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Supporting Algebraic Reasoning through Personalized Story Scenarios: How Situational Understanding Mediates Performance

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Abstract

Context personalization refers to matching instruction to students' out-of-school interests and experiences. Belief in the benefits of matching instruction to interests is widely-held in the culture of schooling, however little research has empirically examined how interest impacts performance and learning in secondary mathematics. Here we investigate these issues with a series of problem-solving sessions where 24 Algebra I students were presented with story problems on linear functions, some of which were personalized to their interests. Our analyses focus on performance, strategy use, and mistake patterns. Results suggest that personalization supported situational reasoning (Nathan, Kintsch, & Young, 1992) about the actions and relationships in the scenario, improving performance for weaker students and on harder problems. However, personalized scenarios seemed to act as a distraction when stronger students in the sample worked easier problems. Thus context personalization may have the potential to provide assistance and support performance as students learn new concepts.

Supporting Algebraic Reasoning through Personalized Story Scenarios: How Situational Understanding Mediates Performance

One important aspect of recent reform movements in mathematics education has been the idea that placing content in "real world" contexts that are accessible to students' lives and experiences is an important focus for instruction. Such recommendations are seen in a variety of standards documents in the United States (Common Core State Standards Initiative, 2010; National Council of Teachers of Mathematics, 2000; 2006; 2009), and have been given emphasis in a number of different countries (Palm, 2009; Xin, 2009). The justifications given for placing mathematics in everyday contexts vary – for example, these problems may make mathematics more accessible to students, they may help bridge the gulf between "real world" problem solving and "school mathematics" problem solving, and they may draw upon students' interests to impact motivation (Boaler, 1994).

Research in mathematics education has shown that problems situated in everyday or "real world" contexts (i.e., contexts referencing specific people, places, and activities in the world) can provide students with access to mathematical ideas. Students may build *situation models* (Nathan, Kintsch & Young, 1992) to reason about these problems, which represent their situational understanding of the actions and relationships in the scenario. Students can leverage real-world knowledge when solving story problems (Baranes, Perry, & Stigler, 1989; Cognition and Technology Group at Vanderbilt, 1997), drawing on informal strategies (Carpenter, Fennema, & Franke, 1996; Carraher, Carraher, & Schliemann, 1987; Johanning, 2004; Koedinger & Nathan, 2004) that support problem solving. Students can use meaningful, real world situations in which mathematics is useful to build powerful models, bringing their own personal meaning to bear on testing and iterating their current mathematical understandings (Lesh, Cramer, Doerr, Post & Zawojewski, 2003; Lesh & Harel, 2003; Lesh & Zawojewski, 2007). Curricula that accentuate students investigating and modeling realistic or concrete situations have shown great promise in fostering student understanding (Gravemeijer & Doorman, 1999; Roschelle, Kaput, & Stroup, 2000; Carraher, Schliemann, Brizuela, & Earnest, 2006; Moses & Cobb, 2001).

However, research that includes using more traditional story problems as a bridge between school mathematics and mathematics in practice has shown problematic findings – everyday contexts may not always support problem-solving. Students' knowledge of the world can actually be at odds with the expectations of many school mathematics tasks (Boaler, 1994; Cooper & Dunne, 1998; Cooper & Harries, 2009; Inoue, 2005; Kazemi, 2002; Ladsen-Billings, 1995; Roth, 1996) and students may not engage in realistic sense-making when confronted with school tasks like word problems (Greer, 1997; Palm, 2008; Reusser & Stebler, 1997; Xin, 2009). Further, the ways in which mathematical ideas are placed in everyday contexts in school settings are not always well-matched to how they are used in practice (Lave & Wenger, 1991; Masingila, Davidenko, & Prus-Wisniowska, 1996; Saxe, 1988).

The idea that problems situated in everyday contexts may elicit *interest* in students, which can impact various motivational variables, has been less examined in mathematics education research and will be the focus of the study presented here. Interest has been defined as learners' predispositions to engage with particular topics, ideas, or activities (Hidi & Renninger, 2006). A considerable body of research has shown that presenting instruction in the context of learner's interests can be effective for learning, impacting persistence, attention, and engagement (e.g., Ainley, Hidi, & Berndorff, 2002; Flowerday, Schraw, & Stevens, 2004; Hidi, 1990). The idea that it is beneficial to make connections to students' interests is also a widely-held assumption in the culture of schooling. For example, Fives and Manning (2005) presented pre-service and practicing teachers with an imaginary scenario about a struggling student, asking them what strategies they would use to address the student's difficulties. The second most common approach mentioned by teachers was to connect instruction to the students' personal interests, and this was second only to contacting the student's parents. The notion of connecting instruction to interests can be traced back to Dewey (1916), who advocated for an educational system where learning takes place in the context of students' experiences:

> In the concrete, the value of recognizing the dynamic place of interest in an educative development is that it leads to considering individual children in their specific capabilities, needs,

> and preferences. One who recognizes the importance of interest will not assume that all minds work in the same way because they happen to have the same teacher and textbook. (p. 136)

Although there is a firmly established theoretical and empirical basis for the role of interest in promoting important educational outcomes, little work has specifically examined the role of interest in mathematics learning. One exception is a line of research examining the instructional principle of *context personalization*, or the idea that it is beneficial to provide instruction targeted to individual learners' out-of-school interests and experiences (e.g., Anand & Ross, 1987; Cordova & Lepper, 1996). For example, rather than being given a generic mathematics word problem about harvesting wheat from a field of grain, a student may receive a "personalized" variation of this problem based on their interests; perhaps a mathematical story scenario relating to playing a video game. This personalization could be accomplished during instruction or one-on-one sessions if the instructor is aware of students' interests (e.g., Renninger Ewen, & Lasher, 2002), or it could be implemented though adaptive technology-based instructional systems that collect and utilize data on student interests (e.g., Carnegie Learning, 2011). Similarly, instruction could be personalized to the more general set of interests that students of a certain age group typically hold (e.g., Lopez & Sullivan, 1992), or to the interests of an individual student (e.g., Renninger et al., 2002).

In summary, the benefits of eliciting interest during instruction seem to be widely-held by practitioners and curriculum developers with a long history in the discourse of educational philosophy. Recent research in education and the learning sciences further underlines the potential of interest for supporting student learning (e.g., Hidi & Renninger, 2006). However, little research has examined the impact of interest-based interventions on students' performance and learning in mathematics. It is also important to note that current studies examining the role of interest in mathematics learning have largely been conducted using only simple arithmetic problems. The assumption that an interest intervention like personalization can support learning in secondary mathematics where students must transition from concrete to abstract forms of mathematical reasoning remains largely untested by educational research.

In the study to be presented here, we focus on an interest-based personalization intervention targeted to high school Algebra I students. Algebra I has been identified as a course on which students' future educational opportunities and advancement depends (e.g., Moses & Cobb, 2001; Cogan, Schmidt, & Wiley, 2001). As a result, much more attention is being given to the teaching and learning of Algebra, especially in light of policies pushing for Algebra to be taught in 8th or 9th grade (Stein, Kaufman, Sherman, & Hillen, 2011). Given the pressing problems with student motivation and access that face secondary mathematics subjects like algebra (e.g., Kaput, 2000; Loveless, Fennel, Williams, Ball, & Banfield, 2008; Mitchell, 1993), it is critical to explore how an interest-based instructional design principle like context personalization can mediate student outcomes in this area.

Theoretical Framework

Topic Interest

Here we frame the benefits of context personalization in terms of *interest*, a psychological state that "is characterized by focused attention, increased cognitive and affective functioning, and persistent effort" (Ainley et al., 2002, p. 545). Researchers have differentiated two types of interest – *individual interest* refers to enduring and stable preferences of a learner for particular topics or activities, while *situational interest* is a short-term response to surprising or evocative characteristics of a context or environment (Schraw & Lehman, 2001). Recent frameworks for interest also discuss *topic interest*, which is interest that is triggered when a specific topic is mentioned during instruction (Ainley et al., 2002). Topic interest has aspects of both situational and individual interest, and may be most in line with the idea of context personalization.

Context personalization may spur individual or situational interest (Heilman, Collins, Eskenazi, Juffs, & Wilson, 2010; Reber, Hetland, Chen, Norman, & Kobbeltvedt, 2009; Renninger et al., 2002). When students notice that instructional materials have been personalized to their interests, this can trigger situational interest, which may or may not be maintained over time. For instance, having learners generate ways in which content is personally relevant to them can trigger situational interest and increase perceived utility value, particularly for lower-performing students (Hulleman, Godes, Hendricks, & Harackiewicz, 2010). Personalization in the form of example choice also can increase self-reported interest (Reber et al., 2009).

If instructional materials are designed to be especially well-connected and relevant to topics and activities that learners are personally interested in, individual interest may also be activated. In a recent study where reading topics were chosen based on individual interests, this personalization improved performance, as measured by an immediate retention post-test, and learning, as measured by a transfer task (Heilman et al., 2010). The impact of interest-based interventions like personalization is also influenced by the learner's level of individual interest in the domain being studied (Durik & Harackiewicz, 2007; Renninger et al., 2002). In one of the few studies examining personal interest in mathematics problem-solving, Renninger et al. (2002) used several case studies to suggest that if students are interested in mathematics, the effect of the story context is less important, and students may work personalized and normal problems similarly. This study also makes the important point that individual interest has both knowledge- and value- related components – meaning that interest can leverage both the learner's prior knowledge of the topic area and the value or feelings they ascribe to that topic area.

Supporting Situational Understanding

The benefits for personalization are often framed generally in terms of interest and motivation. Of import to the current study are the means or mechanisms by which personalization and the associated interest spurred by personalization can enhance performance in mathematics. Research on interest has shown that interest mediates learner focus of attention (Durik & Harackiewicz, 2007; Hidi, 1995; McDaniel, Waddil, Finstad, & Bourg, 2000; Renninger & Wozniak, 1985). Renninger et al. (2002) suggest that personalization of mathematics story problems can focus attention on the scenario and away from keywords, allowing learners to make connections between the story context and the mathematics content. When students solve personalized mathematics story problems, interest may promote focus of attention on the story scenario, which in turn may support a situational understanding of the relationships described in the text. Further, learners may be able to leverage their prior knowledge of familiar everyday contexts to facilitate problem-solving when given story problems connected to their experiences (Baranes et al. 1989; Carraher, et al., 1987; Saxe, 1988).

Nathan et al. (1992) propose a model of problem-solving for mathematics story problems based on Kintsch's (1986) model of text comprehension and Kintsch and Greeno's (1985) work on arithmetic story problems. They describe how when presented with a story problem, students coordinate three levels of representation: (1) a *propositional textbase* containing the relevant information given in the scenario, (2) a *situation model*, or an understanding of the actions, events, and relationships in the story, and (3) a *problem model*, including formal mathematical operands, variables, and equations. Nathan et al. (1992) found that when students are given support to construct more coherent situation models, they have better learning outcomes. This is attributed to the situation models facilitating inference-making about the relationships described in the story, effectively integrating students' prior knowledge with their problem-solving actions. Nathan et al.'s (1992) and Kintsch and Greeno's (1985) work is differentiated from other more general work on placing mathematics in everyday contexts in that it generates hypotheses about the underlying cognitive processes (i.e., formation and coordination of situation and problem models) that account for how students understand and solve story problems. We thus use the terms "situational reasoning" or "situational understanding" to reference this idea of building situation models from text.

Schiefele (1999) also used Kintsch's (1986) model of text comprehension to explore whether individual interest supports situational understanding in reading. Two studies reported medium correlations between a reader's level of interest in the topic of a text they were reading, and deep-level processing measures. This was compared to lower correlations between interest and surface-level processing. Similarly, McDaniel et al. (2000) used the results from a series of reading studies to suggest that interest promotes automatic allocation of attention, which in turn frees up cognitive resources which may be devoted to organizing information or creating situation models from text.

In sum, research has shown that interest mediates attention allocation, which may in turn promote situational understanding. The topic interest spurred by personalization may support appropriate situational interpretation of story contexts. Personalization may also support students' situational understanding by leveraging their everyday knowledge of the situations described in personalized story contexts. Nathan et al.’s (1992) framework suggests that supporting such situational understanding can be framed as promoting the creation and elaboration of appropriate and relevant situation models of mathematical scenarios.

Personalization in Elementary Mathematics

Research results on the impact of personalization on performance and learning in mathematics are mixed, and it is important to note that the few studies that exist have been conducted with elementary or middle grade students. One of the most well-known studies of personalization in mathematics is Cordova and Lepper (1996), where fourth and fifth grade students engaged in computer-based learning games on order of operations. For students in the personalization condition, incidental elements of the game were personalized to students’ background, based on a prior questionnaire. Students who received the personalized version of the game had significantly higher performance on a post-test.

Using arithmetic word problems involving addition, subtraction, and fractions, other studies (Anand & Ross, 1987; Davis-Dorsey, Ross, & Morrison, 1991; Lopez & Sullivan, 1992) found positive effects for personalizing problems to students’ individual interests as measured by questionnaires. A study of fifth and sixth grade students engaging in a computer-assisted lesson on fractions found that personalized contexts improved post-test performance. However, students with lower scores on standardized mathematics and reading tests seemed to benefit most from personalization, whereas high-achievers performed equally well on generic and personalized story problems (Anand & Ross, 1987). Another study of seventh grade students solving one-step and two-step arithmetic story problems found that both group-level and individual-level personalization improved performance on two-step problems. The researchers interpreted this result as indicating that familiarity with story contexts is more important for complex, two-step problems (Lopez & Sullivan, 1992). Thus there is some suggestion in the literature that personalization is most beneficial for lower-achieving students, and on harder problems. However, other more recent studies have found that personalization does not lead to increased performance. Bates and Weist (2004) found no increase in fourth grader’s performance on arithmetic story problems when they were personalized based on interest inventories. Caker and Simsek (2010) also found that personalization of arithmetic story problems did not increase performance for seventh grade students.

The mixed results of this research may be a result of personalization being primarily beneficial when the difficulty of the problems is well-matched to student ability, and the support provided by personalization is needed. Further, methodological approaches to, and even definitions of personalization are different across studies. Personalization is sometimes accomplished by changing incidental aspects of mathematical scenarios (e.g., inserting the students' birthday), rather than aspects relevant to problem solving (e.g., asking students to reason with a familiar quantity). Personalization can also be accomplished using either questionnaires (Cordova & Lepper, 1996) or individual interviews (Renninger et al., 2002), and problems can be personalized to individuals or groups of students (Lopez & Sullivan, 1992). Finally, differences in age and language background of students have important implications for personalization, as they impact verbal comprehension of story scenarios (Koedinger & Nathan, 2004).

Placing Algebra Instruction in Everyday Contexts

Research on context personalization in mathematics has been conducted almost exclusively with elementary and middle grade students solving simple arithmetic scenarios. Here, we focus on Algebra I, and thus provide a brief review of some of the applicable research on the development of algebraic reasoning. We note that algebra is a difficult mathematical subject for students to learn, as learners must make a difficult transition from reasoning about fixed quantities and known numbers to reasoning about variable quantities and unknown numbers (Common Core State Standards Initiative, 2010). Skills involving algebraic symbolization are particularly challenging for students to learn (Filloy & Rojano, 1989; Hercovics & Linchevski, 1994; Koedinger & McLaughlin, 2010; Stacey & MacGregor, 1999), with research pointing to several important directions for supporting the development of algebraic reasoning.

First, research has revealed the ways in which students use informal methods, such as systematic guess and check, when confronted with algebraic tasks (Carraher et al., 2006; Hall, Kibler, Wenger, & Truxaw, 1989; Johanning, 2004; Kieran, 1988; Koedinger & Nathan, 2004; Nathan & Koedinger, 2000a; 2000b; Nathan, Stephens, Masarik, Alibali, & Koedinger, 2002). These strategies grow out of students' proficiency with arithmetic and their consideration of relationships and quantities, and much of this research has shown that these strategies can support students in developing algebraic understanding. Second, research has demonstrated the powerful ways in which algebraic reasoning can be developed based upon students' everyday experiences interacting with the world (Bardini, Pierce, & Stacey, 2004; Carraher et al., 2006; Chazan, 2000; Lampert, 2001; Moses & Cobb, 2001). For example, in the learning trajectory used in the *Algebra Project* curriculum, students experience a physical event, like a trip on the metro, and then model this experience using progressively more abstract representations (Moses & Cobb, 2001). Personalization may thus be an especially effective support for the development of algebraic reasoning, as it may help students to construct powerful and appropriate situation models of problem scenarios, which can leverage their everyday knowledge and informal ways of reasoning.

One way in which situational reasoning is investigated in algebra is through the use of *difficulty factors assessments* (Baker, Corbett, & Koedinger, 2007; Heffernan & Koedinger, 1998; Koedinger, Alibali, & Nathan, 2008; Koedinger & Nathan, 2004; Rittle-Johnson & Koedinger, 2005). In this methodology, students complete assessments that systematically vary different contextual factors that may impact problem difficulty, to allow for hypothesis about cognitive processes involved with problem solving to be drawn from performance data. Using this approach, Koedinger and Nathan (2004) compared student performance on algebra story problems to word equations (i.e., general, verbal descriptions of operations, such as "Starting with some number, I multiply it by 6.") and symbolic equations, and found that high school students have significantly higher performance on word equations and story problems than matched symbolic algebra equations. This finding was attributed to concrete and verbal contexts eliciting informal strategies that followed the episodic structure of the problem.

However, Koedinger and Nathan (2004) did not find significant differences in performance between word equations and everyday story scenarios. The findings supported their *verbal facilitation hypothesis*, or the idea that story problems are easier for students because they are written in English rather than mathematics notation, not because they leverage situational knowledge. The study also found that story problems were easier than word equations when they included decimals, and that stories encouraged the *unwind* strategy, which was less prone to conceptual error than other strategies. Although this study suggests that verbal support is more important to problem solving than everyday contexts, the story problems used were not personalized, and were uniform across all students. Additional work using this methodology by Koedinger, Alibali, and Nathan (2008) found that for more advanced problems, symbolic representations were easier for students than matched verbal scenarios. In the present study, we will use a difficulty factors assessment methodology to explore the performance impact of matching story problems to student interests through context personalization.

Research Questions

Context personalization is an emerging trend in the science of instruction, reflecting a widely-held assumption in the culture of schooling that connecting instruction to personal interests is beneficial for educational outcomes. However, in the domain of algebra especially, little research has investigated how topic interest mediates performance and learning, and critically considered when personalization might be beneficial and the mechanisms by which personalization may have the potential to support learning. Further, researchers have not systematically investigated the differential impact of personalization for specific learners and different problem types. The research questions of the present study are as follows:

R.1 Does personalization of algebra story problems impact performance for high school Algebra I students when considering the difficulty of the problem and the performance level of the student?

R.2 Does personalization influence the strategies high school Algebra I students use to solve algebra story problems, and the mistakes they make?

We entered into this study with hypotheses regarding each research question:

H.1 Personalization will have a positive impact on performance on more difficult problems, and for weaker students. This may occur because if a student already has mastered connecting the situations described verbally in stories to mathematical structures, it is less likely that increased situational understanding of the story scenario will improve performance.

H.2 Students will use more informal strategies and make fewer conceptual mistakes when solving personalized problems. This may occur because personalization allows students to have a better understanding of the actions and relationships in the scenario, forming a more coherent situation model. Students may thus focus on sense-making about relationships between quantities and reason more successfully about the problem's structure.

Method

Participants

We recruited seventy-four Algebra I students from the classes of one teacher at an urban Texas high school. Students were offered $20 for their participation in the study, and were told that they would participate in two interviews, one where they would solve math problems while being audio-recorded. Parental consent was obtained from 39 students (52.7%), a relatively high response rate for this type of study. Due to issues with time constraints, student mobility, and absenteeism, 24 of these 39 students participated in the problem-solving sessions. Although the sample was volunteer and not a random selection, the demographics of the participants closely matched the school (see Table 1).

As can be seen from Table 1, many of the students in the sample were of low socioeconomic status, and 9 of the 24 students did not pass the state standardized exam in mathematics during the year of the study. Although the average values of characteristics of the sample closely matched school-level averages relating to achievement, race/ethnicity, gender, and socioeconomic background, this was a volunteer sample, so it is somewhat problematic to make generalizations from this sample to the entire 9th grade population at the school. For instance, although the mean achievement scores were very closely matched, the level of variance might be different in the school population. Further, all these students had a similar characteristic of being in the class of the same algebra teacher. However, the school used an algebra curriculum that was standardized throughout the school year, and the textbook (Holt Algebra I) was widely-adopted nationally.

[Insert Table 1 around here]

Materials and Procedure

We first engaged the 24 students in an entrance interview where they were asked how they use mathematics in their everyday lives, where they see and have to deal with numbers, and what activities and hobbies they are interested in. The researcher asked the students pre-determined general questions about their interests, as well as questions regarding 5-10 specific interest topics, such as sports, video games, and shopping. Interviews lasted between 15 and 20 minutes, and were audio-recorded.

After the interview, two personalized problems on linear functions were written for each student that were variations on 14 base story problems from the *Cognitive Tutor Algebra* curriculum (Carnegie Learning, 2008). This relatively large number of base items was used so that when students mentioned specific scenarios from their everyday experiences that involved rate of change, there would be a variety of number choices (large, small, decimal) and problem structures (positive slope and positive intercept, negative slope and positive intercept, no intercept, etc.) to match to their story. See Appendix A for a description of the base items used in this study.

In a follow-up session, the researcher asked students to solve two personalized problems, along with one unchanged “normal” story problem from the Cognitive Tutor curriculum that was one of the 14 base problems. In this way, we used an approach similar to the previous-described difficulty factors assessment method (Baker et al., 2007; Heffernan & Koedinger, 1998; Koedinger & Nathan, 2004), in that we systematically varied connection to students’ interests. Each story scenario had four parts – two result unknowns (parts a and b in Table 2), writing an algebra rule (part c in Table 2), and one start unknown (part d in Table 2). While result unknowns are often solved by a single application of a forward arithmetic calculation, start unknowns may require students to work backwards or use trial-and-error techniques. Koedinger and Nathan (2004) showed that start unknowns tend to be more difficult for students than result unknowns, describing how “When students solve a start-unknown problem, they must do everything they need to do to solve an otherwise equivalent result-unknown problem (e.g., comprehend the problem statement, perform arithmetic operations) in addition to dealing with the fact that the arithmetic operations cannot be simply applied as described in the problem” (p.156).

[Insert Table 2 around here]

Since students solved three problems with four parts, each participant solved 12 total problem parts that are included in the analysis. Students also solved 1-2 additional algebra problems on linear functions during the session that were part of a related study, but were neither normal nor personalized. Two students received a normal problem for which there was no personalized version of the base problem. This occurred because the base problem had a structure that was difficult to match to student interests (negative slope, negative intercept). The results for this base problem are omitted from the analysis of performance. Time ran out during one session, so three problem parts for one student were never solved and are also omitted. Finally, 4 students received a problem that had 3 result unknown problem parts instead of 2 result unknowns and 1 start unknown.

We asked students to solve each problem part while thinking aloud (Ericsson & Simon, 1998) and recording their work. The sessions took place one-on-one in a private room with the primary researcher. Problems were printed on a piece of paper (all four parts on one page) with space for student work. At the beginning of each problem-solving session, the student was asked to solve a multiplication problem with two multi-digit numbers to practice thinking aloud. The researcher then instructed the student that they would be audio-recorded solving some additional problems. The researcher let the student know these problems were not for a grade, but to try to solve each one. The researcher also instructed students that they could not ask for assistance. As the session progressed, when the student forgot to verbalize steps, or when their thinking was not clear, the researcher would give a generic probe asking the student what they were doing. The researcher also used spontaneous questioning to further probe student understanding. The session closed with the researcher asking which problem was easiest and which problem was hardest, and why. The order in which problems were presented to students was randomized.

Data Sources and Methods of Analysis

We first coded each session with whether the student obtained the correct or incorrect answer to each of the 12 problem parts they were presented with. Two researchers coded all problem solutions (i.e., numerical answers for result and start unknown problem parts, and symbolic equations for algebra rule problem parts) for correctness based on student work and verbalizations, and obtained a high degree of inter-rater reliability (kappa = 0.96). All discrepancies were resolved.

R.1 Does personalization impact performance when considering the difficulty of the problem and the performance level of the student? In order to address this research question, we first explore descriptive statistics of different students' success rates on different types of problems. Specifically, we classify both student performance level and problem difficulty level, and examine how the impact of personalization on accuracy varies by each of these factors.

A student is classified as being *high-scoring* during their session if they solved 75-100% of their problem parts correctly, *medium-scoring* if they solved 50-75% correctly, and *low-scoring* if they solved fewer than 50% correctly. This allows for the students to be divided roughly into thirds, with 9 students in the low-scoring group, 7 students in the medium-scoring group, and 8 students in the high-scoring group, and allows for the divisions to be at precise quartiles (50%, 75%). Dividing the students into exact thirds (8 in each group) was not possible, because two students with identical performance levels (42%) were on the border between low and medium. In order to verify that students' accuracy during the problem-solving session was an appropriate proxy for performance in the larger context of Algebra I, the average score on the state standardized mathematics exam for the low-scoring group was compared to the average score for the medium and high-scoring groups. Students in the low-scoring group scored significantly lower on the state standardized mathematics exam (t (22) = 2.73, $p < .05$).

In terms of problem difficulty, a base problem is classified as being hard if accuracy was under 50%, as medium if the success rate was 50-75%, and as easy if the success rate was 75-100%. This again allows for the divisions to be at precise quartiles and divides the base problems roughly into thirds, with 5 hard problems, 4 medium problems, and 4 easy problems (see Appendix A). An examination of the mathematical structure of each problem confirmed that these classifications based on performance made sense mathematically; problems with no intercept terms were generally easier, problems with decimals, percents, and large numbers were generally harder.

Along with presenting descriptive statistics of student performance on normal and personalized problems, we also explore the statistical significance of the observed trends. In a similar study, Koedinger and Nathan (2004) used a difficulty factors assessment methodology to examine differences in performance between story problems, word equations, and symbolic expressions. In their analysis, they conducted two ANOVAs, one with student as a random effect (i.e., repeated measures), and one with base problem as a random effect, in order to control for both sources of variation. One possible disadvantage of this methodology is that it does not account for variation due to student effects and base problem effects simultaneously. For this reason, we decided to conduct a mixed-effects logistic regression analysis (Snijders & Bosker, 1999), which can control for both student and item effects. However, the results from this analysis were similar to those obtained using the more traditional ANOVA method for analyzing difficulty factors assessment data. All in all, the regression and ANOVA approaches are similar – both model the same fixed and random effects, and both use accuracy as the outcome variable.

The sample size for this analysis is approximately 12 repeated observations of each of 24 students, which corresponds to a raw sample size of $N = 288$. The effective sample size is smaller, due to resemblance between observations of the same student and observations of the same base problem. The usual recommended sample size for analyses of this kind is 25 groups of 25 (Paterson & Goldstein, 1991), although simulation studies have found that regression coefficients and their variance components (the parameters examined in this paper) remain unbiased for samples as small as 10 groups of 5 (Maas & Hox, 2005). Further, although the sample size was small, the study was designed to be within-subjects, meaning that each participant received *both* normal and personalized problems. This allows for increased power, as there are 24 participants in each of the two conditions. This design also allows for reduced error variance, given that each participant acts as their own control group, which accounts for variance due to individual differences. Regardless, this is a small sample size to be used for a mixed effects regression analysis, so results pertaining to statistical significance should be viewed as exploratory and in need of future verification. We thus recommend that readers give the descriptive analysis the most attention.

The dependent variable in the regression analysis is whether the student got the problem part correct or incorrect, coded as 0 or 1. Fixed effects include whether the story problem is normal or personalized, and whether the problem part is result unknown, start unknown, or writing an algebra rule. Random effects include which of the 24 students is solving the problem part, and which of the 13 base problems (linear functions) is being solved. The readability level[1] of the problem was not a significant predictor of performance ($p = 0.185$), nor were student background characteristics including gender, race, or having a Spanish-speaking guardian ($p = 0.768$, 0.786, and 0.287, respectively). The interaction of these factors with problem type was also not significant.

The regression equation used in the analysis is:

$$logit(P) = \gamma_0 + \gamma_1 \times Problem\,Type + \gamma_2 \times Problem\,Part + \gamma_3 \times Student\,Level + \gamma_4 \times Problem\,Level + U_{0\,Student} + V_{0\,Base\,Problem}$$

See Snijders and Bosker (1999, pp. 208-220) for more information on the form and assumptions of this logistic model. The regression equation was modeled using the R software package (R Core Development Team, 2010) with the *lmer* function (Bates & Maechler, 2009).

R.2 Does personalization impact strategies and mistakes? For the analysis of student strategies and mistakes, session verbalizations and student work were entered into QSR International's NVivo 8 software, and blocked such that one block was one student solving one part of one problem. We coded the blocks with problem type, problem part, whether the correct answer had been obtained, general strategy categories for solving result and start unknowns, and general mistake categories students made when solving result unknowns, start unknowns, and writing algebra rules. A second researcher coded a sample of 7 of the 24 sessions for these categories; kappa values of at least 0.8 were obtained in each case (see Appendix B). Coding discrepancies were discussed and resolved before the remaining 17 sessions were coded. Each problem part is coded with one strategy (except for writing the algebra rule, which had no strategy code). In the rare case the student had attempted multiple strategies, only the strategy they used to arrive at their final answer is coded. A single problem part can be coded with multiple mistakes; for instance, a student may have made an arithmetic error and forgotten the intercept term.

We identified two strategy categories for solving result unknowns – students either directly perform arithmetic operations on the numbers given in the story, or first write a symbolic equation based on the story, and then plug the numbers given in the story into the symbolic equation. We identified five strategy categories for solving start unknowns. Some students use informal *forward-driven arithmetic strategies* to solve start unknowns, which include trial-and-error approaches, repeated addition approaches, and proportional reasoning. In trial-and-error approaches, the student tests different values of the independent variable in a symbolic equation they generated, or in a process they understood informally from the story, in an attempt to reach the dependent value given in the problem. In repeated addition approaches, the student continuously adds the rate of change in order to reach the given dependent value. In proportional reasoning approaches, the student "scales up" or "scales down" a previous answer to try to reach the given dependent value. Although the precise definitions of these strategies are not of central importance to this analysis, the overarching idea is that students are showing an understanding of going forwards in a functional relationship, and their strategy remains closely tied to the precise action and numbers in the story.

Students also use informal *unwind strategies* (Koedinger & Nathan, 2004) to solve start unknowns, where they attempt to arithmetically undo the operations described in the story scenario to solve for the independent variable. This strategy uses the same general approach of "undoing operations" as formal equation solving; however there is no notion of operating on both sides of an equation to maintain equality. Students occasionally use formal *equation-solving strategies* to solve start unknowns, where they operate on both sides of an algebraic expression, canceling out terms to maintain equality. Strategies that do not fit into any of these five categories are classified as *other*.

We identified a number of mistakes in students' work. For the purposes of the analysis presented here, the most important mistake was also the most prevalent – students often forgot to use the intercept term given in the story when solving result and start unknowns, and writing algebra rules. Often a student would include the intercept term for some problem parts (like result unknowns), but fail to take it into account for others (like writing the rule) within the same problem. This mistake seems to be central in analyzing whether the student is using a coherent and consistent situation model of the actions and relationships in the story across problem parts. The finding that y-intercept values are difficult for students to accurately conceptualize in linear relationships, especially in qualitative contexts, has been reported elsewhere, specifically in the domain of graphing algebraic expressions (Hattikudur, Prather, Asquith, Alibali, Knuth, & Nathan, 2012). In the present study, we explore the prevalence of this mistake to examine differences between students' solving of normal and personalized problems, and make hypotheses about how these mistakes reflect differences in situational understanding.

Results

R.1 Does personalization impact performance when considering the difficulty of the problem and the performance level of the student?

Descriptive Analysis. We first examine accuracy on normal versus personalized problems based on the performance of students in the three subgroups described earlier (low-, medium-, and high-scoring) and the performance across the three levels of problem difficulty described earlier (easy, medium, and hard). Results are given in Figures 1 and 2. Error bars show standard error of the mean.

Low-scoring students (Figure 1, diamonds) and medium-scoring students (Figure 1, squares) in the sample have higher accuracy on personalized problems than normal problems. However, high-scoring students in the sample (Figure 1, triangles) have slightly lower accuracy on personalized problems than normal problems. This trend supports the first hypothesis, that personalization has a positive impact on performance for weaker students who may be more in need of problem-solving support. Results also show that when solving hard problems (Figure 2, diamonds) performance levels for students in the sample are higher on personalized problems than for normal problems. However, there does not seem to be a large performance difference on medium difficulty problems (Figure 2, squares). For easy problems, performance on personalized problems is actually lower than performance on normal problems (Figure 2, triangles). These trends from the data also support the first hypothesis, that personalization has a positive impact on performance for harder problems where students may need support to reason through difficult mathematical structures.

[Insert Figures 1 and 2 around here]

Other Trends. Taking a closer look at the session data, several other trends are apparent. Six students in the sample got each part of their normal problem wrong, but had varying amounts of success (25-100%) on their personalized problems. This suggests that personalization may have a scaffolding effect for the students who struggled during the problem-solving sessions. Across all problem parts, students were more likely to not give an answer at all to a normal problem (8.6% no response rate), compared to a personalized problem (1.6% no response rate). This suggests that personalization may have impacted these students' willingness to attempt to reason through a problem.

An interesting and related trend is that when we asked students at the end of the session which problem was easiest and which was hardest, the students overwhelmingly (18/22 students[2]) chose one of their personalized problems as easiest. Six of these students named a personalized problem where they had obtained an incorrect answer for multiple problem parts. Each student was asked why the problem they chose was easy, and responses were coded as falling into one of several non-mutually exclusive categories[3]. The most common justification students cited, given by 9 of the 18 students who chose a personalized problem as easiest, related to the problem's structure and the operations needed to solve it. One representative response from this category was, "Because… maybe it was an easy form of an equation to use. It was just talking of money and the amount of messages you use so it's just multiplying and that was easier." The next most common justification for a personalized problem being easy (6/18 students) given by students was that the problem connected to the students' lives and something they actually did. For example, a student given a personalized problem relating to his job at the flea market named the problem as easiest, responding, "Well, that made me remember what I worked on, so I did what I usually do at my work." While these students seemed to be attuned to the complexity of the mathematical structure of the problems they were solving, a number of them also identified the role that personalized contexts played in supporting situational understanding.

Inferential Analysis. We also examine the impact of personalization on performance using a mixed-effects logistic regression model (Table 3). In this model, problem type, problem part, student level, and problem difficulty are significant predictors of performance, as are interactions between problem type and student level, problem type and problem difficulty, and student level and problem difficulty. The random effects in this model are student and base problem. Interactions between problem part and problem type[4], problem part and problem difficulty, and problem part and student level are not significant (χ^2 (2) = .9207, $p = 0.63$; χ^2 (4) = 4.04, $p = 0.40$; χ^2 (4) = 3.08, $p = 0.55$). For the fixed effects, the second column of Table 3 gives the raw logit coefficients, which are not directly interpretable. The fourth column gives the exponentiated coefficients, which are in odds form; these can be more directly interpreted as the change in the relative chance of getting the problem correct due to the level of the independent variable. Odds are a common measure of effect size in logistic models.

[Insert Table 3 around here]

Given the large number of interaction terms, the static display of base categories, and the non-direct interpretation of the logits, the coefficients and the significance tests are difficult to directly interpret from Table 3. Table 4 provides a summary of the results using the regression coefficients from Table 3 (placed into the logistic function) to estimate the size of the significant effects for result unknowns[4]. Table 4 is divided into 9 cells that represent different subgroups of the sample[5]. Each cell describes whether personalization was predicted to increase, decrease, or cause no significant change in performance, compared to predicted performance for that subgroup on normal problems.

[Insert Table 4 around here]

Table 4 shows several interesting trends that match the descriptive analysis. First, personalization seems to be detrimental to performance when high-scoring students in the sample solve easy problems. On the other hand, personalization enhances performance on the hard problems that these students solved, specifically for the low and high-scoring students. In this sample, personalization is always neutral or beneficial for low-scoring students and for hard problems, and is always neutral or harmful on easy problems. The tables suggest that personalization may act as a scaffold or a distraction, depending on the characteristics of the learner and the problem. These trends provide support for the first hypothesis that personalization provides support for weaker students, and on harder problems, but we also find an unexpected reversal effect. In order to better understand why personalization may be beneficial or harmful, we turn to an analysis of strategies and mistakes.

R.2 Does personalization impact strategies and mistakes?

In this section we provide an overview of student strategies and mistakes when solving normal and personalized problems. Unlike the regression models, the percentages presented here do not control for base problem effects or student effects, thus statistical tests do not make sense because of issues with independence. However, the descriptive analysis we present in this section is intended to contextualize and explore the results of the regression analysis presented in the previous section.

Analysis of strategies for result unknowns. Result unknown problem parts require a simple, forward calculation, usually multiplication and addition. For result unknowns, we found that students in the study most often use arithmetic strategies rather than writing a formal algebraic equation from the story scenario. However these students are more likely to write and use a symbolic equation to solve result unknowns for normal problems than they are for personalized problems (Table 5).

[Insert Table 5 around here]

Analysis of strategies for start unknowns. As discussed previously, students use informal and formal strategies to solve start unknown problem parts. The interview context and the personalization of problems seemed to elicit informal strategies, cueing these students that this type of reasoning was acceptable and valued. Forward-driven informal strategies like repeated addition and trial-and-error require continuous and sometimes lengthy arithmetic calculations. The informal unwind strategy is also arithmetic-based, but requires reversing operations. The formal equation-solving strategy requires the student to operate on both sides of a symbolic equation to isolate x.

Table 6 shows the incidence of the various start unknown strategies for normal and personalized problems. Personalized problems included in this study have a higher incidence of forward-driven strategies, and a lower incidence of unwind and formal strategies. The trend seen for start unknowns in Table 6 is similar to the trend seen in Table 5 for result unknowns. When these students are presented with start unknowns, normal problems elicit formal strategies around 10% of the time, whereas personalized problems more rarely elicit formal strategies. No response rates are higher for normal problems than for personalized problems in these data, and this trend seems to be more pronounced for the more challenging start unknown problem parts. Personalization seemed to provide resources that these students could use to reason informally about the situation, scaffolding the formation of coherent situation models that allowed for forward-driven calculations tied closely to situational understanding.

[Insert Table 6 around here]

The overall lack of use of formal strategies in this sample is notable, given that these students are in an Algebra I course and had significant exposure to this method. Looking across the data from all problem types (including problems that were neither normal nor personalized) used in the larger study, 8 students of the 24 attempted equation-solving strategies a total of 13 times, and in 8 of these cases (for 5 students) the equation-solving approach led to the correct answer. In two of these instances the student began by using equation solving, but abandoned this strategy for a different approach. Equation-solving strategies were used successfully, but not by the majority of students in this sample.

Table 7 gives the overall success rates in the study for each strategy to solve a start unknown, and shows that forward-driven strategies have higher success rates than unwind strategies. Going forward in a functional relationship through multiple arithmetic calculations, though sometimes lengthy, may be less prone to error for these students than undoing operations. For example, one student used an unwind strategy incorrectly on his normal problem, forgetting to use the intercept term. However, this same student solved one of his personalized problems correctly using a trial-and-error strategy, appropriately taking into account the intercept term.

[Insert Table 7 around here]

As suggested in Table 7, personalized problems may have more correct answers because they elicit forward-driven strategies from these students, which have higher success rates. Informal forward-driven strategies like systematic trial-and-error may better leverage these students’ situation models, as these approaches correspond more directly to the actions and relationships stated in the problem text. Johanning (2004) in a study of children’s informal strategies for solving algebra story problems argues that "In order to devise a system to systematically guess and check with, students had to understand the underlying structure of the problem and articulate it into a formal plan" (p. 385). Thus in terms of strategy use, we found support for the first part of the second hypothesis, that personalization increases use of informal strategies that may build on situational understanding.

Analysis of mistakes for result unknowns, start unknowns, and written algebra rules. Few of the mistakes coded for result unknown and start unknown problem parts in this study were arithmetic mistakes (9% of mistakes); most were conceptual errors. While these conceptual errors varied widely and often seemed tied to a specific problem's wording and structure, the most prevalent conceptual error made when these students solved result unknown, start unknown, and algebra rule problem parts was to leave out the intercept term. This error is important because it may indicate instances where these students are not consistently forming situation models that appropriately represent the actions and relationships given in the story scenario. If personalization does support the formation of coherent and accurate situation models, this error may occur less often if the problem is personalized. The analysis of student mistakes (shown in Table 8) supports this hypothesis, and shows that these students are less likely to omit the intercept term for personalized problems.

[Insert Table 8 around here]

Overall, the trends found for these students' strategies and mistakes support the second hypothesis, that personalization may have better facilitated an implicit understanding of the actions and relationships in the story scenarios, allowing for performance gains when these students worked challenging problems. These gains may occur because these students are more likely to attempt the problem and try to reason through the story, students are more likely to use informal, forward-driven strategies that mirror the action of the story, and students are more likely to avoid leaving off the intercept term when conceptualizing a linear relationship from text. The analysis of strategies and mistakes suggests that personalization may have contributed to the formation of more coherent and accessible situation models of the actions and relationships in story scenarios for these students, and that situation models can in turn support problem-solving accuracy.

Strategies and mistakes by subgroup. In order to take a more detailed look at how personalization may impact strategies and mistakes, we conduct a focused analysis on two of the cells in Table 4 where personalization seemed to have an important effect on performance. We examine strategies and mistakes for high-scoring students solving easy problems (to investigate the reversal effect) and for low-scoring students solving hard problems (to investigate the scaffolding effect).

When the high-scoring students in the sample solved easy problems, if the problem was a normal story problem they never got a problem part wrong, except in one case[7]. However, when easy problems were personalized, the high-scoring students made a variety of mistakes. One student left out an intercept term while writing a simple equation, while another made an arithmetic error when solving a start unknown using an unwind strategy. A different high-scoring student got most of a personalized problem on watching TV shows wrong through what appeared to be confusion in coordinating his implicit knowledge of watching repeated, 30-minute TV shows with the operations needed to solve the problem. This suggests that personalization may have acted as a type of distraction when stronger students in our sample were solving easy problems.

When the low-scoring students in the sample solved hard problems, they never got any problem part correct, except when the problem was personalized. Of the 8 low-scoring students who solved a hard personalized problem, two students were able to successfully solve their start unknowns using trial-and-error and unwind approaches, two students were able to write correct symbolic equations, and four students were able to successfully solve result unknowns using arithmetic strategies. Further, when low-scoring students solved hard problems that were personalized, they forgot the intercept term approximately one third of the time (29% of all problem parts), and when they solved normal hard problems, they forgot the intercept nearly two thirds of the time (65% of all problem parts). Personalization seemed to allow the low-scoring students in our sample to have some measure of success on hard problems, perhaps supporting the development of situation models that included intercept terms and promoted the use of informal arithmetic strategies.

In summary, personalization seemed to provide a scaffolding effect when these students solved difficult problems, allowing them to appropriately use informal approaches and forget the intercept term less often. This suggests that students in the sample were able to form more detailed and appropriate situation models representing the actions and relationships in the story when problems are personalized, and then use these situation models to support problem solving accuracy. On easy problems, personalization sometimes seemed to be distracting to these students, causing tension between their situational understanding and their formal problem-solving strategies.

Conclusion

In this study, personalizing instruction to out-of-school interests seemed to provide an additional resource for some students who were faced with a challenging algebra story problem. One explanation for this phenomenon is that interest may support situational understanding (McDaniel et al., 2000; Schiefele, 1999), allowing students to construct coherent situation models of the actions, objects, and relationships described in the text. We would expect students who have constructed a coherent situation model to have an important resource for reasoning and problem solving which students who are unable to do so would lack (Nathan et al., 1992). However, the benefits of personalization were not uniform. Like Renninger et al. (2002), we found that while personalized mathematical contexts can provide support, they may also be superfluous or distracting. Here we provide new evidence within our sample suggesting that personalization may be most beneficial when problems are on the periphery of students' problem-solving competency, and show data suggesting how this may come about in terms of the types of strategies students use, and the mistakes they make.

With this research we extend the body of work on personalization of instruction to student interests, which has traditionally focused on concrete, elementary-level concepts in mathematics (i.e., Anand & Ross, 1987; Cordova & Lepper, 1996; Davis-Dorsey et al., 1991; Lopez & Sullivan, 1992; Renninger et al, 2002). Here, we investigate how making connections to interests can impact students' thinking about algebraic concepts like rate of change and intercept. The positive impact of personalization in our sample was strongest for weaker students and students working on harder problems. These students seemed to make use of the situational resources provided by a personalized context that they were familiar with, leveraging use of informal strategies closely tied to the action of the story. Thus we build on previous work on informal strategies in algebra (Hall et al., 1989; Koedinger & Nathan, 2004; Nathan et al., 2002), and find that use of certain types of informal reasoning may be closely tied to the students' level of connection to the story context. And like other studies of the development of algebraic reasoning (e.g., Bardini et al., 2004; Carraher et al., 2006; Chazan, 2000; Lampert, 2001), we find that relevant contexts may be an important scaffold for learning algebra. However here we take a new perspective by framing what counts as "relevant" in terms of students' individual interests.

The effectiveness of relevant contexts as a scaffold did not seem to be present for high-scoring students in our sample when they were working on easier problems. These students were working on problems that were not on the periphery of their problem-solving ability, but were well within their reach. The personalization of the context may have been superfluous and possibly distracting for these students, interfering with mathematical procedures they have already mastered. Thus the role of personalization and other interest-based interventions may be conceptualized as providing scaffolding for students who are struggling to solve problems, with this type of assistance faded out as expertise develops. This idea may help to explain why experimental research on context personalization has shown mixed results (e.g., Bates & Weist, 2004; Caker & Simsek, 2010) – the support provided by personalization many only be helpful under certain circumstances.

With this work, we begin to generate hypotheses for an account of how activating interest with personalized mathematical scenarios might impact learner outcomes. The literature suggests two explanations for why students who receive personalized problems may form more accurate and coherent situation models. First, the interest spurred by receiving a personalized problem may promote focus of attention, engagement, and persistence (Ainley et al., 2002; Durik & Harackiewicz, 2007; Flowerday et al., 2004; Hidi, 1995; McDaniel, et al., 2000; Renninger & Wozniak, 1985), which may in turn allow for students to be more successful at the difficult task of constructing a situation model. Second, students' informal, everyday knowledge of the quantities and topics described in story contexts may directly improve or promote situational understanding when this knowledge is relevant to the problem at hand (Baranes et al., 1989). These two explanations correspond to Renninger et al.'s (2002) conception that individual interest has components of both *stored value* and *stored knowledge*.

There is evidence for both explanations in the qualitative data collected as part of this study. For example, when one student was asked why he named a problem with a short, generic story context as hardest, he discussed how interesting contexts can elicit engagement and attention:

> It didn't give much information, and it's not interesting. Like, when the problem is interesting you want to figure it out because you're curious to find out, it seems like, it's something that you want to know, you're not just doing because you're asked to do a question... It's not just for a grade or, whatever it's for.

However, we also found evidence that situational knowledge can more directly support problem solving both in the self-report data when students were asked why they found personalized problems easiest, and in the data from when students were in the process of problem-solving. For example, one student who received a personalized problem about earning money at his job realized that his initial answer was unreasonable based on his everyday experiences.

Limitations

Although the sample size presented here is relatively small for a statistical analysis and presents issues with generalizability, this study is exploratory, with deeper analyses of strategies and mistakes complementing performance data. In addition to the sample size being relatively small, the sampling of students from the algebra classes was non-random – students had to get parental consent to participate. Both of these issues impact the generalizability of the results, and the potential for replicability. However, promisingly, we have replicated the major result presented here – that interest-based problems promote performance gains for weaker students – with a much larger sample of students, in a different school setting (Walkington, 2012). This provides credence for the claim that the trends found in this study were legitimate, and that the deeper analysis we were able to engage in given the small sample size and the level of detail of student work and explanations can help illuminate *why* these trends hold. Our work extends and is consistent with previous literature in elementary mathematics which suggests that personalization can improve learning (Cordova & Lepper, 1996), and that this effect may be largest for weaker students (Anand & Ross, 1987) and on harder problems (Lopez & Sullivan, 1992).

It is also important to note that the conditions in this study were not strictly experimental, in that the interviewer questioned students as they worked. Further, there were a wide variety of problem structures, numbers, and story contexts used, so there may be unmeasured covariates. Finally, this study was conducted in an interview context rather than a classroom context. However, the strength of analyzing problem-solving sessions like the ones presented here is that it allows for hypothesis to be made about how topic interest may impact problem-solving for a population that has not been studied in previous literature, secondary algebra students. Furthermore, this type of study also allows for an in-depth examination of factors like strategies, mistakes, and student perceptions.

Implications

Research on context personalization is relatively new, in part because in the classroom connecting instruction to individual students' interests may be viewed as overwhelming for teachers (Hidi, 1990), with such interventions perhaps reserved only for one-on-one tutoring sessions, or for students who are struggling (e.g., Fives & Manning, 2005). However, we believe this line of research has important implications for instructional practice for number of reasons. First, with the advent of learning science technology-based innovations allowing for adaptive instruction (Collins & Halverson, 2009; Papert, 1980; 1993), enacting context personalization on a large instructional scale is becoming increasingly feasible. For example, Carnegie Learning's (2011) new software-based intelligent tutoring system *Mathia* is targeted to middle school students, and allows them to personalize aspects of instruction to their interests, including choosing topics (such as sports, business, art, and music) that guide problem selection. This software fits well with the beliefs of stakeholders in education about how learning is best supported, as evidenced by its current use in over 200 schools during its first year of release. However, we argue that it is critical that research in mathematics education "catches up" with current trends in technology-based curriculum design, in order to inform their development and implementation.

Second, there are a number of ways in which personalization of the type investigated in this study can be implemented in classrooms without the aid of technology. Our program of work has found a great deal of overlap in the topics students of this age group are interested in. Implementing personalization as a teacher could be as simple as making an explicit effort to stay aware of the out-of-school interests of students, and to consider ways of weaving these topics into mathematical problem-solving when students are confronted with difficult topics. Our work suggests that taking advantage of opportunities to gain insight into students' interests, listening and questioning as opportunities arise, can be a valuable tool for teachers. Further, the burden of personalization need not always fall upon teachers – students could take an active role in personalizing their own learning, and the learning of their peers. Databases of mathematical scenarios corresponding to different topic interests could be developed over time by students, teachers, schools, districts, and curriculum developers, such as the personalized "Example Wiki" under development by Reber et al. (2009).

One of the reasons that personalization has the potential to be easily implemented in educational settings is that the type of problem scenarios we are discussing here make relatively simple connections to students' interests. This is contrasted with more authentic investigations, where students explore and model mathematical aspects of complex real world phenomena (e.g., Cognition and Technology Group at Vanderbilt, 1997). However, we argue that students ultimately need to experience mathematics at various levels of authenticity, which includes these more traditional mathematics story problems which are prevalent in textbooks, curricula, and on various exams from kindergarten to college (Jonassen, 2003). Barab et al. (2007) make a compelling case for the importance of students having both rich, embodied experiences with concepts as well as less situated embedded or framed experiences with key ideas, in order to promote flexible learning of disciplinary formalisms. Our own work on project-based instruction also supports this approach (Walkington, Nathan, Wolfgram, Alibali, & Srisurichan, in press).

Further, although "authentic context" approaches typically accentuate the complexity of the problem space and the development of mathematical models, and research of the type presented here accentuates interest, motivation, and affect, these lines of work do overlap. Theoretical principles like interest and motivation have profound significance for investigations across topics in mathematics education, and are these principles are greatly in need of further investigation. Here, we show data suggesting the impact of interest on mathematics problem-solving can be considerable, even when implementing a simple modification. The goal behind this program of research is to take what is currently being done in schools, in this case a high-poverty urban school in danger of being closed under the guidelines of *No Child Left Behind*, and explore ways to incrementally improve instructional practices based on principles from the learning sciences. And broadly speaking, this research allows us to explore and better understand an important element of *why* rich, meaningful everyday contexts may be effective for student learning.

Future Directions

Research findings on the potential of everyday contexts to support mathematical reasoning have been mixed, with some studies suggesting that real world knowledge is not always well-aligned with school tasks (Boaler, 1994; Cooper & Harries, 2009; Inoue, 2005; Kazemi, 2002; Ladsen-Billings, 1995), and other studies suggesting that school knowledge may be of limited use in authentic settings (Masingila et al., 1996; Saxe, 1988). However, here we focused specifically on matching instruction to students' out-of-school interests, and found evidence in our sample that these scenarios can support students' problem-solving. These findings are contrasted with other research suggesting that low-income students, like those in our study, can actually perform worse when presented with relevant story contexts because they may inappropriately take realistic considerations into account in ways that are not intended by the problem authors (Cooper & Dunne, 1998; Cooper & Harries, 2009; Ladsen-Billings, 1995). Our work may show different results from these prior studies for two reasons. First, tapping into student interests through personalized stories is only partially related to drawing upon their prior knowledge of the described situations. The benefits of interest-based scenarios also relate to the focused attention and engagement that can result from the ascribed value that students associate with an interesting topic. Second, as Cooper and Harries (2005) observe, when students are presented with more traditional story scenarios, like those in our study, issues with real world knowledge being inappropriately applied may not arise because students continue to view the problems as standard school mathematics tasks.

Future research should explore how the prior knowledge and the value-related components of individual interest interact to support students' mathematical problem-solving, and should work to further uncover the mathematical aspects of students' out-of-school interests. While the connections made to students' interests here were relatively simple, future research should explore the potential of making more authentic connections to the situations in students' lives that elicit interest, while also critically considering what responses should be valued when instruction is situated in diverse experiences.

Another important finding was that interest-based contexts seemed to be less effective for stronger students in our sample. While this is not a result that was replicated in our own follow-up work (Walkington, 2012), at least one other study in mathematics has shown a comparable result. Durik and Harackiewicz (2007) found that the addition of visually stimulating fonts and pictures (designed to elicit situational interest) to instructional materials on learning a multiplication algorithm diminished the self-reported task involvement of students who were already interested in learning mathematics, while these enhancements benefitted students with low math interest. Future work should thus critically consider situations in which interest-based interventions may be appropriate or inappropriate to support students' learning, based on the characteristics of the learner and the level of scaffolding that is needed.

In our own future work, we are interested in investigating how teachers and students can implement personalized learning during the course of instruction, and how educational resources can be constructed to support the implementation of interest-based adaptations. We are looking more directly at the impact of topic interest not only on performance in secondary mathematics, but on learning efficiency measures, learning orientation measures, and learning measures like long-term retention and transfer. Preliminary results show that adapting instruction to students' interest not only improves their immediate performance while they solve personalized problems, but that this learning transfers to the solving of non-personalized problems and is retained over time (Walkington, 2012).

Research on the role of interest in instruction has the potential to address many of the pressing problems that face mathematics education today, especially at the secondary level where critical issues of motivation and access are central to current debates about teaching and learning. A recent large-scale survey of Algebra I teachers revealed that “working with unmotivated students” was cited as the biggest challenge of teaching algebra, with “making mathematics accessible and comprehensible to all of my students” coming in at second place (Loveless et al., 2008, p. 76). More research is needed to address when interest-based interventions have the potential to support learning in secondary mathematics, and how such interventions should be designed and implemented. However, the study reported here provides a basis for the conceptualization of topic interest as a potential scaffold in algebra problem solving.

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Appendix A

Description of Base Items Given to Participants

All problems had 1 of 14 different linear functions underlying them; each student received a different linear function in each of their problems. The linear functions used are shown in Table A1.

[Insert Table A1 around here]

The wide variety of linear functions was used so that when students mentioned a personal experience during their entrance interview, there would be a variety of problem structures to match their experiences. The numbers in the problem were occasionally slightly modified to better match students' personal stories, but the changes intended to not change problem difficulty (e.g. $y=17.95x$ instead of $y=12.95x$; $y=3x+11$ instead of $y=2x+10$). Two of the base story problems from the source curriculum contained irrelevant/distractor information (i.e. numbers that were not relevant to the problem's solution). However, none of the students attended to these numbers.

Appendix B

Coding Categories for Strategies and Mistakes with Inter-Rater Reliability

Coding Category	**Possible Codes**	**Cohen's Kappa**
Result Unknown Strategies	Use Arithmetic Use Symbolic Equation	0.87
Start Unknown Strategies	Trial-and-Error Proportional Reasoning Repeated Addition Unwind Solve Equation Other	0.80
Result Unknown and Start Unknown Mistakes	Arithmetic mistake Forgot slope Forgot intercept Mixed up slope and intercept Mixed up result unknown and start unknown Took into account data from previous problem Applied invalid proportional thinking Other	0.81
Write Algebra Rule Mistakes	Too general Too specific Inverted operation(s) No independent variable Mixed up slope and intercept Forgot intercept Other	0.96

Footnotes

1. Readability was measured by the Flesh-Kincaid Reading Ease score.
2. Only 22 of the 24 students were asked which problem was easiest.
3. Two coders coded all instances of student responses, and obtained a Cohen's kappa value of 0.92.
4. The model showed no significant interaction between problem part and problem type, so the significance level of the results is the same across all problem parts (result unknown, start unknown, and write equation). However, given the nonlinear nature of the logistic function, the sizes of the effects are different. Performance differences for result unknowns only are provided for brevity.
5. The cell for medium-scoring student solving an easy problem is empty because only personalized problems were solved that fell into this category.
6. This was an instance where the student did not understand a vocabulary word ("break even") in the story of the start unknown problem part, and did not respond as a result.

Tables

Table 1

Demographics of students in sample compared to demographics of all ninth graders at school site

Demographic	Percentage in Sample (of 24 students)	Percentage of Ninth Grade
Gender	58% male 42% female	53% male 47% female
Race/Ethnicity	54% Hispanic 33% White 13% African-American	65% Hispanic 22% White 11% African American
Free/Reduced Lunch (low socioeconomic status)	79%	75%
Passed state exam in mathematics	63%	62%
Passed state exam in reading	79%	80%

Note. Demographic percentages for the ninth grade were not available for gender and race/ethnicity, so these percentages are school-wide figures.

Table 2

Examples of normal and personalized problems given during problem-solving session

Problem Type	Example
Normal Story Problem	Some early Native Americans used clam shells called Wampum as a form of currency. Tagawininto, a Native American, had 80 wampum shells, and spends 6 of them every day. a) How many shells did Tagawininto have after 10 days? (result unknown) b) How many shells did he have after a week? (result unknown) c) Write an algebra rule that represents this situation using symbols. (write algebra rule) d) After how many days did he have 8 shells? (start unknown)
Personalized Story Problem	You are playing your favorite war game on the Xbox 360. When you started playing today, there were 80 enemies left in the locust horde. You kill an average of 6 enemies every minute. a) How many enemies are left after 10 minutes? (result unknown) b) How many enemies are left after 7 minutes? (result unknown) c) Write an algebra rule that represents this situation using symbols. (write algebra rule) d) If there are only 8 enemies left, how long have you been playing today? (start unknown)

Table 3

Regression output for full mixed-effects logistic regression model

Fixed Effects	Raw Coeff	SE	Exp(Coeff)	z value
(Intercept)	2.067	1.089	7.900	1.898 .
Problem Type-Normal	Ref.			
Problem Type-Personalized	-1.097	1.100	0.334	-0.997
Problem Difficulty-Easy	Ref.			
Problem Difficulty-Medium	-3.349	1.155	0.0351	-2.899 **
Problem Difficulty-Hard	-5.758	1.271	0.003	-4.530 ***
Student Performance-Low	Ref.			
Student Performance-Medium	5.161	1.569	174.3	3.289 **
Student Performance-High	0.976	1.097	2.654	0.890
Problem Part-Result Unknown	Ref.			
Problem Part-Start Unknown	-0.450	0.3767	0.638	-1.193
Problem Part-Write Equation	-1.068	0.3813	0.344	-2.800 **
Problem Type-Personalized× Problem Difficulty-Medium	2.399	1.104	11.01	2.173 *
Problem Type-Personalized× Problem Difficulty Hard	3.849	1.200	46.95	3.208 **
Problem Type-Personalized× Student Performance-Medium	-2.735	1.088	0.065	-2.514 *
Problem Type-Personalized× Student Performance-High	-0.939	1.021	0.391	-0.920
Problem Difficulty-Medium× Student Performance-Medium	-2.126	1.336	0.119	-1.591
Problem Difficulty-Medium× Student Performance-High	-2.085	0.977	0.124	-2.134 *
Problem Difficulty Hard× Student Performance-Medium	-1.716	1.367	0.180	-1.255
Problem Difficulty Hard× Student Performance-High	3.086	1.003	21.89	3.077 **

Note. The estimates for the raw coefficients in are logits. The exponentiated coefficients can be more directly interpreted in terms of odds, as the change in the relative risk of getting the problem part correct. The reference categories are: normal problem type, result unknown problem part, low-scoring student, easy problem.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 4

Performance differences for personalized problems compared to normal problems, for result unknowns

	Easy Problem	**Medium Problem**	**Hard Problem**
Low-Scoring Student	No significant effect	No significant effect	Personalization predicted to **increase** performance ($p < .01$) *(predicted increase from 2% to 28%)*
Medium-Scoring Student		No significant effect	No significant effect
High-Scoring Student	Personalization predicted to **decrease** performance ($p < .05$) *(predicted decrease from 96% to 73%)*	No significant effect	Personalization predicted to **increase** performance ($p < .05$) *(predicted increase from 59% to 90%)*

Table 5

Strategy Use for Result Unknown Problem Parts

	Normal Story Problem (N = 50)	Personalized Story Problem (N = 97)
Used arithmetic	86%	98%
Used symbolic equation	10%	2%
No response	4%	0%

Table 6

Prevalence of strategy use for start unknown problem parts, for normal and personalized problems

	Normal Story Problem (N = 20)	Personalized Story Problem (N = 47)
Forward-Driven	15%	42%
Unwind	55%	40%
Formal	10%	4%
Other	5%	11%
No Response	15%	2%

Table 7

Success rate when students use different strategies to solve start unknown problem parts

Start Unknown Strategy	**Overall Success Rate**
Forward-Driven (N = 23)	65%
Unwind (N = 30)	47%
Formal (N = 4)	75%

Table 8

Incidence of student forgetting to include intercept term, for normal and personalized problems

Problem Part	Normal (% Forgot Intercept)	Personalized (% Forgot Intercept)
Result Unknown	26% (*N* = 50)	11% (*N* = 97)
Start Unknown	25% (*N* = 20)	13% (*N* = 47)
Algebra Rule	17% (*N* = 23)	15% (*N* = 48)

Table A1

Linear functions underlying normal and personalized story problems given during sessions

Linear Function	**Special Factors of Ease/Difficulty**	**Difficulty Classification**
y = 20x	No intercept	Easy
y = (60/30)x	Unit conversion, no intercept	Easy
y = 12.95x	Decimal, no intercept	Easy
y = 10x - 500	Negative intercept	Easy
y = 2x+11	None	Medium
y = 0.25x	Percentage, no intercept	Medium
y = 4x+175	None	Medium
y = 80 – 6x	Negative slope	Medium
y = 15x+60	None	Hard
y = 1500x + 500	Large numbers	Hard
y = 1.25x + 2.5	Decimal	Hard
y = 0.23x – 7.87	Negative intercept, decimal	Hard
y = x – 0.25x + 10	Double reference unknown, percentage	Hard
y = -2.5x - 35	Negative slope and intercept, decimal *(omitted from performance analysis – no personalized versions)*	N/A

Figures

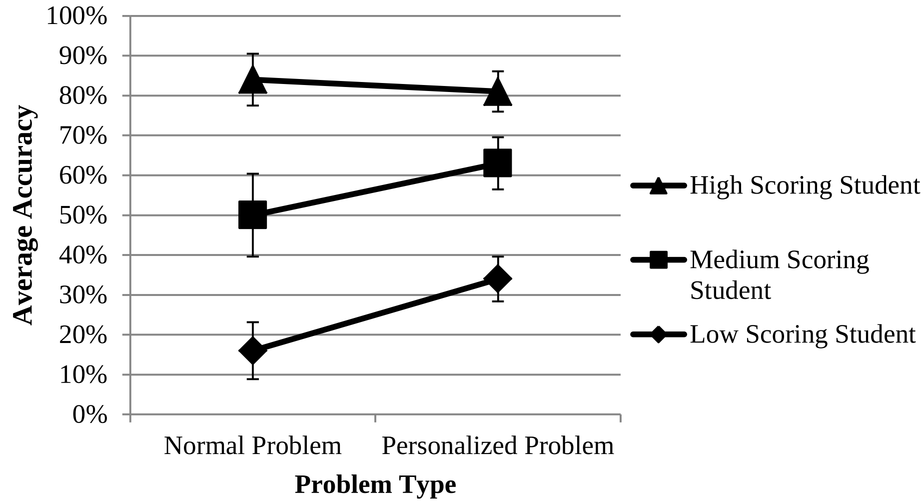

Figure 1. Average performance level (measured in percentage of correct answers) for normal and personalized problems, depending on whether student was classified as low-, medium-, and high-performing

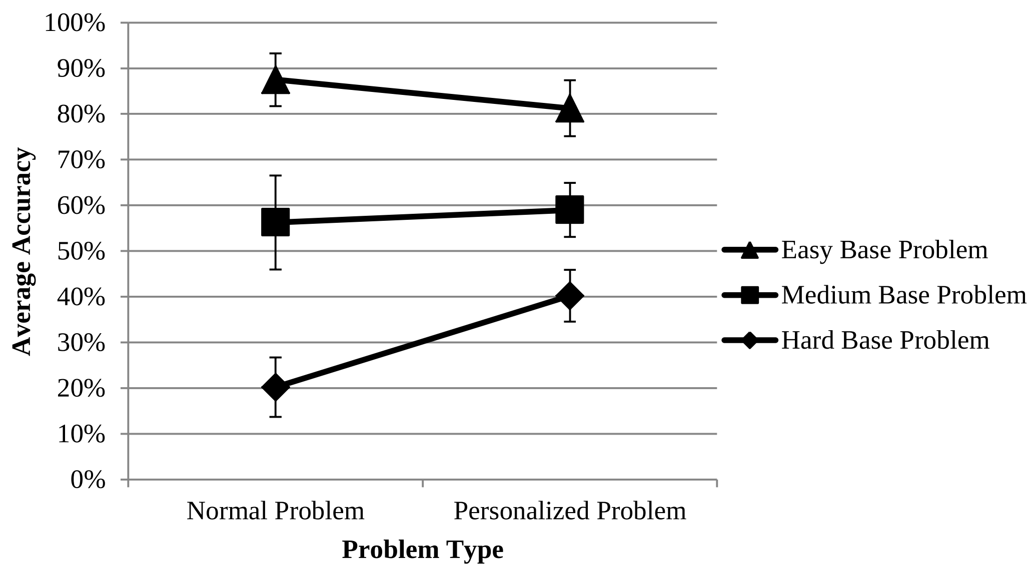

Figure 2. Average performance level (measured in percentage of correct answers) for normal and personalized problems, depending on whether problem was classified as easy, medium, or hard