conducted that isolate the effect of relevant contexts on student problem-solving, and that explore the mechanisms by which such relevance can support learning in challenging, abstract domains like algebra.

Theoretical Framework

One approach for placing instruction in contexts relevant to students' lives that is popular in computer-aided instruction is *context personalization*. In such interventions, instruction is adapted to individual students' lives and experiences, often using technology (Cordova & Lepper, 1996; Anand & Ross, 1987; Davis-Dorsey, Ross, & Morrison, 1991; Heilman et al., 2010; Reber et al., 2009).

Personalization is often hypothesized to support learning by increasing *individual* or *situational interest* (Ainley, Hidi, & Berndorff, 2002), which in turn mediate focus of attention (Durik & Harackiewicz, 2007; Hidi, 1995; McDaniel et al., 2000; Renninger & Wozniak, 1985). However, the mechanisms by which such attentional support may impact the learning of mathematics are unclear from previous research, as are the conditions under which personalization can be successful. Reading research has proposed that interest can elicit deep situational understanding (Schiefele, 1999; McDaniel et al., 2000) by supporting students' formation of *situation models* of text (Kintsch, 1986). Using case studies of three students solving personalized math problems, Renninger et al. (2002) suggest that interest may focus students' attention on story scenarios instead of keywords (which may promote *direct translation* approaches – Hegarty Mayer, & Monk, 1995), allowing learners to make connections between the story context and the mathematics content.

However, there are few personalization studies in mathematics that clearly show learning gains (Cordova & Lepper, 1996, is one exception), with some showing only immediate performance differences (Davis-Dorsey, Ross, & Morrison, 1991; Lopez & Sullivan, 1992) and others showing no differences (Bates & Weist, 2004; Caker & Simsek, 2010). In addition, the studies that have been conducted have all been within the domain of elementary school mathematics. Here, we investigate the impact of context personalization on student learning in algebra in terms of immediate performance and efficiency effects, as well as long-term learning and transfer effects. We seek to advance a theoretical understanding of how personalization is able to support learning in abstract domains like algebraic symbolization.

Methods

This paper reports on a study taking place during normal instruction as 145 ninth grade Algebra I students used the *Cognitive Tutor Algebra* software environment. Cognitive Tutor is an intelligent tutoring system where instruction is individualized through adaptive problem selection, hints, and error feedback (see Koedinger & Corbett, 2006 matched to their out-of-school interests obtained through a computer survey administered to both conditions. The personalized problems were written based on prior surveys (*N*=60) and interviews (*N*=29) with high school students. There were 27 story problems in the unit, and 4 variations on each problem were written to correspond to 9 different student interest categories (sports, music, etc.; see Table 1). For each problem, students were asked to fill in different cells of a table as they solved result and start unknowns (Figure 1). In result unknowns (questions 1-2, Figure 1), students solve for the y variable in a linear function given a specific x value - these are often solved by forward arithmetic calculation. For start unknowns (questions 3-4, Figure 1), students solve for the x variable given a y value, which may require working backwards. Students were also asked to write symbolic algebraic expressions.

Figure 1. Example of normal story problem scenario - upper text shows result and start unknown

in terms of correct answers and time measures. The level 1 unit of analysis was a student filling in one cell in Figure 1 (*N*=73,953), and level 2 random intercepts indicated which student was solving the problem part (*N*=145), which cover story was used (*N*=135), and which linear function (e.g., y = -1550-7x) was described in the scenario (*N*=27). Fixed effects included which condition the student was in (experimental or control) and which concept was being covered (e.g., solving start unknowns, result unknowns, writing expressions). We also used these models to examine student performance in the next expression-writing section, Unit 10, to see if performance differences held once the treatment was removed, indicating transfer. These models allowed for an examination of which students the treatment was most beneficial for, as well how performance was impacted on different mathematical concepts.

Thus measures more closely related to learning were also examined. An important issue with intelligent tutoring systems is that students sometimes “game the system” (Baker, Corbett, Koedinger, & Wagner, 2004) by entering answers quickly and repeatedly, or clicking through hints until given the answer. This may reflect an orientation towards immediate performance outcomes, rather than a focus on learning the underlying concepts. Using the *Cognitive Tutor Gaming Detector*

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