloane, 2000). Efforts to introduce alternative assessments into ongoing classroom practices have been less publicized, but have also met with problems relating to costs (primarily in terms of time) and to teachers' level of preparation and acceptance (e.g., Chittenden, 1991; McCallum, Gipps, McAlister, & Brown, 1995; Plemons, 2015; Shepard, 1995; Stauffer & Mason, 2013). The rationale for developing and using alternative assessment has remained quite compelling, however. Alternative assessments, compared to traditional tests, have offered the potential for greater "ecological validity" and relevance, assessment of a wider range of skills and knowledge and adaptability to a variety of response modes (e.g., Baron, 1991; Darling-Hammond & Adamson, 2014; Gardner, 1992; Haertel, 1999; Malcom, 1991; Wiggins, 1989, 1993). Liu, Lee, Hofstetter and Linn (2008) maintained that traditionally, science assessments in national and international tests relied heavily on multiple-choice items that primarily required the recollection of scientific information. These assessments motivated teachers to focus on drill and memorization strategies, neglecting student critical thinking (Yeh, 2006). This problem has generated a call for more authentic assessments that emphasize complex thinking (Gordon Commission on Future Assessment in Education, 2013; National Research Council, 1996, 2000; Pellegrino, Chudowsky, & Glaser, 2001).

Embedded assessments were an integral part of the adaptive personalization platform developed for this study. Conventional assessment methods have judged the student's work based only on the final answer. By comparison, an ITS gathered data on intermediate steps as well as the final answer, so it has been able to obtain as much data on a student by assigning only one or two tasks to be completed (VanLehn, 2005).

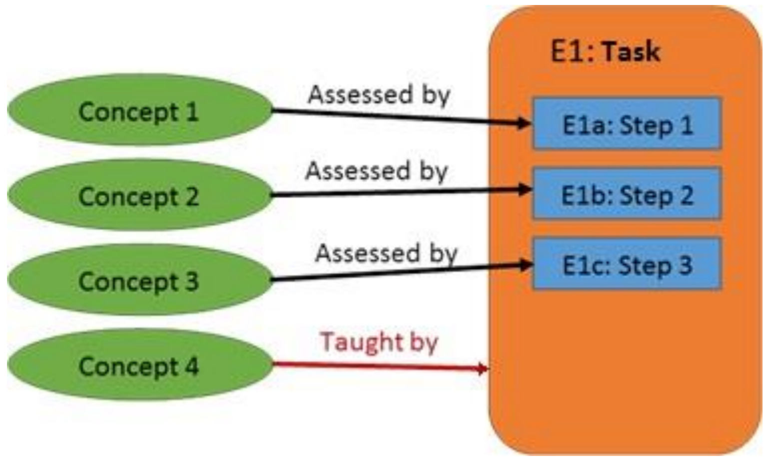


Figure 1. Embedded Assessments

For example, as shown in Figure 1, Concept 4 was taught by Task E1, Task E1 had three steps and each of those three steps assessed a different concept prerequisite to Concept 4. When task E1 was recommended as an instructional unit which claimed to teach concept 4 to the leaner, the system also collected relevant assessment data about concepts 1, 2 and 3 as the learner completed task E1. This type of assessment had several benefits as opposed to the traditional assessments: First, it allowed somewhat more authentic tasks to be used for assessment and that increased the validity of the assessment. Second, it provided strategic and meta-cognitive assessments. Because an ITS monitored the steps leading up to a solution, an ITS was able to observe a student's problem-solving strategy, which was difficult or impossible to observe when only the final answer was entered (VanLehn, 2005). In fact, as the learner completed interactive tasks, the current system collected not only content-specific assessment data like "*Solve quadratic equations by factoring*", but also some long-term skills related assessment data, for example "*Model with mathematics*", "*Attend to precision*", or "*Look for and make use of structure.*" It was logical to suppose that this feature gave the platform a great deal of theoretical advantage about assessing the learners compared to any other CAI platforms, which did not use a similar approach.

Assessing the development of students' understanding of particular concepts and skills (as opposed to current status only) required a model of how student learning developed over a certain period of (instructional) time. A developmental perspective helped us move away from one-shot testing situations and away from cross-sectional approaches to defining student performance—toward an approach that focused on the process of learning and on an individual's progress through that process (Wilson & Sloane, 2000).

Motivation

Research suggested motivation was a critically important factor for academic learning and achievement across childhood through adolescence (Elliot & Dweck, 2005). Academic intrinsic motivation has played an important role with regard to school learning and achievement because of its inherent relatedness to cognitive processing and mastery as well as relationships to academic competency (Gottfried, 1985). Academic intrinsic motivation has been defined as enjoyment of school learning characterized by an orientation toward mastery, curiosity, persistence, task-endogeny; and the learning of challenging, difficult and novel tasks (Gottfried, 1985). Academic intrinsic motivation was the drive or desire of the student to engage in learning "for its own sake." Students who were intrinsically motivated engage in academic tasks because they enjoyed them. They felt that learning was important with respect to their self-image and they sought out learning activities for the sheer joy of learning (Middleton, 1992/1993a). Their motivations tended to focus on learning goals such as understanding and mastery of mathematical concepts (Ames & Archer, 1988; Duda & Nicholls, 1992; Dweck, 1986). In this study, two particular types of homework assignments have been compared and one of the main goals of the study was to investigate whether these types would have any effect on students' intrinsic motivation toward studying/learning mathematics.

Gender and Ethnic Differences

Previous studies have shown that girls have reported not enjoying the use of computers as much as boys and they have also reported experiencing heightened anxiety when using computers (Christensen et al, 2005; Hargittai and Shafer, 2006). However, this has started to change in more recent years. The findings of a 2007 study among 8^{th} graders stated there was no significant difference between boys and girls with regard to their reported computer enjoyment in addition to the finding that both boys and girls reported feeling virtually no anxiety when using their computers. The same study indicated there were no differences between ethnic/racial groups (Caucasian, African-American, Hispanic and Other) with regard to attitudes toward computer importance, computer anxiety, or computer usage. There were differences between the ethnic/racial groups with regard to computer enjoyment and computer careers, but the effect sizes for both of those variables were very small (Boitnott, 2007). Then, the results of a 2013 study showed a digital divide between white and non-white and female and male students on all measures of the information and communication technology literacy instruments. Specifically, white and female students outperformed their counterparts (Ritzhaupt, Liu, Dawson, & Barron, 2013). Therefore, in this study, the results have also been disaggregated by gender and ethnicity to investigate whether the effect of adaptive personalized platform differs across gender and ethnicity.

Preliminary Pilot

Prior to the actual experiment, which was conducted in this study, two observational pilot studies had been conducted: one with a small group of students and one with a small group of teachers. The primary goal of the preliminary pilot was to observe students and teachers in action and identify potential issues to be able to address them before the actual experiment.

Observational pilot with students. Four students were recruited for a pilot study, in which they used the adaptive personalized platform for two hours. All students were 9th grade students and all of them had already taken Algebra 1 at school. Prior to the observational pilot, signed consent letters from students' guardians were collected for the students' participation. The flow of the observational pilot has been shown in Figure 2.

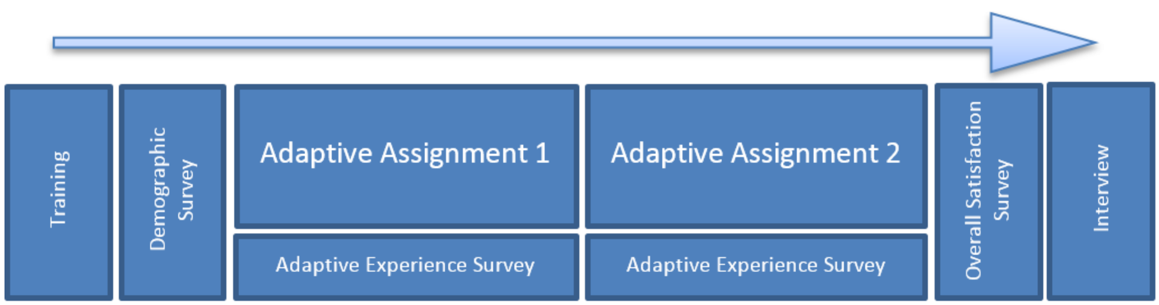


Figure 2. Students' Observational Pilot Design

The entire pilot took about three hours for the students. Each student was given a $50 gift card as a compensation for their time. During the time they took the adaptive assignments, each student was observed by a separate observer. Observers, who were a group of instructional designers worked on the development of the adaptive personalized platform, sat behind a mirror. Students didn't see them, but they were able to see students' faces very well. Using a piece of software called Morae (http://goo.gl/2AyOIo), observers watched their student's screen on their own monitor, took notes whenever necessary and recorded students' screens as well as their faces while they were using the adaptive platform. Students participated in seven assignments in total on Linear Equations. During the pilot, no major issues were observed. Only student 3 had a connectivity issue and got some repetitive content; as a result, he couldn't finish his assignment.

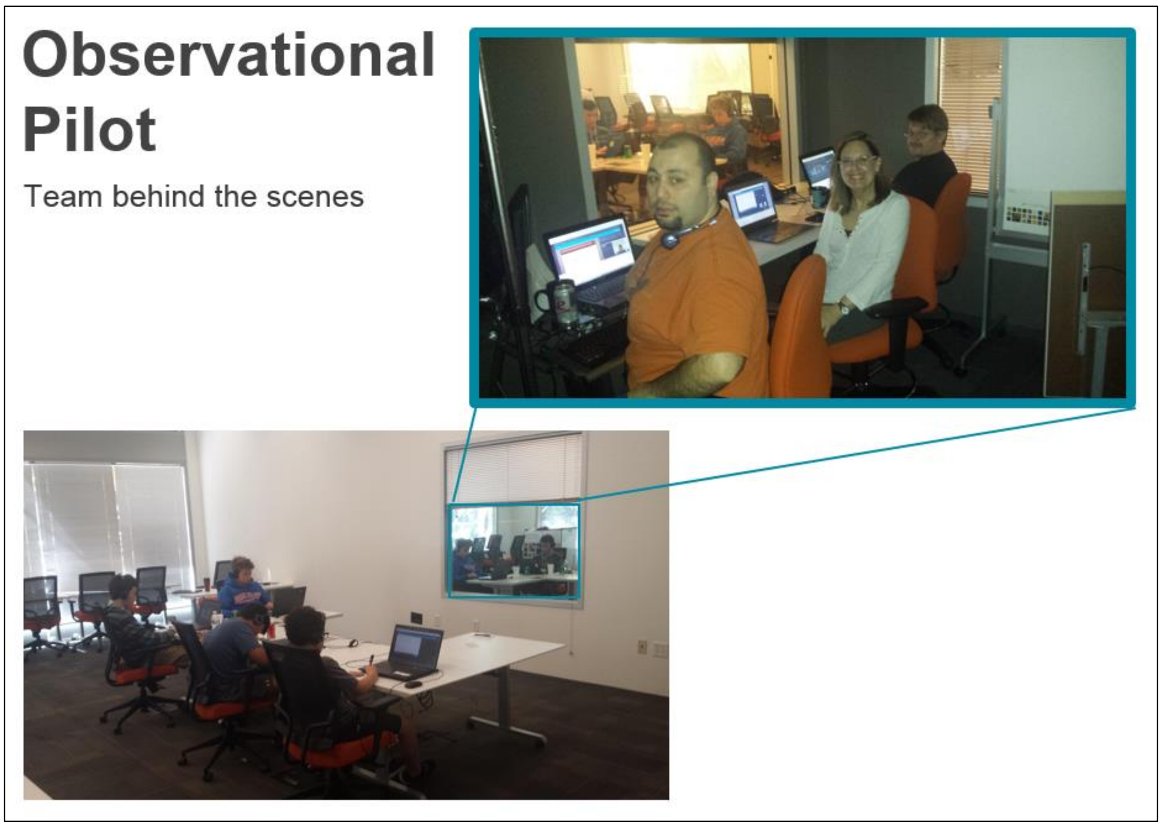


Figure 3. Observational Pilot Setting

Consolidating the observers' notes, the data collected from the surveys conducted and the findings of student interviews, a very useful "*list of actions*" document to improve the platform prior to the actual study was created. The summary of the results of the Likert-type survey questions has been shown in Figure.

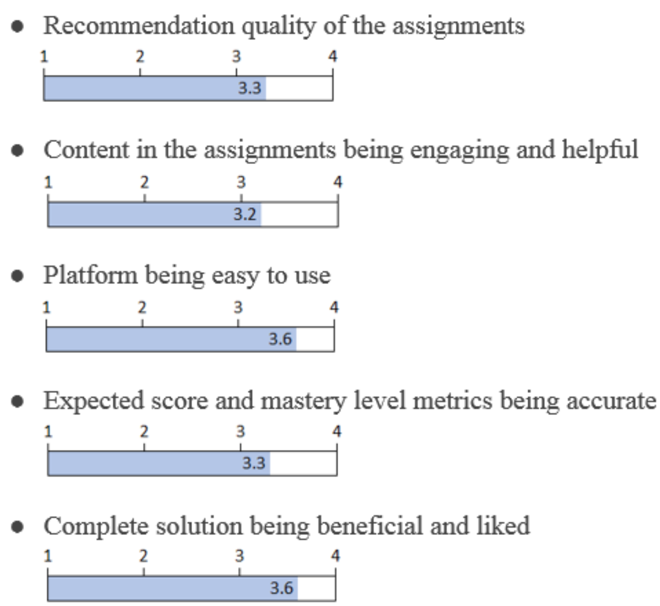


Figure 4. Survey Results [in a 1-4 scale] (N = 4)

Observational pilot with teachers. Three teachers were recruited for a pilot study in which they used the adaptive personalized platform for two hours mimicking a student and then one full week as a teacher. All teachers were teaching high school Algebra at the time of the pilot and all of them had more than ten years of teaching experience (11, 16 and 23 years, respectively). Prior to the observational pilot, signed consent letters were collected from the teachers for their participation. The flow of the observational pilot has been shown in Figure 5.

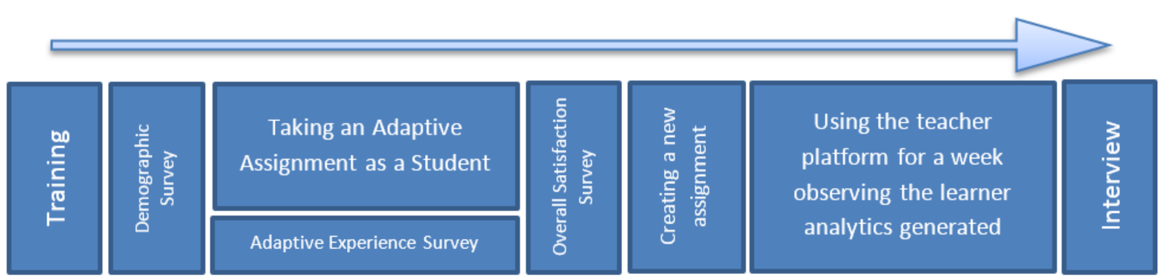


Figure 5. Teachers' Observational Pilot Design

The entire pilot took one week for the teachers. Each teacher was given a $225 gift card as a compensation for their time. During the time they took the adaptive assignments mimicking the students, each teacher was observed by a separate observer. Observers, who were a group of instructional designers worked on the development of the adaptive personalized platform, sat behind a mirror. Teachers didn't see them, but they were able to see teachers' faces very well. Using the Morae software, observers watched their teacher's screen on their own monitor, took notes whenever necessary and recorded teachers' screens as well as their faces while teachers were using the adaptive platform. One teacher performed an assignment on Linear Equations and other two did an assignment on Quadratic Equations. During the pilot, major issues were observed. On the student platform, no teachers were able to finish their assignment. Teacher 2 and 3 got into a loop and couldn't manage to get out. On the teacher platform, teacher 1 encountered more technical errors than teachers 2 and 3.

Another very useful "*list of actions*" document to improve the platform prior to the actual study was created with the data collected from the surveys conducted, teacher interviews and observers' notes. The summary of the results of the Likert-type survey questions has been shown in Figure 6.

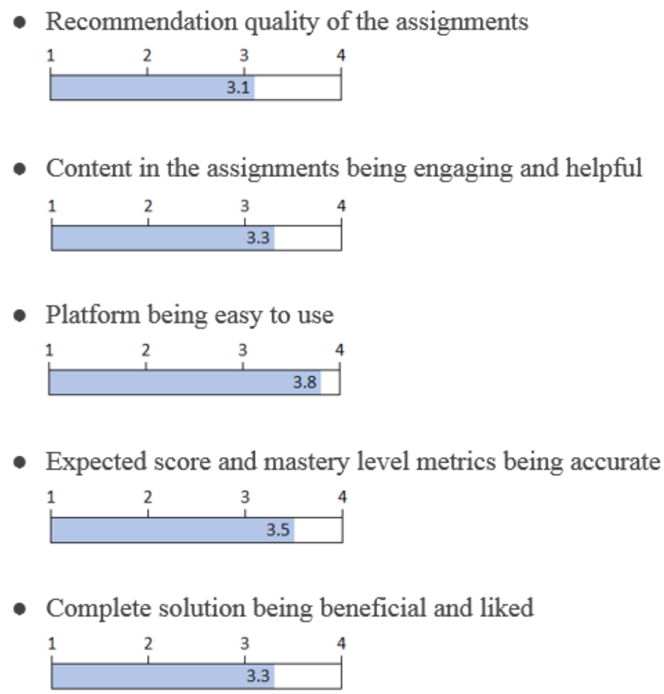


Figure 6. Survey Results [in a 1-4 scale] (N = 3)

Both pilots revealed important information about the critical issues and improvements in the adaptive personalized platform, which were mostly taken care of before the actual experiment started. Then, the design of the experiment was set by choosing the variables, identifying the research questions and developing the instruments as described in the following sections.

Independent Variables

Two types of homework assignments were prepared for the study and the participants were randomly assigned to one type of assignment. In the first type, linear flow was used. For linear flow, students received a set of modules in a pre-defined order. Once they completed every single module in the linear flow regardless of what scores they got from the assessment of each module, they completed the assignment. In the second type, adaptive personalized learning paths were used. By comparison, adaptive personalized learning paths were determined by the students' actions, such as answering questions correctly or incorrectly, completing certain instructional modules till the end, skipping certain types of modules before completion, watching the same animation more than once, making mistakes in the interactive tasks, etc. Moreover, the assignment had not been completed until the student reached a satisfactory proficiency level for every concept covered in the assignment. Therefore, the main independent variable manipulated in the study was the type of homework assignment.

- **Type of homework assignment** with the following two categories:
    - **Category 1:** Interactive multimedia assignment with linear flow (Linear)
    - **Category 2:** Interactive multimedia assignment with personalized learning paths (Adaptive)

Additionally, during the analysis of the results, effect of the type of homework assignment was also examined with respect to the following factors:

- **Gender:** Male vs. Female students
- **Ethnicity:** Students from different ethnic groups
- **Math pre-test level:** Low vs. Medium vs. High proficient students according to their pre-test results

Possible extraneous variables that would threaten the internal validity of this study included the teacher effect, prerequisite knowledge and other entry behaviors of the learners and some learner characteristics (socio-economic status (SES), age, gender, ethnicity, amount of parent's involvement in child's home study and other similar factors). The procedures section details how these possible variables have been controlled.

Dependent Variables

- **Post-test score in Algebra 1 Introduction to Quadratics**: measured with a post-test (Appendix C) after the treatment. Pre-test scores were used as a covariate.
- **Math intrinsic motivation score:** measured with the Math Intrinsic Motivation Scale (Skaalvik & Rankin, 1995) (Appendix D) before and after the treatment.
- **Overall experience score**, **Content experience score** and **Adaptive experience score:** all measured with surveys (Appendices E, F and G) including Likert-type items, which were conducted after the treatment.

Research Questions

In order to explore the effect of personalized learning paths, this study was conducted to investigate the following research questions:

The first four research questions focused on students' learning:

- **RQ1.** Does the adaptive personalized flow lead to higher learning compared to the linear flow when used in learning quadratics?
- **RQ2.** How does the adaptive personalized flow affect learning of the students from different genders compared to the linear flow?
- **RQ3.** How does the adaptive personalized flow affect learning of the students from different ethnicities compared to the linear flow?

- **RQ4.** How does the adaptive personalized flow affect learning of the students with different proficiency levels compared to the linear flow?

One research question focused on students' intrinsic motivation:

- **RQ5.** Does the adaptive personalized flow lead to a higher intrinsic motivation towards math compared to the linear flow when used in learning quadratics?

The last three research questions focused on students' satisfaction with their assignment experience:

- **RQ6.** Does the homework assignment with personalized learning paths lead to a higher overall satisfaction compared to one with the linear flow when used in learning quadratics?
- **RQ7.** Does the homework assignment with personalized learning paths lead to a higher content satisfaction compared to one with the linear flow when used in learning quadratics?
- **RQ8.** How satisfied are the adaptive group students about their overall adaptive experience?

The literature on personalized learning suggested students exposed to a learning platform with personalized learning paths may demonstrate higher levels of learning, intrinsic motivation and overall satisfaction compared to one with the linear sequence. Hence, this study was conducted using an experimental format to compare these two platform conditions.

Chapter 2

METHOD

Participants

This adaptive personalization platform was prepared for 9th-grade Algebra 1 students. Therefore, the participants were 9th-grade Algebra 1 students attending a large Phoenix metro high school. Preliminary power analysis showed that the study should involve at least 210 participants in total for a medium effect size, however, the school was only able to provide 202 students for the study.

Out of 202 participants, 188 participants took the demographic survey. The tables below showed the distribution of these 188 participants in terms of gender, ethnicity, computer and Internet access at home, being English language learners and having any special education needs.

The distribution of students by gender was shown in Table 1.

Table 1

Distribution of Students by Gender

Category	Linear		Adaptive		TOTAL	
Male	49	52%	47	51%	96	51%
Female	46	48%	46	49%	92	49%
TOTAL	95		93		188	

One of the questions in the demographic survey was “*Is English your primary language?*” Additionally, the school provided us with the list of ELL students. Participants’ answers to the survey question were combined with the data from the school to get the final list of ELL students as shown in Table 2.

Table 2

Distribution of ELL Students

Category	Linear		Adaptive		TOTAL	
ELL	16	17%	15	16%	31	16%
TOTAL	95		93		188	

The school also provided the list of students with the special needs as shown in Table 3.

Table 3

Distribution of Special Ed students

Category	Linear		Adaptive		TOTAL	
Special Ed	4	4%	10	11%	14	7%
TOTAL	95		93		188	

The distribution of students by ethnicity was shown in Table 4.

Table 4

Distribution of Students by Ethnicity

Category	Linear		Adaptive		TOTAL	
White or Caucasian	32	34%	33	35%	65	35%
Hispanic or Latino	22	23%	27	29%	49	26%
Black or African American	12	13%	10	11%	22	12%
Asian or Pacific Islander	5	5%	6	6%	11	6%
Native American or American Indian	3	3%	2	2%	5	3%
Mixed	3	3%	4	4%	7	4%
Other	2	2%	4	4%	6	3%
Unknown	16	17%	7	8%	23	12%
TOTAL	95		93		188	

During the analysis of the results, students identifying themselves as Black or African American, Asian or Pacific Islander, Native American or American Indian, Other and Mixed were grouped under one category named "Other" for the sake of a stronger statistical analysis. Students who did not wish to provide ethnicity information were not used in the ethnicity-related analyses. Therefore, during the analyses, the groups reflected the data presented in Table 5.

Table 5

Modified Distribution of Students by Ethnicity

Category	Linear		Adaptive		TOTAL	
White or Caucasian	32	41%	33	38%	65	39%
Hispanic or Latino	22	28%	27	31%	49	30%
Other	25	32%	26	30%	51	31%
TOTAL	79		86		165	

Finally, the distribution of students by computer and Internet access at home was shown in Table 6.

Table 6

Distribution of Students by Computer and Internet Access at Home

Category	Linear		Adaptive		TOTAL	
Yes, both laptop and Internet	64	67%	70	75%	134	71%
No to a laptop, yes to Internet	15	16%	11	12%	26	14%
Yes to a laptop, no to Internet	6	6%	4	4%	10	5%
I don't have access to either at home	2	2%	3	3%	5	3%
Unknown	8	8%	5	5%	13	7%
TOTAL	95		93		188	

Design

The experiment was a two-group, between subjects, pre-test, post-test comparison. To be able to control the teacher effect and the effect of other learner characteristics, students of each teacher were randomly assigned to one of the two treatment groups – condition 1 or 2.

Figure 7. The Study Design

Most of the results have been analyzed with one-factor or two-factor ANCOVA procedures for analyzing the students' post-test scores based on the type of treatment and other categorical factors and using the pre-test scores as the covariate. The intrinsic motivation results have been analyzed with one-way repeated measures ANOVA; and finally, one-factor or two-factor ANOVA was used for the other analyses that did not require a covariate. Interviews, surveys and questionnaires were used in evaluating the user experience of both platforms.

Instruments and Data Sources

Demographic survey (Appendix A). The demographic survey was a short survey that consisted of nine short-answer or multiple-choice questions to collect the demographic information of the participants. It was conducted in the pre-test session at the beginning of the experiment.

Pre-test (Appendix B). The pre-test assessment was a diagnostic mathematics test that consisted of 12 multiple-choice items, the first 10 measuring students' readiness to Quadratics and the last 2 measuring their existing knowledge in Introduction to Quadratics concepts. It was conducted in the pre-test session at the beginning of the experiment.

Reliability. When the reliability analysis was performed on the pre-test items, Cronbach's alpha was found to be .57. Then the 12th item, which was the one with the lowest item-total correlation, was removed from the test and final alpha was calculated as .61. In all statistical analyses, students' pre-test scores were calculated based on these 11 remaining items.

Construct validity. The items in this test have been developed solely for this study and by a mathematics content developer who was also a mathematics educator and a former high school mathematics teacher with more than five years of teaching experience. The test has also been reviewed by a subject matter expert to ensure its validity.

Post-test (Appendix C). The post-test assessment was a summative mathematics test that consisted of 10 multiple-choice items measuring students' learning in the Introduction to Quadratics topic. The test was conducted in the post-test session at the end of the experiment.

Reliability. When the reliability analysis was performed on the post-test items, Cronbach's alpha was found to be .39. Then the items #1 and #4, which were the ones with the lowest item-total correlation, were removed from the test and the final alpha was calculated as .47. In all statistical analyses, students' post-test scores were calculated based on these eight remaining items.

Possible reasons for low reliability. The concept map prepared for the adaptive personalized platform consisted of very granular knowledge components (such as *Determine the range of quadratic functions within specified domains when its graph is given.*) and every item in both pre-test and post-test measures only one of these granular knowledge components, which was a necessity in the backend to be able to use them to set up meaningful relations between all assets of the platform. As a result, there was almost no concept-wise overlap between the concepts measured by these items of the same test and this affected the reliability of the entire test adversely because reliability has been developed to be a measure of internal consistency checking whether all items are measuring the same construct and whether they were consistent with each other (Schweizer, 2011). Additionally, the number of items in these tests had to be limited due to the set of instruments given to the participants in one class period. Test length was another important factor for the low reliability; generally, the longer a test is, the more reliable it is (Cohen & Spenciner, 2007).

Construct validity. The items in this test were developed solely for this study by a mathematics content developer who was also a mathematics educator and a former high school mathematics teacher with more than five years of teaching experience. The test was also reviewed by a subject matter expert to ensure its validity.

The Math Intrinsic Motivation Scale (Appendix D). This survey consisted of 15 Likert-type items. Skaalvik & Rankin (1995) described this scale as:

> Math intrinsic motivation (MMOT) was defined as interest in working, or liking to work, with tasks in the respective domains in school or in future education and jobs. There were 15 items on the intrinsic motivation scale, 8 items on the anxiety and effort scales and 6 items on the scale measuring general motivation for schoolwork. Low scores on the anxiety scales indicated high anxiety. Cronbach's alphas for the MMOT were .95 and .97 for sixth and ninth grades, respectively.

Reliability. When the reliability analyses were performed on the math intrinsic motivation scale items with the data of this study, Cronbach's alphas were found to be .94 and .95 for pre-test and post-test, respectively.

Overall experience survey (Appendix E). The overall experience survey consisted of seven Likert-type items that measured students' overall satisfaction about the platforms on which they worked. It was conducted in the post-test session at the end of the experiment.

Reliability. When the reliability analysis was performed on the overall experience survey items, Cronbach's alpha was found to be .90.

Content experience survey (Appendix F). The content experience survey consisted of four Likert-type items that measured students' satisfaction about the interactive multimedia content used in the study to determine whether the students found the content engaging and helpful. It was conducted in the post-test session at the end of the experiment.

Reliability. When the reliability analysis was performed on the content experience survey items, Cronbach's alpha was found to be .52. Then item #4, which was the one with the lowest item-total correlation, was removed from the test and final alpha was calculated as .67. In all statistical analyses, students' content experience scores were calculated based on these three remaining items.

Adaptive experience survey (Appendix G). The adaptive experience survey consisted of eight Likert-type items that measured students' satisfaction about their adaptive experience. It was conducted in the post-test session at the end of the experiment.

Reliability. When the reliability analysis was performed on the adaptive experience survey items, Cronbach's alpha was found to be .80.

System logs. The amount of time students spent on the assignment had a critical role on the analysis of results. First of all, students who did not spend any time in the program were not included in the analyses even though some of them took the pre-test or the post-test. Further, the data that showed the amount of time students spent on the program has been used in some of the satisfaction analyses to evaluate whether low vs. high usage made any difference on students' satisfaction. That data was also provided to the teachers so that they could give appropriate incentives ($10 gift cards and extra homework credit) to the students.

Data from the school. The list of students with special needs and the list of the English language learner (ELL) students were provided by the school.

Qualitative instruments. Because the quantitative findings of this study were limited, qualitative analyses played an important role in explaining the reasons for it. Student and teacher interviews (Appendix I and J), researcher's field notes based on the classroom observations and the overall experience survey with open-ended questions (Appendix H) were used as the qualitative data sources.

Procedures and Materials

In this study, the teachers continued to use their regular curriculum and textbook and students stayed in their current classes. Students of the same teacher were randomly assigned to one of the two groups. In all, 202 students listed by the school were first grouped by their Algebra teachers and then by their gender. Students of the same gender and the same teacher were randomly assigned to one of the two conditions. With this method, half of the students of every teacher were assigned to the linear condition and the remaining half to the adaptive condition. Similarly, half of the female students were assigned to the linear condition and the remaining half to the adaptive condition; and half of the male students were assigned to the linear condition and the remaining half to the adaptive condition. Randomization was performed using MS Excel's "=rand()" function. With this distribution, in every class, there were students from either of the two groups. For two weeks, the teachers made an assignment to each group to be completed by the end of the second week. Students worked on their assignment individually or after class hours; therefore, all students in the same class were not in the same treatment condition. Because the software used was online, the platforms could be accessed from anywhere (e.g. home, school computer lab, neighborhood library, boys and girls club, etc.). For students with no computers or Internet access at home, the school computer lab was allocated for this study for one hour every day after school. Both platforms were browser-based so that no installation of software was necessary and access would be available across different operating system platforms. The content used in both the adaptive and linear platforms was exactly the same. The only difference between them was the adaptivity.

The study was conducted parallel to the teacher's timeline when the Quadratics unit was covered in class at school. The total length of the study for each student was about two weeks considering how much time the teachers allocated for the Introduction to Quadratics topic within their curriculum.

Random assignment of students to the treatment and control groups eliminated many of the internal validity threats including the teacher effect, students' prerequisite knowledge and other entry behaviors, learner characteristics e.g. SES, age, gender and ethnicity. The multimedia content was exactly the same between groups, so, no content effect existed either.

All surveys and tests were given in paper-and-pencil form due to the complexity of all participants having access to a computer at the same time. Prior to the experiment, the demographic survey, pre-test math assessment, and the motivation survey were given together in the same session. At the end of the experiment, the post-test math assessment, motivation, and satisfaction surveys were again given together in the same session. The duration of each testing session was considered to be 45 minutes, which was decided in collaboration with the school administration.

To support quantitative data with some qualitative evidence, seven students were interviewed after the study. These students were randomly selected among the voluntary, adaptive group students who completed (or almost completed) their assignments. Four of the participating teachers were also interviewed. All interviews were recorded with a voice-recording device.

Chapter 3

ANALYSIS AND RESULTS

Primary Analysis by Variable

Of 202 participants assigned by the school to the study, 189 participants took the pre-test; and among them, 176 participants spent some time in the program. Again, of 202 participants, 188 participants took the post-test; and among them, 176 participants spent some time in the program. The number of participants who took both the pre-test and post-test and also spent some time in the program was 166. Therefore, the analyses that involve both pre-test and post-test were based on 166 participants, whereas the analyses that involve either one of the tests were based on 176 participants. In some cases, the total number of participants used in the analyses were even smaller due to the lack of information the participants provided. For example, not all participants wanted to share their ethnicity information. Of the 176 participants who spent some time in the program and took the post-test 88 were in the linear condition and the remaining 88 students were in the adaptive condition.

The results from the measure of the following five dependent variables were analyzed: post-test score, intrinsic motivation score, overall experience score, content experience score and adaptive experience score. Table 7 provides a summary of the study's research questions and analytic approaches. For all statistical comparisons, the family-wise Type I error rate was set at the 0.05 level. SPSS's partial eta squared was used as an effect size index, where 0.01, 0.06 and 0.14 correspond to small, medium and large effect sizes, respectively (Cohen, 1988). Preliminary checks were conducted prior to each analysis to ensure that there were no violations of the assumptions of normality, linearity, homogeneity of variances, homogeneity of regression slopes and reliable measurement of the covariate.

Table 7

Summary of Analytic Approaches

	Research Question	Data Source	Analyses
1	Does the adaptive personalized flow lead to higher learning compared to the linear flow when used in learning quadratics?	Pre-test Post-test	ANCOVA
2	How does the adaptive personalized flow affect learning of the students from different genders compared to the linear flow?	Pre-test Post-test	ANCOVA
3	How does the adaptive personalized flow affect learning of the students from different ethnicities compared to the linear flow?	Pre-test Post-test	ANCOVA
4	How does the adaptive personalized flow affect learning of the students with different proficiency levels compared to the linear flow?	Pre-test Post-test	ANOVA
5	Does the adaptive personalized flow lead to a higher intrinsic motivation towards math compared to the linear flow when used in learning quadratics?	The Math Intrinsic Motivation Scale	Split-Plot ANOVA
6	Does the homework assignment with personalized learning paths lead to a higher overall satisfaction compared to one with the linear flow when used in learning quadratics?	Overall Experience Survey System logs	ANOVA

Table 7 (Continues)

Table 7 (Continued)

	Research Question	Data Source	Analyses
7	Does the homework assignment with personalized learning paths lead to a higher content satisfaction compared to one with the linear flow when used in learning quadratics?	Content Experience Survey System logs	ANOVA
8	How satisfied are the adaptive group students about their overall adaptive experience?	Adaptive Experience Survey System logs	ANOVA

Findings by Research Question:

Research Question 1. Does the adaptive personalized flow lead to higher learning compared to the linear flow when used in learning quadratics?

In this study, pre-test and post-test are not parallel instruments. The pre-test consisted of 12 multiple choice items, the first 10 items measuring students' readiness to Quadratics, in other words, measuring the skills prerequisite to Quadratics and the last 2 items measuring their existing knowledge in Introduction to Quadratics concepts; whereas the post-test consisted of 10 multiple choice items all measuring students' knowledge only in Introduction to Quadratics. Since they are not parallel instruments, here *learning* refers not to the difference between pre-test and post-test scores, but to the post-test score itself.

When the pre-test and post-test scores were compared, a strong positive correlation between them was observed, $r(164) = .55$, $p < .01$. Figure 8 shows this correlation. This strong correlation indicated that the pre-test could be used as a covariate in most post-test-related analyses.

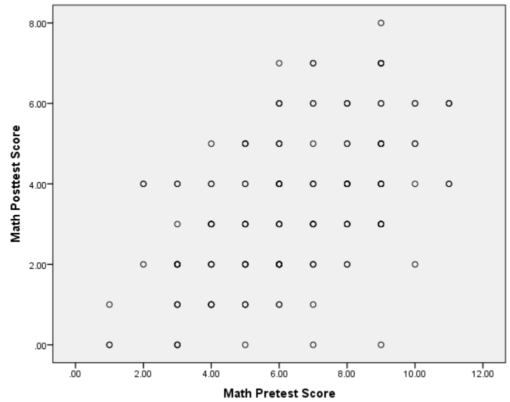


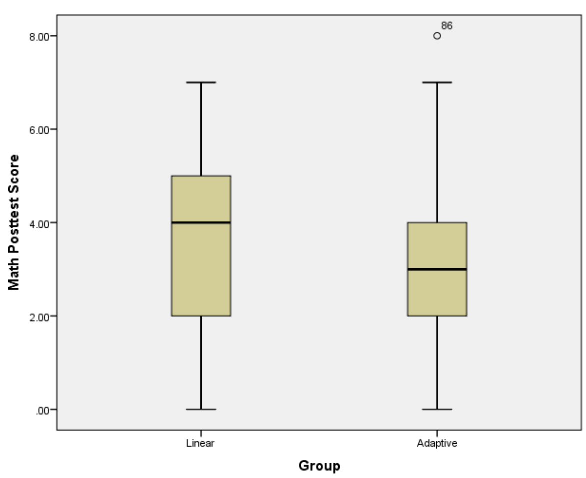
Figure 8. Math Pre-test and Post-test Correlation Plot

The means and standard deviations of the post-test scores reported in Table 8 and distribution of the post-test scores shown in Figure 9 indicate that the students in the linear group scored somewhat higher in the post-test compared to the students in the adaptive group.

Table 8

Post-test Mean Scores and Standard Deviations

Group	*Mean*	*SD*	*N*
Linear	3.58	1.82	81
Adaptive	3.22	1.79	85
Total	3.40	1.81	166



Box plots used in this figure as well as the ones used throughout this dissertation are quite useful for comparing distributions. In a box plot, the central part of the data is represented by means of a box. The box is bounded by the first and the third quartile and the median is represented with a line in between these two quartiles. In addition, a box plot indicates extremely large and extremely small values using dots. Box plots usually contain lines or whiskers that reach down to the smallest and up to the largest sample value that are not considered extreme values (Goos&Meintrup, 2015).

Figure 9. Distribution of Math Post-test Scores across Groups

Then, a one-factor analysis of covariance (ANCOVA) was conducted to assess the effectiveness of two treatment conditions in learning quadratics. The independent variable was the type of homework assignment (Linear vs. Adaptive). The dependent variable was scores on the post-test. Scores on the pre-test were used as the covariate to control for individual differences.

Preliminary checks were conducted to ensure that there was no violation of the assumptions of normality, linearity, homogeneity of variances, homogeneity of regression slopes and reliable measurement of the covariate. After adjusting for the pre-test scores, as expected due to the strong correlation between pre-test and post-test scores, the results of the ANCOVA suggested a statistically significant effect of the covariate, pre-test score, on the dependent variable, post-test score, $F(1, 163) = 69.079$, $p < .001$. However, there was no significant effect for the type of homework assignment, $F(1, 163) = 1.208$, $p = .273$. These results suggested that neither of the two assignment types led to higher learning compared to each other. Results of the ANCOVA analysis are summarized in Table 9.

Table 9

Analysis of Covariance Summary for the Post-test Scores by Group

Source	Sum of Squares	*df*	Mean Square	*F*	*p*	Partial Eta Squared
Math Pre-test Score	158.495	1	158.495	69.079	.000	.298
Group	2.772	1	2.772	1.208	.273	.007
Error	373.987	163	2.294			

Research Question 2. How does the adaptive personalized flow affect learning of the students from different genders compared to the linear flow?

The means and standard deviations of the post-test scores for each group and condition reported in Table 10 and distribution of the post-test scores shown in Figure 10 indicated students from both genders scored higher in the linear condition than the ones in the adaptive condition.

Table 10

Post-test Mean Scores and Standard Deviations by Gender

Group	Gender	*Mean*	*SD*	*N*
Linear	Male	3.54	1.92	41
	Female	3.63	1.72	40
	Total	3.58	1.82	81
Adaptive	Male	3.11	1.81	44
	Female	3.34	1.78	41
	Total	3.22	1.79	85
Total	Male	3.32	1.87	85
	Female	3.48	1.75	81
	Total	3.40	1.81	166

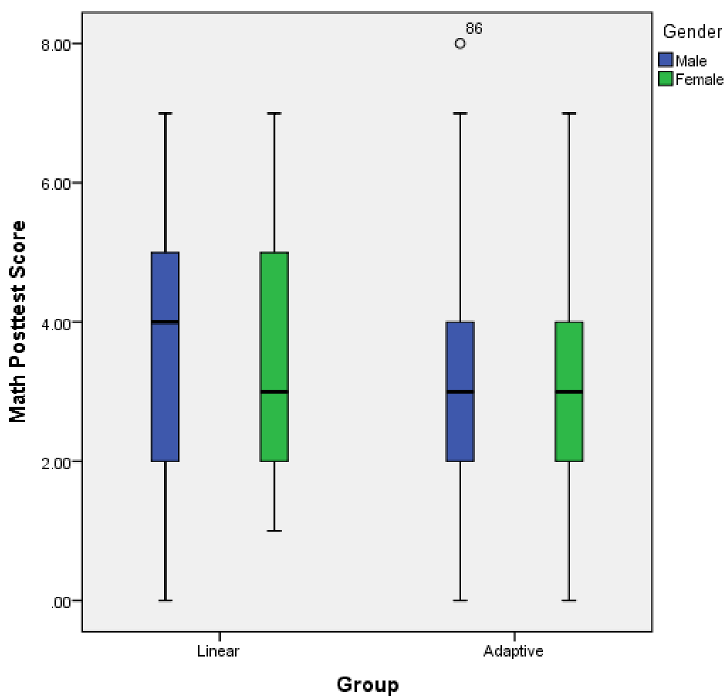


Figure 10. Distribution of Math Post-test Scores across Groups and Gender

A 2 assignment type x 2 gender between-groups analysis of covariance was conducted to assess the effectiveness of two treatment conditions in learning quadratics for male and female participants. The independent variables were the type of homework assignment and gender. The dependent variable was scores on the post-test. Scores on the pre-test were used as the covariate to control for individual differences.

Preliminary checks were conducted to ensure that there was no violation of the assumptions of normality, linearity, homogeneity of variances, homogeneity of regression slopes, and reliable measurement of the covariate. After adjusting for the pre-test scores, there was no significant interaction effect between group and gender, $F(1, 161) = 0.383$, $p = .537$. Neither of the main effects for assignment type nor gender were statistically significant: group, $F(1, 161) = 1.205$, $p = .274$; and gender, $F(1, 161) = .571$, $p = .451$. These results suggested that neither of the two assignment types affected learning of male and female students differently. Results of the ANCOVA analysis are summarized in Table 11.

Table 11

Analysis of Covariance Summary for the Post-test Scores by Group and Gender

Source	Sum of Squares	*df*	Mean Square	*F*	*p*	Partial Eta Squared
Math Pre-test Score	159.388	1	159.388	69.014	.000	.300
Group	2.783	1	2.783	1.205	.274	.007
Gender	1.320	1	1.320	.571	.451	.004
Group × Gender	.886	1	.886	.383	.537	.002
Error	371.833	161	2.310			

Research Question 3. How does the adaptive personalized flow affect learning of the students from different ethnicities compared to the linear flow?

The means and standard deviations of the post-test scores for each group and condition have been reported in Table 12 and distribution of the post-test scores has been shown in Figure 11 and indicated that students from all ethnicities scored slightly higher in the linear condition than the ones in the adaptive condition.

Table 12

Post-test Mean Scores and Standard Deviations by Group and Ethnicity

Group	Ethnicity	*Mean*	*SD*	*N*
Linear	White/Caucasian	3.87	1.71	31
	Hispanic/Latino	3.25	1.80	20
	Other	3.38	1.81	24
	Total	3.55	1.77	75
Adaptive	White/Caucasian	3.61	1.80	31
	Hispanic/Latino	2.92	1.87	25
	Other	3.00	1.52	26
	Total	3.21	1.75	82
Total	White/Caucasian	3.74	1.75	62
	Hispanic/Latino	3.07	1.83	45
	Other	3.18	1.66	50
	Total	3.37	1.76	157

Please note that students identifying themselves as Black or African American, Asian or Pacific Islander, Native American or American Indian, Mixed and Other are grouped under one single category named “Other”. Students who did not provide ethnicity information were not used in the ethnicity-related analyses.

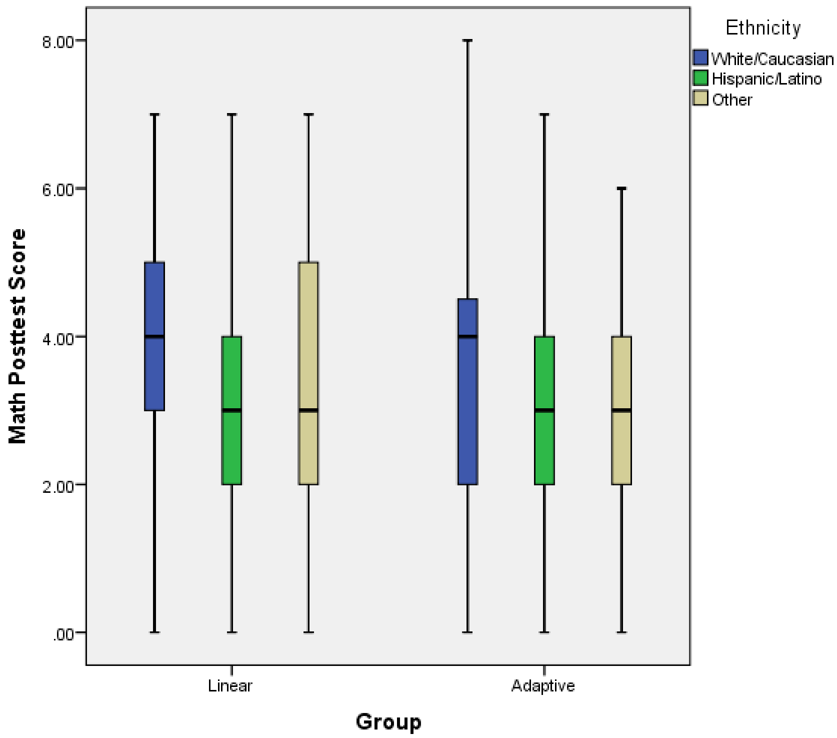


Figure 11. Distribution of Math Post-test Scores across Groups and Ethnicity

A 2 assignment type x 3 ethnicity group between-groups analysis of covariance was conducted to assess the effectiveness of two treatment conditions in learning quadratics for participants from different ethnic backgrounds. The independent variables were the type of homework assignment and ethnicity. The dependent variable was scores on the post-test. Scores on the pre-test were used as the covariate to control for individual differences.

Preliminary checks were conducted to ensure that there was no violation of the assumptions of normality, linearity, homogeneity of variances, homogeneity of regression slopes, and reliable measurement of the covariate. After adjusting for the pre-test scores, there was no significant interaction effect between group and ethnicity, $F(2, 150) = .196$, $p = .822$. Neither of the main effects for group and ethnicity were statistically significant:

group, $F(1, 150) = 1.221$, $p = .271$; and ethnicity, $F(2, 150) = .430$, $p = .562$. These results suggested neither of the two assignment types was more effective in terms of learning of students from different ethnic backgrounds. Results of the ANCOVA analysis are summarized in Table 13.

Table 13

Analysis of Covariance Summary for the Post-test Scores by Group and Ethnicity

Source	Sum of Squares	*df*	Mean Square	*F*	*p*	Partial Eta Squared
Math Pre-test Score	133.153	1	133.153	60.359	.000	.287
Group	2.694	1	2.694	1.221	.271	.008
Ethnicity	1.895	2	.948	.430	.652	.006
Group × Ethnicity	.865	2	.432	.196	.822	.003
Error	330.901	150	2.206			

Research Question 4. How does the adaptive personalized flow affect learning of the students with different proficiency levels compared to the linear flow?

As the results of the analysis for Research Question 1 suggested, neither of the two assignment types led to higher learning when all students in the adaptive condition were compared to all students in the linear condition. But, what if the adaptive personalized platform was more effective for the low-proficient students, or maybe the high-proficient students? To investigate this, all students have been grouped as Low, Medium, or High proficient according to their pre-test scores. Students whose pre-test scores are less than "*Mean* – 1×*SD*" have been labeled as low-proficient, students whose pre-test scores are between "*Mean* – 1×*SD*" and "*Mean* + 1×*SD*" have been labeled as medium-proficient and finally students whose pre-test scores are higher "*Mean* + 1×*SD*" have been labeled as high-proficient.

The means and standard deviations of the post-test scores for each group and condition have been reported in Table 14, distribution of the post-test scores shown in Figure 12 and estimated marginal means of the post-test scores shown in Figure 13 indicated the low-proficient and high-proficient students scored slightly higher in the adaptive condition whereas the medium-proficient students scored slightly higher in the linear condition.

Table 14

Post-test Mean Scores and Standard Deviations by Group and Math Pre-test Level

Group	Math Pre-test Level	*Mean*	*SD*	*N*
Linear	Low	1.71	1.50	7
	Medium	3.52	1.66	58
	High	4.63	1.86	16
	Total	3.58	1.82	81
Adaptive	Low	1.80	1.37	15
	Medium	2.94	1.45	49
	High	4.90	1.55	21
	Total	3.22	1.79	85
Total	Low	1.77	1.38	22
	Medium	3.25	1.58	107
	High	4.78	1.67	37
	Total	3.40	1.81	166

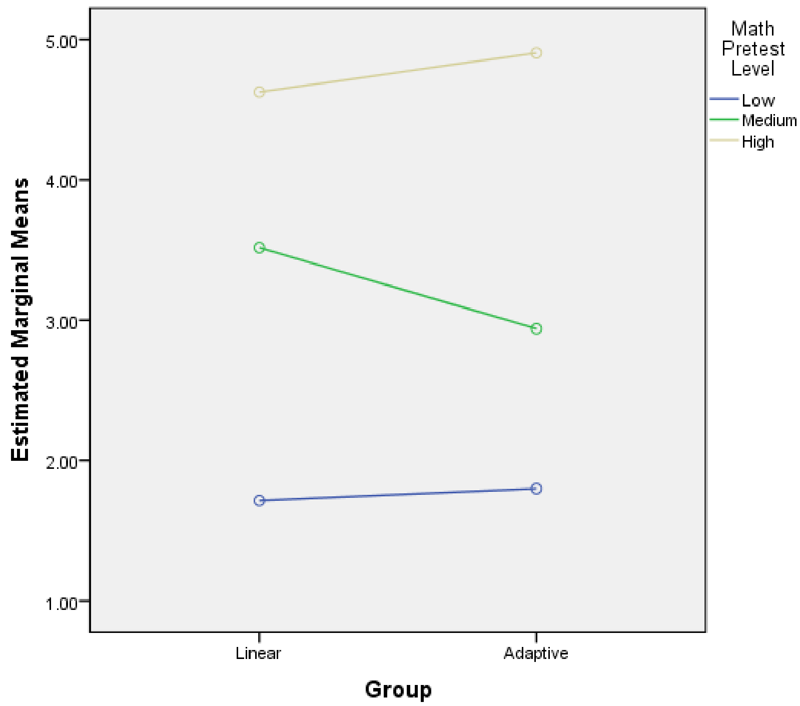


Figure 12. Estimated Marginal Means of Math Post-test Scores across Groups and Math Pre-test Levels

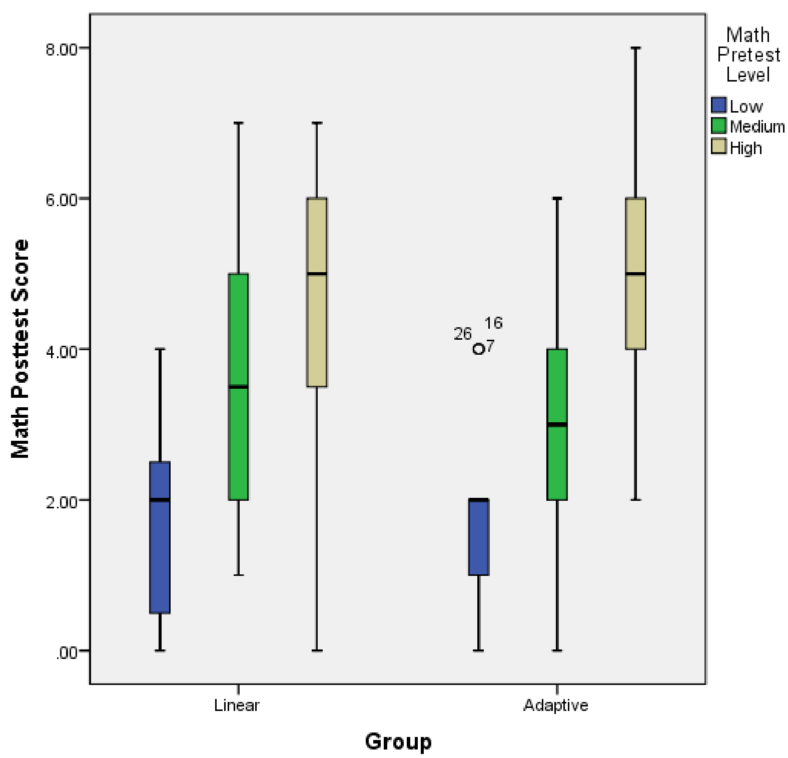


Figure 13. Distribution of Math Post-test Scores across Groups and Math Pre-test Levels

A 2 assignment type by 3 pre-test math level between-groups analysis of variance (ANOVA) was conducted to assess the effectiveness of two treatment conditions in learning quadratics for participants from different ethnic groups. The independent variables were the type of homework assignment and math pre-test level. The dependent variable was scores on the post-test.

Preliminary checks were conducted to ensure that there was no violation of the assumptions of normality and homogeneity of variances. There was no significant interaction effect between group and math pre-test level, $F(2, 160) = 1.174$, $p = .312$. These results suggested neither of the two assignment types was more effective in terms of learning of students from different proficiency levels. Results of the ANOVA analysis have been summarized in Table 15.

Table 15

Analysis of Variance Summary for the Post-test Scores by Group and Math Pre-test Level

Source	Sum of Squares	*df*	Mean Square	*F*	*p*	Partial Eta Squared
Group	.127	1	.127	.051	.821	.000
Math Pre-test Level	122.337	2	61.169	24.672	.000	.236
Group × Math Pre-test Level	5.820	2	2.910	1.174	.312	.014
Error	396.687	160	2.479			

Research Question 5. Does the adaptive personalized flow lead to a higher intrinsic motivation towards math compared to the linear flow when used in learning quadratics?

Items in the Math Intrinsic Motivation Scale (Skaalvik & Rankin, 1995) were Likert type items with the following six levels: False, Mostly False, Sometimes False, Sometimes True, Mostly True, True. To statistically analyze these results, each level has been assigned a score from 1 to 6. Then the sum of these scores have been calculated by reversing the scores of negative-oriented item statements. Finally, the total score has been divided by the number of items in the survey to place the final score of each student back on the original 1-6 scale. The mean scores reported in Table 16 should be interpreted along with the scale summarized in Figure 14.

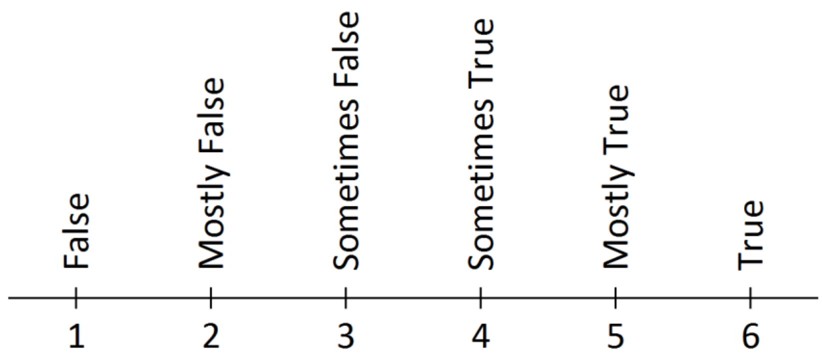


Figure 14. Motivation Scores Interpretation Scale

The means and standard deviations of the motivation pre-test and post-test scores for each condition reported in Table 16 and estimated marginal means of the two scores shown in Figure 15 indicated the motivation post-test scores are slightly lower than the motivation post-test scores for both linear and adaptive conditions.

Table 16

Motivation Scores and Standard Deviations by Test and Group

Motivation Score	Group	*Mean*	*SD*	*N*
Motivation Pre-test Score	Linear	3.33	1.08	82
	Adaptive	3.23	1.20	84
	Total	3.28	1.14	166
Motivation Post-test Score	Linear	3.17	1.11	82
	Adaptive	3.07	1.21	84
	Total	3.12	1.16	166

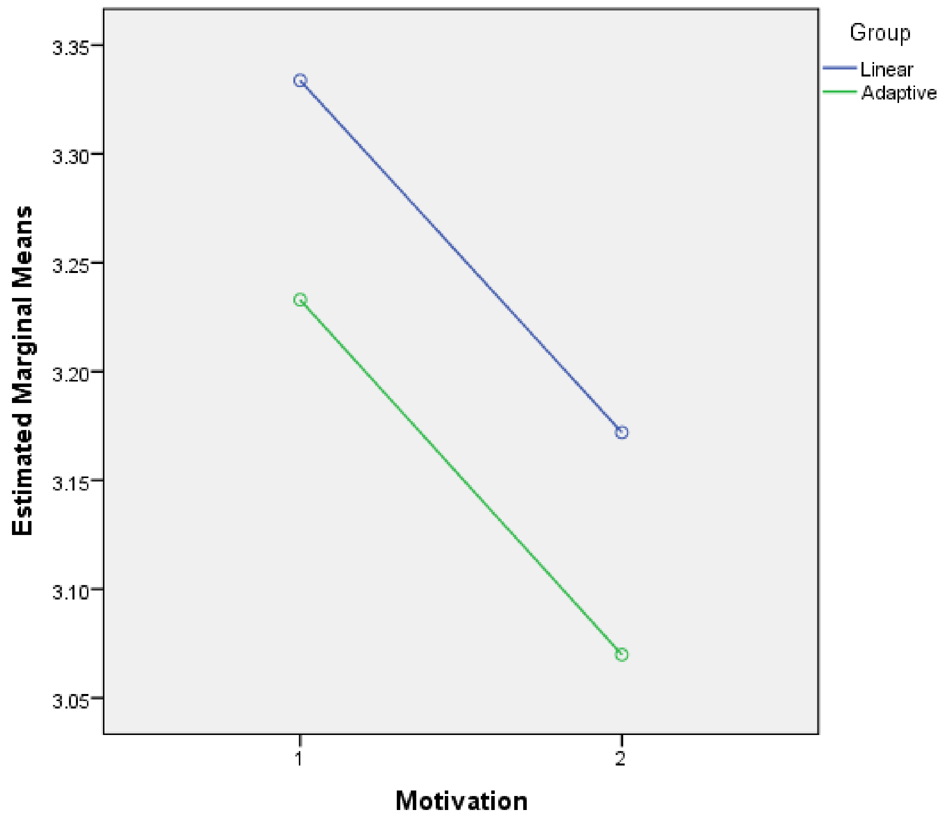


Figure 15. Estimated Marginal Means of Motivation Scores across Groups and Tests

A two-factor split-plot (one between-subjects factor and one within-subjects factor) ANOVA was conducted to compare the effect of assignment types on students' intrinsic math motivation in linear and adaptive conditions. The between-subjects factor was the type of homework assignment (linear vs. adaptive) and the within-subjects factor was the scores on the motivation tests (motivation pre-test and motivation post-test).

Preliminary checks were conducted to ensure that there was no violation of the assumptions of normality and homogeneity of variances. There was no significant interaction effect between group and motivation, $F(1, 164) = .000$, $p = .989$, and there was no significant between-subjects main effect for the type of homework assignment, $F(1, 164) = .345$, $p = .558$. However, a statistically significant within-subjects main effect for motivation was observed, $F(1, 164) = 12.403$, $p = .001$. The effect size based on Cohen's (1988) conventions was medium. The observed power was .94, which indicates that a Type I error is very unlikely. These results suggested both assignment types have the same strong negative effect on students' motivation.

Research Question 6. Does the homework assignment with personalized learning paths lead to a higher overall satisfaction compared to one with the linear flow when used in learning quadratics?

Items in the overall experience survey are Likert type items with the following four levels: Strongly agree, Agree, Disagree, Strongly disagree. To statistically analyze these results, each level has been assigned a score from 1 to 4. Then the sum of these scores was calculated by reversing scores for the negative-oriented item statements. Finally, the total score has been divided by the number of items in the survey to to place the final score of each student back on the original 1-4 scale. The mean scores reported in Table 17 should be interpreted along with the scale summarized in Figure 16.

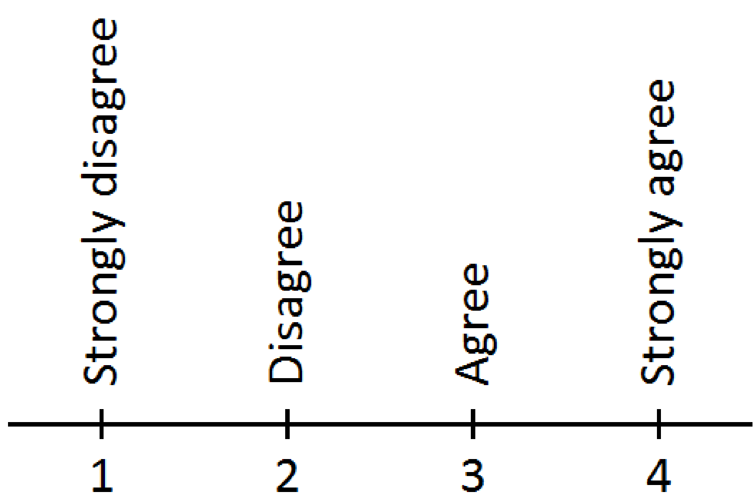


Figure 16. Overall Satisfaction Scores Interpretation Scale

The means and standard deviations of the overall satisfaction scores for each group reported in Table 17 and distribution of these scores shown in Figure 17 indicated students in both linear and adaptive groups rated their overall experience very similarly.

Table 17

Overall Satisfaction Mean Scores and Standard Deviations

Group	*Mean*	*SD*	*N*
Linear	1.99	.67	89
Adaptive	1.98	.74	88
Total	1.99	.71	177

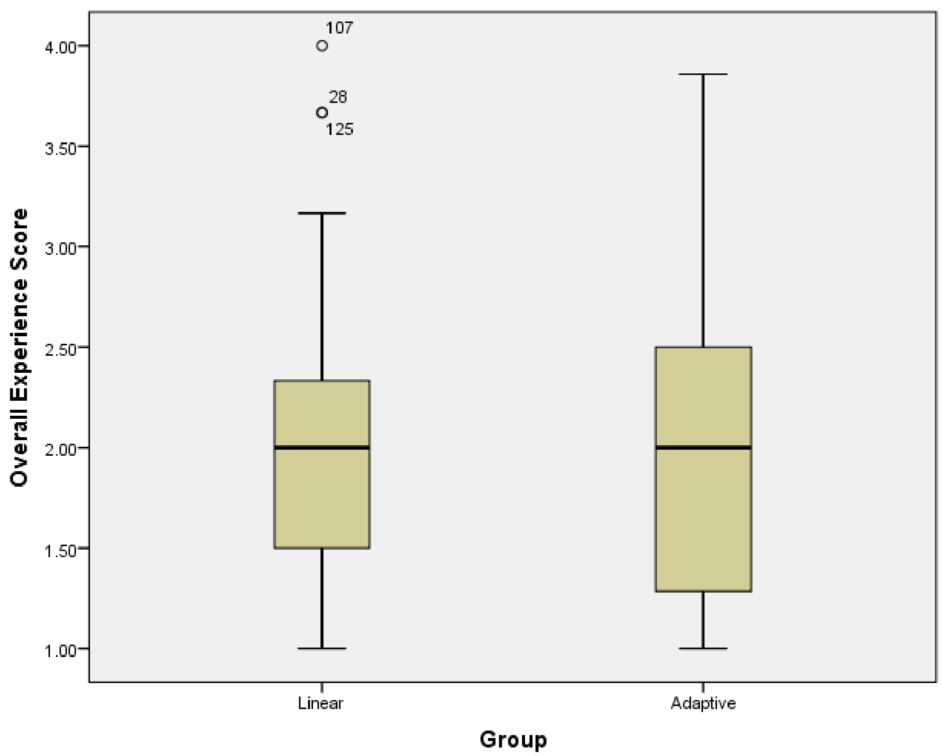


Figure 17. Distribution of Overall Satisfaction Scores across Groups

Then, a one-factor analysis of variance (ANOVA) was conducted to assess the effect of two treatment conditions on students' overall satisfaction with the assignment. The independent variable was the type of homework assignment (Linear vs. Adaptive). The dependent variable was scores on the overall experience survey.

Preliminary checks were conducted to ensure that there was no violation of the assumptions of normality and homogeneity of variance. There was no significant effect between the two groups, $F(1, 175) = .016$, $p = .899$. These results suggested neither of the two platforms led to different overall satisfaction on students. The overall satisfaction of the students from both conditions was slightly on the negative side of the Likert scale.

Because the overall satisfaction mean scores were very close to each other for linear and adaptive conditions, no further analyses were conducted.

Research Question 7. Does the homework assignment with personalized learning paths lead to a higher content satisfaction compared to one with the linear flow when used in learning quadratics?

Like the items in the overall experience survey, items in the content experience survey are also Likert type items with four levels. Therefore, the results of the content satisfaction analysis should also be interpreted in the same way.

The means and standard deviations of the content satisfaction scores for each group reported in Table 18 and the distribution of these scores shown in Figure 18 indicated students in the linear condition rated their content experience slightly higher than the adaptive group students.

Table 18

Content Satisfaction Mean Scores and Standard Deviations

Group	*Mean*	*SD*	*N*
Linear	2.14	.70	89
Adaptive	2.00	.75	86
Total	2.07	.72	175

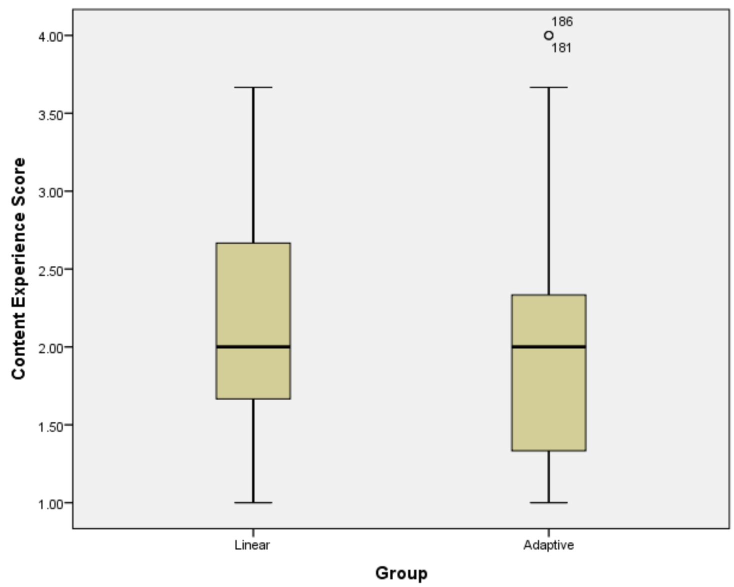


Figure 18. Distribution of Content Satisfaction Scores across Groups

Then, a one-factor analysis of variance (ANOVA) was conducted to assess the effect of two treatment conditions on students' content satisfaction from the assignment. The independent variable was the type of homework assignment (Linear vs. Adaptive). The dependent variable was scores on the content experience survey.

Preliminary checks were conducted to ensure that there was no violation of the assumptions of normality and homogeneity of variance. There was no significant effect between the two groups, $F(1, 173) = 1.656$, $p = .200$. These results suggested neither of the two platforms led to a different content satisfaction for students. The content satisfaction of the students from both conditions was slightly on the negative side of the Likert scale.

Research Question 8. How satisfied are the adaptive group students about their overall adaptive experience?

Like the items in the overall experience and content experience surveys, items in the adaptive experience survey are also Likert type items with four levels. Therefore, the results of the adaptive experience satisfaction analysis should also be interpreted in the same way.

The means and standard deviations of the adaptive experience satisfaction scores for each group reported in Table 19 and distribution of these scores shown in Figure 19 indicated the adaptive experience satisfaction of the students was slightly on the negative side of the Likert scale.

Table 19

Adaptive Experience Satisfaction Mean Scores and Standard Deviations

	Mean	*SD*	*N*
Adaptive Experience Score for the Adaptive group	2.34	.60	87

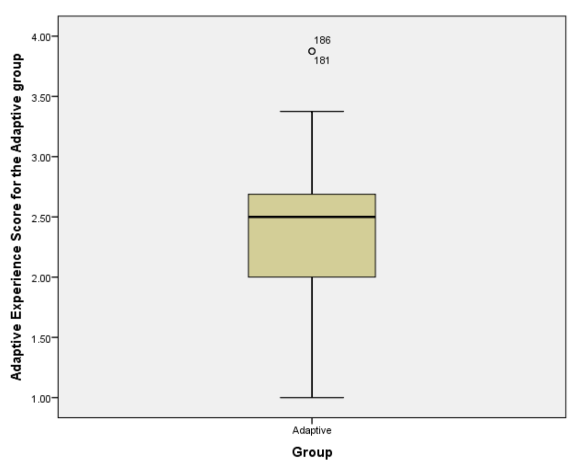


Figure 19. Distribution of Adaptive Experience Satisfaction Scores

Qualitative Feedback

As part of the overall experience survey with open-ended questions (Appendix H), students were solicited to: (a) Provide feedback on how they thought the system could be improved; and (b) Describe their experience with the program using three words. In turn, the qualitative feedback was coded based on the subject of each student response in order to identify the trends. Then, emergent trends in subject codes developed into categories, which are reported in the following two subsections.

Suggestions to improve the program. 4 suggestions were identified based on 10 codes assigned to students' responses. Frequency of students' responses are summarized in Figure 20.

LINEAR (*N* = 89)		Suggestion	ADAPTIVE (*N* = 89)	
Frequency	Percent		Frequency	Percent
28	46%	Make the content more understandable	18	31%
21	34%	Make it more engaging and interesting	11	19%
		Improve the progress bar	9	16%
		Improve the recommendation quality	8	14%
3	5%	Increase the variety of the content	4	7%
		Provide more clear instructions	4	7%
6	10%	Change the voice artist	2	3%
		Add a feature to chat with a teacher	1	2%
		Fix the content errors	1	2%
3	5%	Improve the navigation		

Figure 20. Qualitative Analysis of Students' Suggestions to Improve the Program

Feelings about the program. Figure 21 presents the keyword analysis of students' descriptions of the platforms on which they worked. It showed students' feelings about both platforms were quite negative (Linear condition = 70% negative, Adaptive condition = 71% negative).

LINEAR (*N* = 89)				ADAPTIVE (*N* = 88)		
Frequency	Percent of each category	Percent (P/N)	Descriptions	Frequency	Percent of each category	Percent (P/N)
7	3%	30%	**Extremely positive** Great, Nice, Smart, Cool, Creative	12	5%	29%
27	11%		**Positive** Beneficial, Descriptive, Fun, Good, Interesting	16	7%	
60	25%		**Somewhat positive** Different, Somewhat educational, Helpful, Meaningful, Understandable	58	24%	
17	7%	70%	**Somewhat negative** Semihelpful, Not that great, Slow, Needs work, Hard	34	14%	71%
89	37%		**Negative** Confusing, Learned nothing new, Not very engaging, Boring, Bad	80	33%	
40	17%		**Extremely negative** Lost, Distracting, Time consuming, Annoying, Frustrating	39	16%	

Figure 21. Qualitative Analysis of Students' Descriptions of the Platforms

Field notes. In the first week of the study, teachers brought their classes to the computer lab once for the students' initial training and students spent about 1 hour in the program during these sessions. In the second week, some teachers used the laptop cart in their regular classes and some of the students continued working on their assignments. Fields notes were generated based on researcher's observations in the computer lab and classroom. According to the field notes, the most common issues throughout the study were: (a) Many students skipped modules before finishing them completely, (b) Most students struggled in the modules teaching "*The domain and range of quadratic* *functions*", (c) Many "*repeated recommendations*" observed and they caused frustration, (d) Computer labs were not easy to reserve for additional lab sessions.

Student and teacher interviews. To be able to take students' responses to the survey questions one step further and get the story behind their experiences, seven voluntary students from the adaptive group were interviewed after the study. Students' comments supported the qualitative findings from the surveys. Moreover, four of the six participating teachers were interviewed to hear directly from them about how their students reacted to the programs. Three main trends were captured from the interviews:

(a) Content was hard. The following quote was from one of the students interviewed, who found the content difficult: "It was hard to say the least, it was really hard, but then again I'm not good at math, so it was hard for me. But I guess you know everyone else's opinion it would be easier, but for me I just pretty hard."

(b) Progress bar was discouraging. The following quote was from one of the students interviewed, who found the progress bar discouraging: "The progress bar was helpful but it was also very stressful in a sense, because, when I finally finished one page, then all of a sudden it just moved a small amount. That made me realize how vast it was and I just told myself that this was going to take forever. Because it took me thirty minutes to complete one thing, and then it just made a small amount of progress; I thought that it was just going to take a huge chunk of my time, and I just didn't bother with it." The following quote was from another student interviewed, who also found the progress bar discouraging: "In my opinion, it was kind of annoying, because like I wouldn't progress, it seemed like it would just stay there and I have so much more to do

and that made me just focus on that instead of just being focused on the work. So, yes, I felt it was kind of annoying."

(c) Repeated recommendations were frustrating. The following quote was from a teacher interviewed, who thought the repeated recommendations could cause students eventually stop studying: "They will shut down if they are not reaching their goal and moving on. They would maybe do it a second time, but if they don't get it the second time, I think they would shut down and be done."

The homework assignment challenge. All teachers had a common comment that their students did not do homework at home. The following quote was from one of the teachers interviewed: "My students don't do anything at home, even homework does not get done at home; it gets done at school if it's going to get done."

Students' not doing homework at home caused the average time students spent on the program stay very low as shown in Table 20.

Table 20

Amount of Time Students Spent in the Program

	Mean	*SD*	*N*	*Min*	*Max*
Amount of Time Students Spent in the Program	00:50:45	00:34:53	188	00:10:42	3:55:40

Chapter 4

DISCUSSION AND CONCLUSION

Even though the initial number of participants was not low for the study, qualitative data show that the most substantial drawback of the study was the low usage of the platforms. The content for the study had originally been prepared for the entire quadratics unit that consisted of three sections: (a) Introduction to quadratics, (b) Solving quadratic equations, and (c) Graphing quadratic functions; and it usually takes about a month to teach the entire unit in a typical 9^{th}-grade Algebra class. However, three of the four teachers and the majority of the students were not very enthusiastic about using the platforms after the first assignment. This low usage prevented students from being exposed to the platforms long enough to foster a potential difference between the groups. Field notes from observations, teachers' and students' comments in the one-on-one interviews, and students' responses to open-ended qualitative instruments pointed to five major reasons for low usage and attrition, which prevented the efficacy of use of the platforms. First, unmotivated and tired teachers and students were not very enthusiastic about the study because it was near the end of school year. Second, computer access was a challenging issue at the school. Third, the majority of the students found the content boring or difficult. Fourth, repeated recommendations built into the feedback system in the programs created frustration. Fifth, a barely moving progress bar caused disappointment.

Unmotivated teachers and students. Quadratics was the next to last chapter in the pilot school's algebra curriculum. At the time the quadratics chapter started to be covered at the school, all state exams had been completed and both the students and teachers were already in the “mood” for the end of the school year. All teachers had a common comment that their students did not do homework at home. This study was an extra homework assignment for the students, but very few students (less than 5%) continued working on their assignments at home (71% of the students stated that they had access to a laptop and Internet connection at home). Teachers gave extra homework credit to the students for working on their assignments however, it did not help much. In the first week, all teachers took their students to the school computer lab once; but in the following weeks, students were supposed to work on their assignment after class (either at home or at the school computer lab). The school computer lab was allocated for this study for one hour every day after school however, no students came to any of these sessions. Seventy students who spent the most amount of active time in the program were promised a $10 gift card incentive, however, that did not help much either.

In the future, conducting the experiment at a school which covers the topic earlier in the school year, or, which can benefit from the study for their upcoming exams could increase students’ interest and engagement and decrease the attrition rate.

Challenge to access to computers. The school had a computer lab with 40 desktop computers available. Nevertheless, it was a very large high school with 3700 students and the lab was always allocated for different classes. All teachers were able to take their students to the computer lab once in the first week; but they could not find opportunities in the following weeks although some of them wanted to take their students. To be used in the study, the school was provided with a laptop cart with 12 computers, but only one teacher was able to utilize them in her class because of the split plans of the math classrooms.

In the future, conducting the study not only as a homework assignment but also as part of the regular classes and allocating the computer lab upfront for the entire study could increase students' participation.

Difficult and not engaging content. The majority of the students found the content boring or difficult. In all, 28 multimedia interactive modules, 77 multimedia animations, 17 text-based modules and 557 multiple-choice assessment items had been prepared for this study. Among them, some modules have been found to be boring or difficult by the majority of the students.

In the future, detecting the un-engaging and most difficult content modules with a pre-pilot and replacing them with more targeted modules might increase students' engagement and participation.

Repeated recommendations. In the adaptive condition, the platform captures students' actions and behavior and recommends the next module to work on by consolidating these actions and adjusting it towards the goal. A goal has three components: 1. Target content area, 2. Target score, 3. Due date.

According to the field notes from the experiment, many students tended to skip modules before finishing them completely. Student and teacher interviews, and the open ended survey showed that many students found the content un-engaging and boring. This seems to be the main reason for the students to skip modules. The assumption before the experiment was that the percentage of the students skipping modules would not be very high however, it turned out to be quite high in reality. This behavior prevented the platform from generating meaningful completion data on certain modules. As a result, the recommendation engine of the program assumed that the student did not study those modules and recommended the same ones later on.

Another reason for the repeated recommendations was the high target score. The platform calculates an assignment score as the student progresses on the assignment and it does not consider the assignment done unless the student's score reaches or exceeds the target score. If a low-proficient, or medium-proficient student has studied all instructional modules without skipping any but, could not reach the target score, then the recommendation engine brings in modules from the topics already studied one more time to be able to give the student another chance to perform better and eventually reach the target score.

These repeated recommendations created frustration for students. In the future, finding a way to send fractional completion data to the recommendation engine when a student skips a module; and instead of setting a single high target score for all students, setting multiple target scores (for instance 50 for a bronze target, 70 for a silver target and 85 for a gold target) and letting some students complete the assignment with a bronze target could decrease the amount of repeated recommendations and consequently the frustration.

Barely moving progress bar. The progress bar developed for the adaptive platform was using a formula that incorporated the number of modules the student had seen so far in the assignment and the predicted number of modules the student needed to complete to reach the goal. But this formula was taking only the assessment modules into consideration, not the instructional modules. Additionally, the calculation was not very accurate until the student spent quite some time in the program and the system collected enough data about the student. A sample progress bar can be seen in Figure 22.

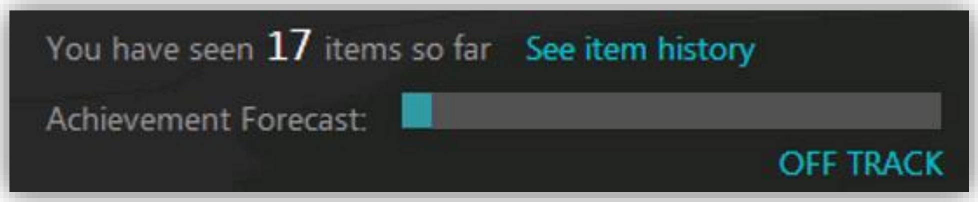


Figure 22. Sample Adaptive Assignment Progress Bar

When the progress bar did not advance due to the reasons explained above as much as the students expected it to move, it discouraged the students and caused further disappointment. Qualitative findings detailed in the Results section as well as the students' responses to item #8 in the adaptive experience survey presented in Figure 23 supported this negative perception.

8. How helpful was the "Achievement Forecast progress bar" in terms of showing your progress and work remaining?

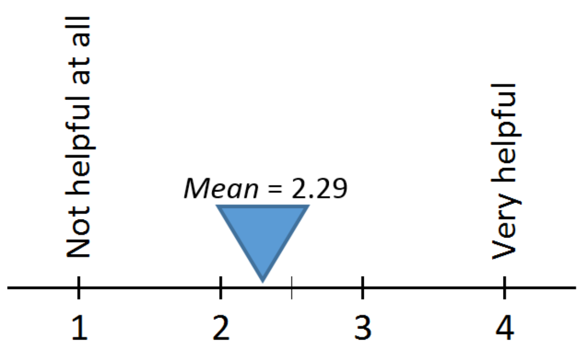


Figure 23. Mean Score for Adaptive Experience Survey Item #8

In the future, developing a better progress bar algorithm that takes into account all modules the student has studied so far and not displaying the progress until the confidence level of the system about the student's progress is quite narrow could encourage students towards the goal and decrease the amount of disappointment.

Limitations

Participant population and subject area. The study was limited to only one public high school in Arizona, only one grade level and only one subject area for practical reasons. Although the demographic makeup of the participants represents the entire population pretty well, different grade levels can react differently to the adaptive personalized solution presented. The quadratics content used in the study was a very well structured subject area with strong prerequisite and post-requisite relations between concepts in a granular level. This relation would be different in a biology or a language arts, or a social sciences course and it will strongly affect the nature of the adaptivity.

Usage scenario. In this study, use of the adaptive personalized platform was limited to after-class use. Using it as part of the teacher's lecture in the classroom, or as an alternative teaching platform completely replacing the teacher could yield different findings and would give educational researchers other valuable information in the area.

Supported platforms. Both platforms were browser-based and did not require installation of any software. Also, the access was available across different desktop operating system platforms (Windows, MacOS and Linux). Even though both the adaptive platform and the content modules have been developed using the HTML5 technology, since this is only the prototype of an R&D project, it was not yet running on any mobile platforms, or any browsers other than Chrome. Extending the capabilities of the platform in a way that it will run on any desktop browser and any mobile device would have a positive influence on the usage.

Suggestions for Future Research

This study aimed to present promising results to motivate students, teachers and school administrators to use an adaptive personalized platform as well as encourage publishers to develop more products of this type. However, the findings were not very promising in that sense. Conducting a similar study after eliminating some of the limitations discussed here and developing an improved adaptive personalization platform by taking the following suggestions into consideration could still achieve the initial goal of this research study.

In the future:

(a) conduct the experiment at a school which covers the topic earlier in the school year, or, which can benefit from the study for their upcoming exams to increase students' interest, engagement and participation, and decrease the attrition rate.

(b) conduct the study not only as a homework assignment but, also as part of the regular classes and allocating the computer lab upfront for the entire study to increase students' participation.

(c) detect the un-engaging and most difficult content modules with a pre-pilot and replace them with more targeted modules to increase students' engagement and participation.

(d) instead of setting a single high target score for all students, set multiple target scores (for instance 50 for a bronze target, 70 for a silver target and 85 for a gold target) and let some students complete the assignment with a bronze target to decrease the amount of repeated recommendations and consequently the frustration.

(e) develop a better progress bar algorithm that takes into account all modules the student has studied so far and not displaying the progress until the confidence level of the system about the student's progress is quite narrow could encourage students towards the goal and decrease the amount of disappointment.

Implications for the PLP Developers

The findings of this study not only make suggestions to the researchers about how to conduct a similar research study, but they also give specific recommendations to the PLP developers about what to be careful with when developing a new PLP platform.

Main recommendations are:

(a) make the content as engaging as possible to prevent students from skipping modules and consequently to capture meaningful usage data.

(b) find a way to send fractional completion data to the recommendation engine when a student skips a module; and set multiple target scores to decrease the amount of repeated recommendations and consequently the frustration.

(c) develop a well-functioning progress bar that takes into account everything the student has done and do not display the progress until the confidence level of the system about the student's progress is quite narrow.

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APPENDIX A

DEMOGRAPHIC SURVEY

About You

Please answer the following questions.

1. How old are you? ____________________

2. What is your grade level at school? ____________________

3. What math course or courses are you taking this semester? ____________________

4. Are you comfortable with using a laptop computer?

A) Yes **B)** No

5. Do you have access to a laptop computer and Internet at home?

A) Yes, both laptop and Internet. **B)** Yes to a laptop, no to Internet.

C) No to a laptop, yes to Internet **D)** I don't have access to either at home

6. What is your gender?

A) Male **B)** Female **C)** I do not wish to provide this information

7. Is English your primary language?

A) Yes **B)** No

8. How do you describe yourself? (please check the one option that best describes you)

- ○ White / Caucasian
- ○ Hispanic or Latino
- ○ Black or African American
- ○ Native American or American Indian
- ○ Asian / Pacific Islander
- ○ Other
- ○ I do not wish to provide this information

9. How helpful are your family members with your math homeworks?

Very helpful ① ② ③ ④ Not helpful at all

APPENDIX B

PRE-TEST

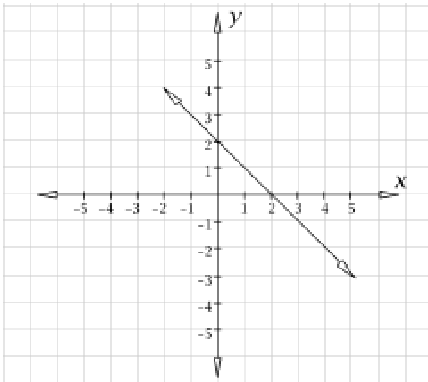
1. What is the simplified form of the following algebraic expression?

$-8x + 5y + 11x - 4y$

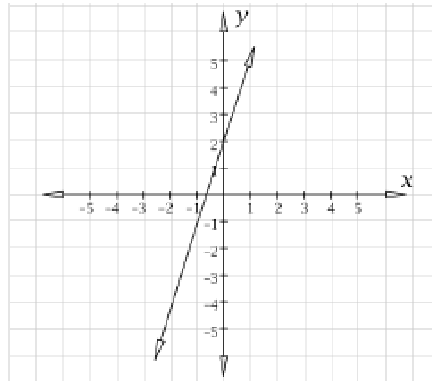
A) $18x + 9y$ **B)** $-3x + 7y$ **C)** $13x + 15y$ **D)** $3x + y$

2. Which of the following is the graph of the linear equation $y = -3x + 2$?

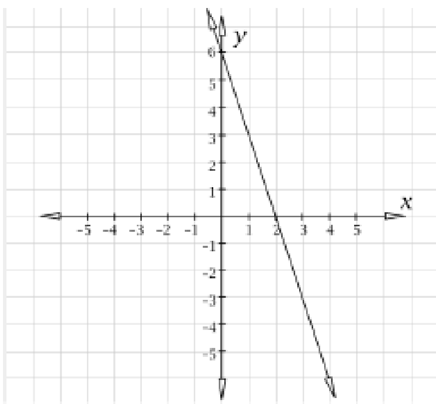
A)



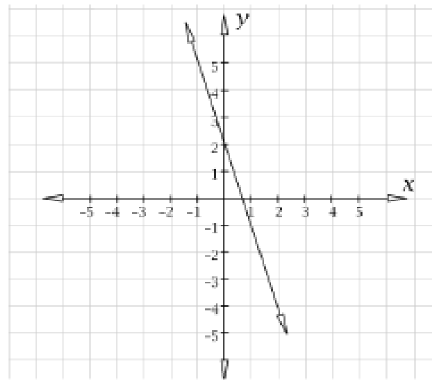
B)



C)



D)



3. Translate the following problem into a one-step equation.

Andrea is 175 centimeters tall. If she is 12 centimeters taller than Maria, then how tall is Maria? (Let Maria be m centimeters tall.)

A) $m + 12 = 175$ **B)** $12 = m + 175$

C) $m = 12 + 175$ **D)** $m = 12$

4. If $2n - 6 = 10$, then $n = ?$

A) 2 **B)** 4
C) 8 **D)** 16

5. Solve the following equation for x.

$3x + 7 = 5x - 2$

A) $\frac{9}{2}$ **B)** $\frac{-9}{2}$
C) $\frac{-5}{2}$ **D)** $\frac{5}{2}$

6. What is the solution of this absolute value equation: $|2x - 5| = 3$?

A) $x = 4$ and $x = 1$
B) $x = 4$
C) $x = 1$
D) The solution set is empty.

7. Solve the following system of equations:

$x - 4y = 3$
$3x + 2y = 9$

A) $x = 3$ and $y = 0$
B) $x = 5$ and $y = -3$
C) $x = 7$ and $y = 9$
D) $x = 11$ and $y = 1$

8. Factor the following expression.

$4x^3 + 4x^2 + 8x$

A) $x(4x^2 + 4x + 8)$ **B)** $4x(x^2 + x + 2)$
C) $4(x^3 + x^2 + 2x)$ **D)** $4x(x^3 + x^2 + 2x)$

9. Factor the following expression.

$9x^2 - 25$

A) $(3x + 1)(3x - 25)$
B) $(9x + 5)(x - 5)$
C) $(3x + 5)(3x + 5)$
D) $(3x + 5)(3x - 5)$

10. Factor the following expression.

$t^2 - 11t + 30$

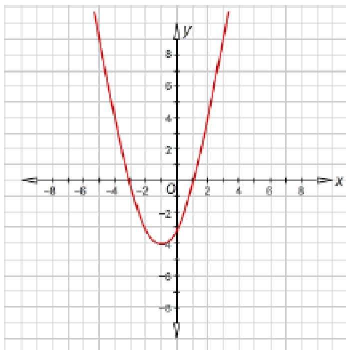
A) $(t - 5)(t - 6)$
B) $(t + 5)(t + 6)$
C) $(t + 5)(t - 6)$
D) $(t - 5)(t + 6)$

11. Complete the given table for $y = -2x^2 - 4x + 6$ and then determine the correct graph of it.

x	y
−3	0
−1	8
0	
1	0

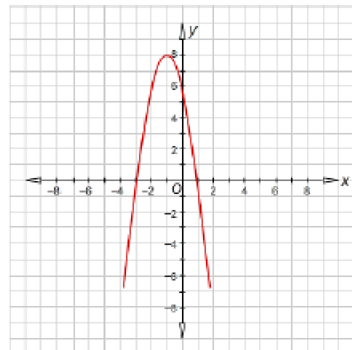
A)

x	y
−3	0
−1	8
0	−3
1	0



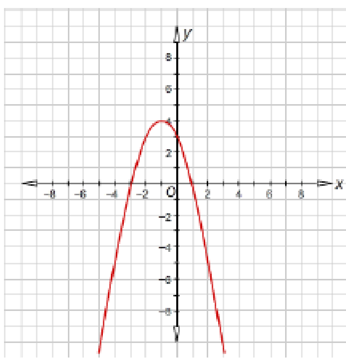
B)

x	y
−3	0
−1	8
0	6
1	0



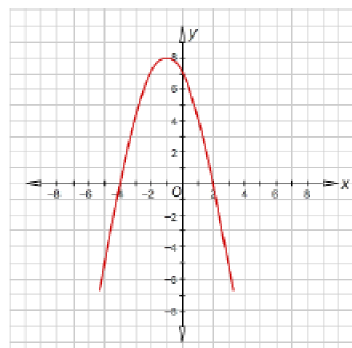
C)

x	y
−3	0
−1	8
0	3
1	0

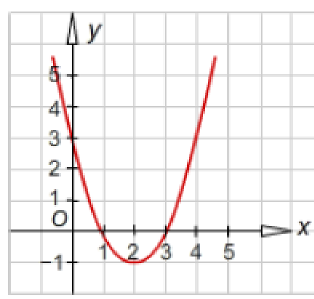


D)

x	y
−3	0
−1	8
0	3
1	0



12. The graph of the function $y = x^2 - 4x + 3$ is given. What is the range of this function when $0 \le x \le 4$?



A) $-1 \le y \le 5$

B) $-1 \le y \le 3$

C) $0 \le y \le 3$

D) $1 \le y \le 3$

APPENDIX C

POST-TEST

1. Which of the following set of data shows a quadratic function?

A)

x	y
-1	3
0	5
1	7
2	9

B)

x	y
-1	-5
0	-4
1	0
2	7

C)

x	y
-1	-4
0	-6
1	-8
2	-10

D)

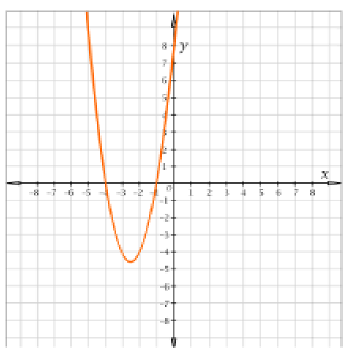
x	y
-1	1
0	-2
1	-5
2	-8

2. Complete the given table for $y = -2x^2 - 10x - 8$ and then determine the correct graph of it.

x	y
0	
-1	0
-2	4
-3	4
-4	0

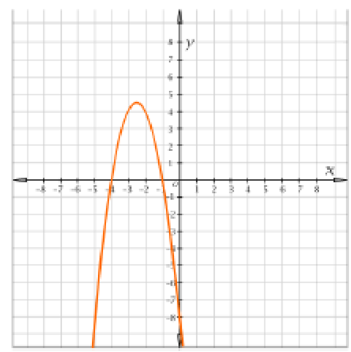
A)

x	y
0	8
-1	0
-2	4
-3	4
-4	0



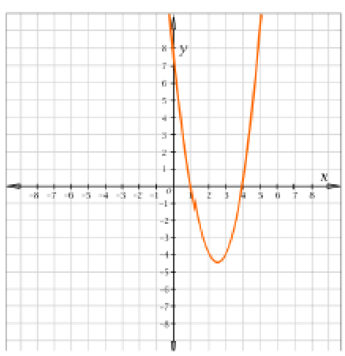
B)

x	y
0	-8
-1	0
-2	4
-3	4
-4	0



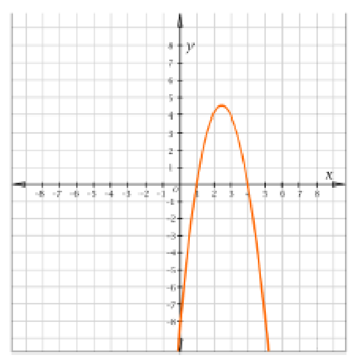
C)

x	y
0	8
-1	0
-2	4
-3	4
-4	0



D)

x	y
0	-8
-1	0
-2	4
-3	4
-4	0



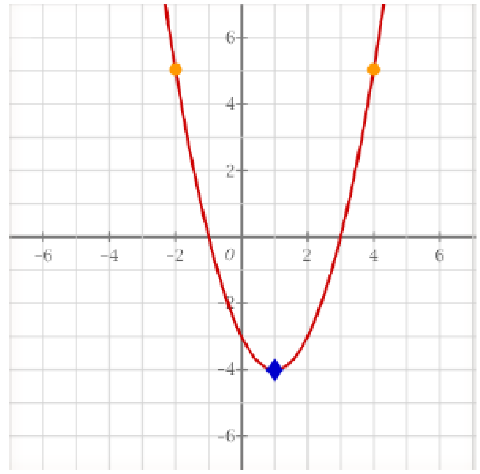
3. The graph of the function $y = x^2 - 2x - 3$ is given. What is the range of this function when $2 \leq x \leq 4$?

A) $-3 \leq y \leq 5$

B) $-4 \leq y \leq 5$

C) $-3 \leq y$

D) $-4 \leq y$



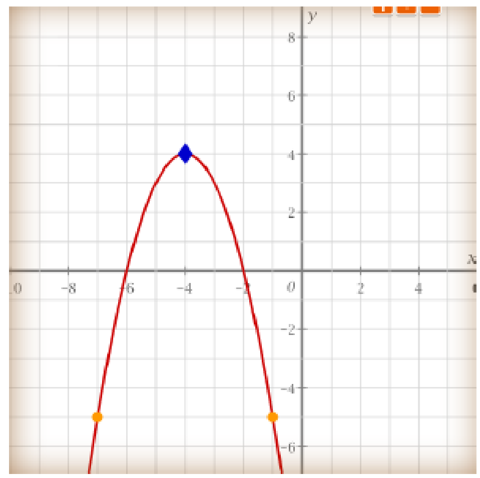
4. The graph of the function $y = -x^2 - 8x - 12$ is given. What is the range of this function when $-7 < x < -2$?

A) $-5 < y < 0$

B) $-5 < y \leq 4$

C) $-5 < y < 4$

D) $-5 \leq y < 4$



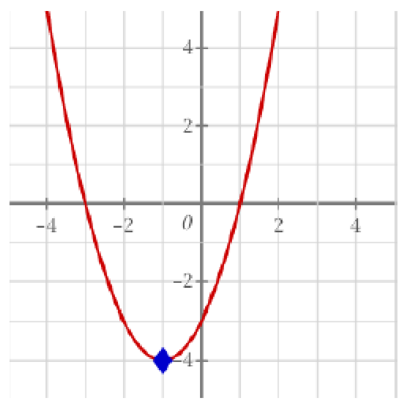
5. What are the x-intercepts of the function with the graph given?

A) (-3, 0) and (1, 0)

B) (0, -3)

C) (-1, -4)

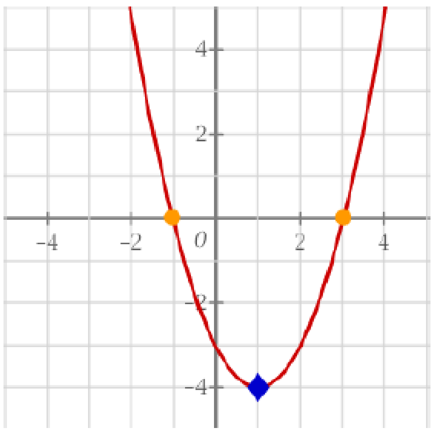
D) $x = -1$



6. Which of the following shows a quadratic relationship?

A) $y = 3x^2 + 2x - 3x^2$
B) $y = 3x - 7$
C) $y = x^2 - 9$
D) $y = 5^2$

7. What is the axis of symmetry of $f(x)$ shown below?



A) x-axis **B)** y-axis
C) $y = 1$ **D)** $x = 1$

8. Which of the following is a quadratic equation in one variable?

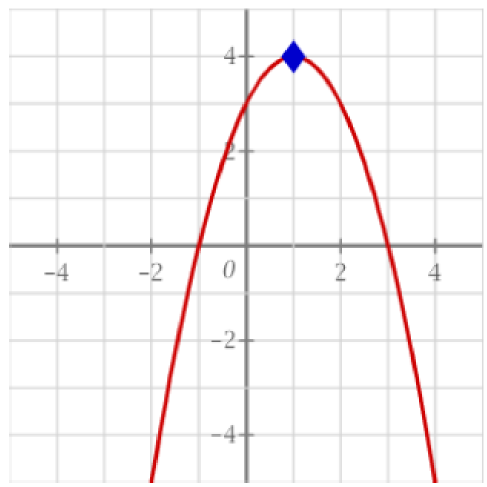
A) $x^2 - y^2 = 9$ **B)** $\frac{3}{x^2} + 2x - 1 = 0$
C) $2x - 9 = 3$ **D)** $3x^2 + 5 = 8x$

9. Write the following quadratic equation in standard form:

$-3(x - 1)^2 = -5$

A) $-3x^2 + 6x + 2 = 0$
B) $3x^2 = 6x + 2$
C) $-3x^2 - 6x + 2 = 0$
D) $-3x^2 + 6x - 8 = 0$

10. What is the y-intercept of $f(x)$ shown below?



A) (-1, 0) and (3, 0) **B)** (0, 3)
C) (1, 4) **D)** $y = 1$

APPENDIX D

MATH INTRINSIC MOTIVATION SURVEY

Using the scale below, please circle the appropriate response under each item.

1. I like mathematics.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

2. I look forward to mathematics lessons.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

3. I wish I did not have to take mathematics lessons.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

4. I hate mathematics.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

5. Mathematics lessons are boring.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

6. I wish we had more mathematics lessons in school.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

7. Working with mathematics is fun.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

8. In high school, I want to get on a track that has as little mathematics as possible.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

9. In my future education, I would like not to have to do mathematics.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

10. I don't mind a lot of mathematics in my further education.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

11. A further education with a lot of mathematics does not appeal to me.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

12. I would like an occupation where I can use mathematics.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

13. In the future, I would like to learn more mathematics.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

14. I want to avoid all mathematics in high school and college.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

15. I want a job where I do not have to do mathematics.

○ False ○ Mostly False ○ Sometimes False ○ Sometimes True ○ Mostly True ○ True

APPENDIX E

OVERALL EXPERIENCE SURVEY

Questions about the Program (for both groups)

Based on your experience with the program, please indicate to what extent you agree or disagree with each of the following statement.

1. I would like to use this program during class.

Strongly agree ① ② ③ ④ Strongly disagree

2. I would like to be assigned this program for homework.

Strongly agree ① ② ③ ④ Strongly disagree

3. Using this program is a good use of my study time.

Strongly agree ① ② ③ ④ Strongly disagree

4. This program gave me practice in topics I needed extra help with.

Strongly agree ① ② ③ ④ Strongly disagree

5. I would recommend this program to a friend.

Strongly agree ① ② ③ ④ Strongly disagree

6. This program flows logically from one video to the next.

Strongly agree ① ② ③ ④ Strongly disagree

7. This program is personalized to my needs. [*for the adaptive group only*]

Strongly agree ① ② ③ ④ Strongly disagree

APPENDIX F

CONTENT EXPERIENCE SURVEY

Questions about the Content Material (for both groups)

Based on your experience with the assignments you completed, please answer the following questions.

1. How engaging was the content you received?

Very engaging ① ② ③ ④ Very boring

2. How helpful were the interactive modules in teaching the concepts?

Very helpful ① ② ③ ④ Not helpful at all

3. Did you enjoy studying math with this program (compared to other math programs)?

Not at all ① ② ③ ④ Very much

4. How often did you need to refer to the "How to Complete" information in order to complete an interactive module? [*for the adaptive group only*]

Very often ① ② ③ ④ Never

APPENDIX G

ADAPTIVE EXPERIENCE SURVEY

Questions about Your Overall Personalized Experience (for the adaptive group only)

Based on your experience with the assignments you completed, please answer the following questions.

1. Did the order in which the materials were given to you make sense?

Not at all ① ② ③ ④ Just right

2. Did the program do a good job of recommending materials so that you had a chance to cover the topics you struggled with?

Did a very good job ① ② ③ ④ Did poorly

3. Did the program do a good job of recommending materials so that you didn't spend too much time on the topics you did well on?

Did a very good job ① ② ③ ④ Did poorly

4. Did the recommended items seem to be at an appropriate level of difficulty for you?

Way too easy or way too hard ① ② ③ ④ Just right

5. Did the recommended items relate well to the goals of the assignment? Or, did you have to study some unnecessary concepts?

Very well related ① ② ③ ④ Too much unnecessary content

6. How would you rate the overall quality of the order of materials you received in your assignments?

Poor ① ② ③ ④ Great

7. Did you feel like the recommended items too scattered?

Very scattered ① ② ③ ④ Well organized

8. How helpful was the "Achievement Forecast progress bar" in terms of showing your progress and work remaining?

Very helpful ① ② ③ ④ Not helpful at all

APPENDIX H

OVERALL EXPERIENCE SURVEY WITH OPEN-ENDED QUESTIONS FOR STUDENTS

Overall experience survey with open-ended questions for students

1. What did you like best about the program? Please explain.

2. How do you think the system can be improved? Can you please name at least one useful feature to add?

3. What would you change about the program?

4. Using three words, describe your experience with the program.

5. How was your material personalized to you? [*for the adaptive group only*]

APPENDIX I

INTERVIEW GUIDELINE FOR STUDENTS

Interview Guideline - Students

Roughly spend 3 minutes for each of the talking points below.

Talking Points

1. Ask about their overall feelings about the program
- Why do you like it?
- Why do you not like it?
- Is it different from or similar to anything you used in the past?
- Etc.

2. Ask questions based on system logs and observations
- I noticed you spent too much time on this assignment, why?
- I noticed you wanted to skip a lot of sections on this assignment, why?
- Etc.

3. Ask about the adaptivity features
- How was your overall personalized experience? Did you feel like the system gave you accurate content? Why? How?
- Did you feel the program was smart?
- Did you get a lot of repetitive content? If so, why do you think it was?
- What did you think about your Expected Score and Mastery Level on the assignment overview page? Did you care them at all? How did they affect your study?
- How helpful was the "Achievement Forecast progress bar" in terms of showing your progress and work remaining?

4. Ask about the content materials
- Did you skip any content? What was the main reason?
- Did you see the "How to Complete" descriptions in the interactive sections? Did you read/use them at all? Why?
- How did you like studying with an interactive program that gives you feedback?
- How did you like animations with voice and illustrations?
- How did you like the voices of the narrators in the materials? Which one did you like the most/least?

5. Ask about platform and navigation
- Did you like the design of the platform in general? What about the colors, text styles, etc?
- Any particular sections difficult to use?
- Any suggestions to improve?

APPENDIX J

INTERVIEW GUIDELINE FOR TEACHERS

Interview Guideline - Teachers

Roughly spend 5 minutes for each of the talking points below.

Talking Points

1. Ask about the teacher's overall feelings about the program.
- Would your students like it? Why or why not?
- How do you like it?
- Is it different from or similar to anything you have used in the past?
- Would you use it?
- How do you think your students would benefit from this program?
- Etc.

2. Ask about the adaptivity features of the program.
- How helpful was the "Assignment Overview page" in terms of summarizing your students' progress on the assignment and their mastery level?
- How useful was the "Course Map" in terms of seeing your students' strong and weak areas?
- How informative were the trendline graphics in terms of evaluating your students' improvement in time?
- How accurate do you think the mastery level calculations of the program?

3. Ask about the assignment creation tool.
- Was it easy to use or confusing?
- Does it have enough detail?
- Any suggestions to improve it?

4. Ask about platform and navigation.
- Did you like the design of the platform in general? What about the colors, text styles, etc.?
- Were any particular sections difficult to use?
- Any suggestions to improve it?

APPENDIX K

ASU IRB APPROVAL LETTER

EXEMPTION GRANTED

Gary Bitter
Division of Educational Leadership and Innovation - Tempe
480/965-4960
bitter@asu.edu

Dear Gary Bitter:

On 4/16/2015 the ASU IRB reviewed the following protocol:

Type of Review:	Initial Study
Title:	study 1) Effect of Personalized Learning Paths on Learning Algebra study 2) The Role of an Adaptive System in Remediation and Knowledge Gains in Algebra: A Study of Personalized Learning as a First-Order Concern
Investigator:	Gary Bitter
IRB ID:	STUDY00002510
Funding:	
Grant Title:	
Grant ID:	
Documents Reviewed:	• Professor to Principal IN LOCO PARENTIS, Category: Consent Form; • Recruitment letter to high school students, Category: Recruitment Materials; • Caroline Savio-Ramos CITY Training, Category: Non-ASU human subjects training (if taken within last 3 years to grandfather in); • Personalized Learning study - Funding Proposal.pdf, Category: Grant application; • Alpay Bicer dissertation proposal, Category: Other (to reflect anything not captured above); • Alpay Bicer CITI Training completion, Category: Non-ASU human subjects training (if taken within last 3 years to grandfather in); • Teacher Recruitment-Consent, Category: Consent Form; • Letter of support from the High School, Category: Consent Form; • Student to Principal IN LOCO PARENTIS, Category: Consent Form; • HRP-503a-PROTOCOL_SocialBehavioral_STUDY.docx, Category: IRB Protocol; • Caroline Savio-Ramos dissertation proposal, Category: Other (to reflect anything not captured above);

The IRB determined that the protocol is considered exempt pursuant to Federal Regulations 45CFR46 (1) Educational settings on 4/16/2015.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

Sincerely,

IRB Administrator

cc: Caroline Savio-Ramos
Alpay Bicer

APPENDIX L

RECRUITMENT LETTER FOR STUDENTS

Recruitment Letter for students (Child assent form)

Dear Students:

We are doctoral students conducting dissertation research on the topic of the Effect of Personalized Learning Paths on Learning Algebra under the direction of Dr. Gary Bitter, Professor of Educational Technology in the Division of Educational Leadership and Innovation at Arizona State University. This research will study the use of an online, adaptive, personalized platform with interactive multimedia content for training Algebra I students by exploring whether or not the system does a satisfactory job in providing teachers with quality student data in real time based on student performance using the adaptive personalized platform. The study also aims at analyzing the ease of using this data to inform instruction measure, aligning curriculum content to existing curriculum, and measuring teacher satisfaction in terms of knowledge and understanding gained by students using the adaptive personalized platform.

We are inviting you to participate in our research study, which will involve participating in and completing revised homework assignments in Algebra I that includes an online, adaptive, personalized platform with interactive multimedia content.

One of your homework assignments would follow with a 15-minute short discussion with the researcher. The discussion will be about how you would describe the adaptive experience you have just had and what you like and do not like about the platform you have just used. The discussion will be recorded with an audio recording device for future analyses.

We would like to audio record this interview. The interview will not be recorded without your permission. Please let me know if you do not want the interview to be recorded; you also can change your mind after the interview starts, just let us know.

Your participation in this study is voluntary. If you choose not to participate or to withdraw from the study at any time, there will be no penalty. You will be able to complete the regular class requirements and receive a grade but your data will be removed from the study.

For full participation in our study, we are providing 100 students, randomly drawn in the form of a lottery, with an incentive of a $10 gift card at the conclusion of the study.

There are no foreseeable risks or discomforts to your participation. We will be collecting your work during the sessions. However, all of your work will be signed only with an anonymous study ID and therefore kept confidential. All of the work collected will be kept in a locked cabinet or on a password-protected computer and will be destroyed after the end of the study. The results of this study may be used in reports, presentations, or publications but your names will not be used

If you have any questions concerning the research study, please contact the research team at: Dr. Gary Bitter (bitter@asu.edu), Alpay Bicer (abicer@asu.edu), Caroline Savio-Ramos (casavio@asu.edu). If you have any questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at (480) 965-6788.

Sincerely,
Alpay Bicer, Doctoral student
Caroline Savio-Ramos, Doctoral student

(continued on the next page)

By signing below, you are giving consent to be interviewed, recorded, and participate in the above study.

______________________________	______________________________	________
Printed Name	Signature	Date

If you have any questions about student rights as a participant in this research, or if you feel students have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the Office of Research Integrity and Assurance, at (480) 965-6788

APPENDIX M

PARENT CONSENT/PERMISSION FORM

Parent Consent/Parent Permission Form

April 21, 2015

Dear Parents of Students:

We are graduate students under the direction of Professor Gary Bitter in the Division of Educational Leadership & Innovation at Arizona State University. We are conducting a research study to measure the effect of personalized learning paths on learning Algebra. The purpose of this form is to provide you with information that will help you decide if you will give consent for your child to opt out of participating in this research.

I am inviting you and your child's participation in this study, which will involve up to 3 hours a week of using our computer software to supplement your child's math courses. You and your child's participation in this study are voluntary. You and your child may decline participation at any time. You may also withdraw yourself or your child from the study at any time; there will be no penalty and will not adversely affect your child's grade. Likewise, if your child chooses not to participate or to withdraw from the study at any time, there will be no penalty.

During the study, we would also like to have a 10-minute short interview with your child. This interview will be about how your child would describe the adaptive experience they have just had and what they like and do not like about the platform they have just used. We would like to audio record this interview. The interview will not be recorded without your permission. Please let us know if you do not want to allow your child to be interviewed and / or audio recorded; you also can change your mind after the interview starts, just let us know.

For full participation in our study, we are providing 100 students, randomly drawn in the form of a lottery, with an incentive of a $10 gift card at the conclusion of the study if they have completed the assignments.

There are no foreseeable risks or discomforts to your participation. We will be collecting your child's work during the sessions. However, all of the work will be signed only with an anonymous study ID and therefore kept confidential. All of the work collected will be kept in a locked cabinet or on a password-protected computer and will be destroyed after the end of the study. The results of this study may be used in reports, presentations, or publications but your child's names will not be used

If you have any questions concerning the research study, please contact the research team at: Dr. Gary Bitter (bitter@asu.edu), Alpay Bicer (abicer@asu.edu), Caroline Savio-Ramos (casavio@asu.edu). If you have any questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at (480) 965-6788.

Sincerely,

Alpay Bicer and
Caroline Savio-Ramos
ASU Doctoral Students

A signature is only necessary if you would like your child *excluded* from this study.

By signing below, you are giving consent for you and your child ____________________ (Child's name) to:

1) Opt out of participating in the study in the above study.

____________________	____________________	____________________
Signature	Printed Name	Date

2) Opt out of being interviewed and audio recorded as part of the above study.

____________________	____________________	____________________
Signature	Printed Name	Date

If you have any questions about you or your child's rights as a subject/participant in this research, or if you feel you or your child have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the Office of Research Integrity and Assurance, at (480) 965-6788.

APPENDIX N

RECRUITMENT LETTER FOR TEACHERS

Recruitment Letter for teachers

Dear Teachers:

We are doctoral students conducting dissertation research on the topic of the Effect of Personalized Learning Paths on Learning Algebra under the direction of Dr. Gary Bitter, Professor of Educational Technology in the Division of Educational Leadership and Innovation at Arizona State University. This research will study the use of an online, adaptive, personalized platform with interactive multimedia content for training Algebra I students by exploring whether or not the system does a satisfactory job in providing teachers with quality student data in real time based on student performance using the adaptive personalized platform. The study also aims at analyzing the ease of using this data to inform instruction measure, aligning curriculum content to existing curriculum, and measuring teacher satisfaction in terms of knowledge and understanding gained by students using the adaptive personalized platform.

We are inviting you and your students who are enrolled in your mathematics courses to participate in our research study, which will involve student participation in and completing revised homework assignments in Algebra I that includes an online, adaptive, personalized platform with interactive multimedia content.

Both you and your students will be provided incentives for participating. The Algebra teacher helping us in coordinating will be provided a $300 gift card. The other participating teachers will be provided $100 gift cards, each. One hundred student names will be drawn in a lottery to receive $10 gift cards. In addition, the school will have one full year free subscription to the material (worth $50,000). There are no foreseeable risks or discomforts to student or teacher participation.

For the participating teachers, we ask no more than 1 hour per week of your time. For students, a homework assignment would follow with a 15-minute short discussion with the researcher. The discussions will be about how participants would describe the adaptive experience they have just had and what they like and do not like about the platform they have just used. The discussions will be recorded with an audio recording device for future analyses.

Your participation in this study is voluntary. If you choose to not participate or to withdraw from the study at any time, there will be no penalty or adverse action.

In addition, student participation in this study is also voluntary. If a student chooses not to participate or to withdraw from the study at any time, there will be no penalty. He or she will be able to complete the regular class requirements and receive a grade but his or her data will be removed from the study.

There are no foreseeable risks or discomforts to student participation, nor to you. Your name and information will be kept confidential. In addition, we will be collecting student work during the sessions. However, all of their work will be signed only with an anonymous study ID and therefore kept confidential. All of the work collected will be kept in a locked cabinet or on a password-protected computer and will be destroyed after the end of the study. The results of this study may be used in reports, presentations, or publications but students' names will not be used.

If you have any questions concerning the research study or student participation in this study, please email Alpay Bicer at abicer@asu.edu or Caroline Savio-Ramos at casavio@asu.edu. If you have any questions about student rights as a participant in this research, or if you feel students have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the Office of Research Integrity and Assurance, at (480) 965-6788

Sincerely,
Alpay Bicer
Caroline Savio-Ramos
Doctoral students

APPENDIX O

IN LOCO PARENTIS LETTER OF PERMISSION FROM PROFESSOR TO PRINCIPAL

Effect of Personalized Learning Paths on Learning Quadratics in Algebra

IN LOCO PARENTIS LETTER OF PERMISSION

Dear Principal:

I am a professor of Educational Technology in the Division of Educational Leadership and Innovation at Arizona State University. I am conducting a research study to investigate how students learn algebra concepts using an online, adaptive, personalized platform with interactive multimedia content.

I am inviting students in your school to participate in my research study, which will involve completing four homework assignments each of which will last approximately two-three hours. In these homework assignments, students will receive instruction on a mathematics concept. They will be asked to complete some exercises on this new material and judge the quality of some solutions. Student participation in this study is voluntary. If a student chooses not to participate or to withdraw from the study at any time, there will be no penalty.

Students and teachers will be provided incentives for participating. There are no foreseeable risks or discomforts to student participation.

I will be collecting student work during the sessions. However, all of their work will be signed only with a pseudonym and therefore kept anonymous. All of the work collected will be kept in a locked cabinet or on a password-protected computer and will be destroyed one year after the end of the study. The results of this study may be used in reports, presentations, or publications but students' names will not be used.

If you have any questions concerning the research study or student participation in this study, please call me at (480) 965-4960 or email bitter@asu.edu .

Sincerely,

Dr. Gary Bitter

By signing below, as principal of ____________________, you are giving consent *in loco parentis* for ___________________________ students to participate in the above study.

________________________________ ________________________________

Printed Name Signature Date

If you have any questions about student rights as a participant in this research, or if you feel students have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the Office of Research Integrity and Assurance, at (480) 965-6788

APPENDIX P

IN LOCO PARENTIS LETTER OF PERMISSION FROM DOCTORAL CANDIDATES

TO PRINCIPAL

Effect of Personalized Learning Paths on Learning Quadratics in Algebra

In Loco Parentis Letter of Permission

Dear Principal:

We are doctoral students conducting dissertation research on the topic of the Effect of Personalized Learning Paths on Learning Quadratics in Algebra under the direction of Dr. Gary Bitter, Professor of Educational Technology in the Division of Educational Leadership and Innovation at Arizona State University. This research will study the use of an online, adaptive, personalized platform with interactive multimedia content for training Algebra I students by exploring whether or not the system does a satisfactory job in providing teachers with quality student data in real time based on student performance using the adaptive personalized platform. The study also aims at analyzing the ease of using this data to inform instruction measure, aligning curriculum content to existing curriculum and measuring teacher satisfaction in terms of knowledge and understanding gained by students using the adaptive personalized platform.

We are inviting students in your school who are enrolled in Algebra I to participate in our research study, which will involve participating in and completing revised homework assignments in Algebra I that includes an online, adaptive, personalized platform with interactive multimedia content.

Student participation in this study is voluntary. If a student chooses not to participate or to withdraw from the study at any time, there will be no penalty. He or she will be able to complete the regular class requirements and receive a grade but his or her data will be removed from the study.

There are no foreseeable risks or discomforts to student participation. We will be collecting student work during the sessions. However, all of their work will be signed only with an anonymous study ID and therefore kept anonymous. All of the work collected will be kept in a locked cabinet or on a password-protected computer and will be destroyed after the end of the study. The results of this study may be used in reports, presentations, or publications but students' names will not be used.

If you have any questions concerning the research study or student participation in this study, please email Alpay Bicer at abicer@asu.edu or Caroline Savio-Ramos at casavio@asu.edu .

Sincerely,

____________________________ ____________________________

Alpay Bicer, Doctoral student Caroline Savio-Ramos, Doctoral student

By signing below, as principal of [INSERT NAME OF HIGH SCHOOL] High School you are giving consent *in loco parentis* for [INSERT NAME OF HIGH SCHOOL] students currently enrolled in Algebra I classes to participate in the above study.

____________________________ ____________________________

Printed Name Signature Date

If you have any questions about student rights as a participant in this research, or if you feel students have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the Office of Research Integrity and Assurance, at (480) 965-6788.