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Mathematics motivation and achievement as predictors of high school students' guessing and help-seeking with instructional software

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Abstract The study was conducted to investigate the relation of adolescent students' mathematics motivation and achievement to their appropriate help-seeking and inappropriate guessing behaviour while using instructional software. High school students ($n = 90$) completed brief assessments of mathematics motivation and then worked with software for geometry instruction. Students' actions with the software were machine-classified to identify instances of appropriate help-seeking and inappropriate guessing. Mathematics teachers provided information about students' achievement (high, average or at risk of failing math class). Results indicated that students with low math self-concept were most likely to engage in inappropriate guessing behaviour. Students with low math achievement were most likely to engage in appropriate help-seeking while working with the software.

Keywords interaction patterns with software, mathematics achievement, mathematics motivation, secondary education.

As computer-assisted learning becomes increasingly integrated into classrooms, interest is growing in how students interact with computer-based teaching systems (Beck 2005; Nguyen & Kulm 2005). In particular, researchers who create instructional software for mathematics have recognized for some time that adolescent students do not always use such systems effectively (Wood & Wood 1999). For example, instructional software for math usually incorporates multimedia features that will help the student learn the material, such as hints, interactive dialogues, videos, worked examples and online feedback. However, some students guess rather than to take advantage of the features to learn how to solve the problem (Baker *et al*. 2004; Murray & Van Lehn 2005; Walonski & Heffernan 2006a). For example, students may rapidly view all the help resources in turn until the final hint or correct answer is revealed, without attending to the intervening explanations (Arroyo & Woolf 2005). Not all such 'gaming-the-system' behaviour by students is associated with poor learning outcomes (Baker *et al*. 2005). However, students who guess are not likely to benefit as much from the resources provided by computer-based instruction as students who use the features more effectively.

Researchers and developers have responded to students' inappropriate guessing by adding software features to detect such behaviour and to try to divert students into more productive interactions. For example, Baker and his colleagues designed a system in which students viewed an animated cartoon character that appeared angry if gaming was detected, and then directed the student to additional exercises on the math material (Baker *et al*. 2006). This feature led to reduced levels of gaming overall, and improved learning outcomes for some students. A similar approach was explored in Walonski and Heffernan (2006b) and

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Arroyo *et al*. (2007), who created displays to show students their rates of gaming behaviour while using instructional software for mathematics. The results indicated that the feedback display led to reduced levels of guessing behaviour.

Other researchers have targeted students' metacognitive skills, training them to think explicitly about the appropriate use of help resources while working with instructional software (Aleven & Koedinger 2000). In a study by Murray and Van Lehn (2005), the student was encouraged to use the software help features only when he or she really needed assistance with a particular math problem. In addition, a brief delay was imposed between the student's request for and the system's provision of multimedia help. This intervention led to reduced guessing and, in turn, to improved learning outcomes for some students. Aleven *et al*. (2006) trained students to request a hint if they were not sure how to solve a math problem, rather than to guess. An evaluation study indicated that the training was associated with better knowledge of good help-seeking strategies, although the impact on math learning outcomes was less clear (Roll *et al*. 2007).

One question raised by these studies is whether interventions might be more effective if targeted specifically to the students who are most likely to engage in guessing behaviours while working with software. The present study was therefore designed to investigate student characteristics that might be related to inappropriate guessing and appropriate help-seeking. One possibility is that students' actions reflect their understanding of the material. More specifically, a student might guess on math problems because he or she does not know how to solve the problems correctly. If this view is correct, then rates of guessing should be highest for students with lowest achievement in math.

An alternative possibility is that students with low achievement might be most likely to seek assistance from the software, by accessing integrated multimedia resources such as worked examples, interactive training and instructional videos to learn the material. It seems reasonable to predict that struggling students who do not understand how to solve a math problem might be most likely to view the integrated instructional resources to learn the solution. However, no studies to date have examined the relation of prior achievement to inappropriate guessing or appropriate help-seeking behaviour. Thus, one goal of the present research was to investigate the role of students' math achievement in their behaviour with instructional software allowing them to guess or to learn the solutions by viewing multimedia explanations.

A second goal of the research was to investigate the possibility that students' mathematics motivation might also influence their behaviour with instructional software (Stoney & Wild 1998). More specifically, the expectancy-value theory of mathematics motivation holds that students' beliefs about their ability in math and the importance that they place on learning math are strong influences on learning behaviours such as persistence with challenging material and appropriate help-seeking from teachers and peers (Eccles *et al*. 1993; Pajares 1996; Wigfield & Eccles 2000; Leder *et al*. 2002; Newman 2002; McCormick 2004; Schunk 2004; Ryan *et al*. 2005). Students' math self-concept beliefs have been shown to be especially strong influences on studying behaviours such as help-seeking (Zimmerman & Martinez-Pons 1986; Leder *et al*. 2002). This research suggests the possibility that some students might guess rather than seek help from instructional software because they doubt their ability to learn challenging material even with assistance. However, no studies to date have examined the relation of students' math self-concept and inappropriate guessing with software. Therefore, the present study included assessments of students' math self-concept, as well as information about their math achievement in the classroom.

Method

Participants

The participants were students in four geometry classes in three high schools located in a large California city. Complete data records were available for 90 students (42 boys, 48 girls).

Materials and instruments

Instructional software

Participating students worked with 'Wayang Outpost', an online tutoring system for geometry problem solving (Beal *et al*. 2007). In the present study, students used a Wayang Outpost module that provided tutoring in Scholastic Aptitude Test (SAT) math problems involving geometry skills such as finding the perimeter of a

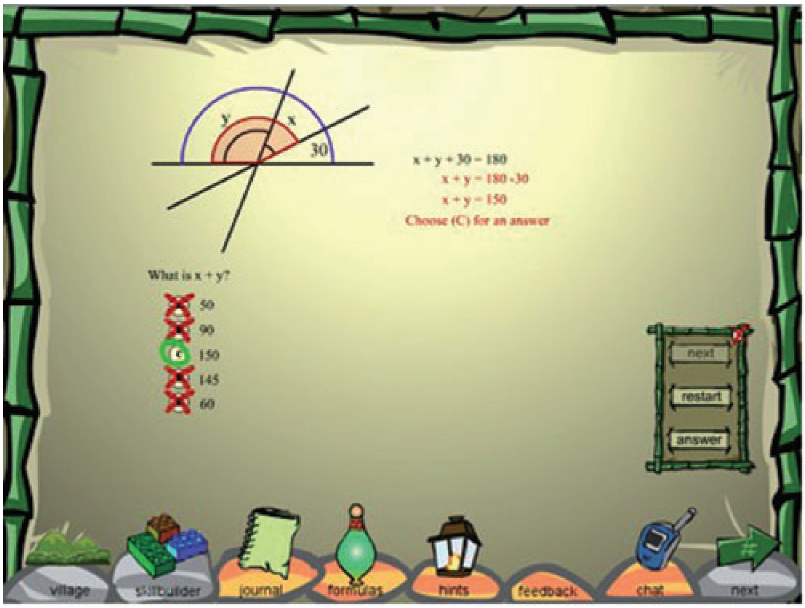

Fig 1 Wayang Outpost screen shot showing SAT-Math problem with accompanying multimedia hint leading to answer (some hint components are audio) and student guessing (all answer options rapidly clicked until correct answer is indicated).

Table 1. Software interaction pattern classification rules and definitions.

Interaction pattern classification	Definition
Solve	Problem available for at least 10 s before student chooses correct answer; no interactive help is viewed.
Solve-errors	Problem available for 10+ seconds before student selects answer; first answer incorrect; at least 10 s before next answer selected; no interactive help viewed
Learn	Problem available for 10+ seconds before first action; interaction with at least one multimedia hint for 10+ seconds before correct answer selected
Guess	Problem presented for under 10 s before answer selected; inter-click intervals on answers less than 10 s; no interactive help requested
Skip	Student does not select answer to current problem; requests new problem

complex figure, identifying angles and describing polygons. Each math problem showed a figure, table or other graphic, the problem or equation to be solved, and five answer options. Students could click on one or more answer options and receive immediate feedback (correct, incorrect). Students could also view a sequence of interactive hints leading to the solution for a problem by clicking the ‘help’ icon. Each ‘help’ click produced a step in the solution path illustrated on the screen, culminating in the answer. Students could view as many of the hints as they chose, or could choose an answer for the problem at any point. A screen shot is shown in Fig 1.

For each math problem completed, the Wayang Outpost software automatically records the number of answer attempts, the number of multimedia hints viewed, and the latencies between actions. Action and latency data for each problem are machine-classified into one of five action patterns: *Solve*, *Solve-errors*, *Learn*, *Guess* or *Skip* (Beal *et al*. 2006). Table 1 shows the action patterns and definition rules used in the classifier. Each student received proportion scores representing the number of problems machine-classified into each of the five patterns, relative to the total number of problems completed.

Math achievement

Math teachers were asked to rate each student’s math achievement (defined in terms of performance on homework, in-class assignments and tests) into one of three categories: (1) high: student is performing above grade-level expectations; (2) average: performance meets grade-level expectations and student will pass the class; or (3) low: student is failing or at risk of failing the class. All teachers had more than 10 years of experience, and reported no difficulty in completing the checklist for their students.

Teachers rated 22 (25%) of the students as high-achievers, 30 (33%) as average-achievers, and 38 (42%) as low achievers. Validity of the teachers' ratings was established through comparison with the proportion of Wayang Outpost problems that each student solved correctly without using multimedia help or making errors (problems machine-classified as *Solve*). An ANOVA was conducted with achievement (high, average, low) as the grouping factor and *Solve* scores as the dependent measure. The results indicated that there was a significant effect of achievement, $F(2,87) = 13.067$, $P < 0.01$. Multiple comparisons (Tukey's HSD tests with $\alpha = 0.05$) indicated that students with high ($M = 0.46$, $SD = 0.20$) and average achievement ($M = 0.36$, $SD = 0.23$) had higher *Solve* scores than students with low achievement ($M = 0.19$, $SD = 0.18$).

A similar analysis with achievement as the grouping factor and *Solve-errors* scores as the outcome measure also revealed an effect of achievement, $F(2,87) = 3.277$, $P < 0.05$. Students rated by teachers as high in achievement made fewer errors ($M = 0.14$, $SD = 0.12$) than students rated as average ($M = 0.22$, $SD = 0.16$) or low ($M = 0.24$, $SD = 0.16$). Thus, teachers' ratings were consistent with students' problem solving while working with the software.

Mathematics motivation

Students' mathematics motivation was assessed with an online self-report instrument based on the paper-and-pencil survey developed and validated by Eccles and colleagues within the expectancy-value framework of mathematics motivation (Eccles *et al*. 1993). The survey included 10 questions in all. Six questions were associated with the math self concept component of the expectancy-value framework, including two questions each for *math self-efficacy*, *perception of math difficulty* and *expected success in math*. Four additional questions were associated with the math value component, including two questions each for *perceived relevance of math* and for *attraction to math*. Students clicked on a five-part Likert-type rating scale to respond to each item.

In prior work, individual item reliabilities (Cronbach's alpha) ranged between 0.86–0.88 (Beal *et al*. 2006). In the present study, responses were automatically averaged by the software for the two questions associated with each construct (e.g. one score for *math self-efficacy* based on the average of two items). Overall item reliability (Cronbach's alpha) was 0.79 (*self-efficacy* 0.71, *math difficulty* 0.81, *expected success* 0.74, *relevance of math* 0.80, *attraction to math* 0.69). The survey items and response options are included in the online supplementary materials.

A principal components approach was used to reduce the *self-efficacy*, *expected success*, *perception of math difficulty*, *attraction of math* and *relevance of math* response data in preparation for analyses related to the research questions. The results indicated that the first principal component accounted for 57% of the variance with eigenvalue = 2.26. This component appeared to capture the math self-concept factor (*math self-concept*, *perception of math difficulty*, *expected success in math*). Values for the first principal component were saved for each student for use in subsequent analyses. Eigenvalues for additional components, i.e. math value, were less than 1 and were not considered further (Kaiser 1960; Kendall 1980).

Two strategies were used to evaluate the validity of students' self-reports of math self-concept. First, math teachers were asked to rate each student's apparent motivation, using a three-level checklist attached to the class roster (Ryan *et al*. 2005). The levels were (1) high: student regularly attends class with the textbook in hand, completes all assignments, appears attentive and asks questions about the material, and expresses the goal of doing well in the class; (2) average: student completes most assignments, usually has the textbook and materials, attends class fairly regularly and seems moderately interested in passing the class; and (3) low: student frequently fails to turn in homework, does not take notes or ask questions in class, misses classes without excuses and expresses a lack of interest in math and in his or her grade. A one-way ANOVA with teachers' ratings as the grouping factor, and math self-concept scores as the outcome measure showed a main effect of teachers' ratings, $F(2,87) = 10.867$, $P < 0.001$. Tukey's HSD *post hoc* comparisons indicated that students who were rated by teachers as showing high motivation in class had higher math self-concept scores than students

Table 2. Mean proportion of machine-classified problem-solving action patterns for students rated by teachers as high, average and low in math achievement. Standard deviations in parentheses.

	Achievement group				
	High (H) ($n = 22$)	Average (A) ($n = 30$)	Low (L) ($n = 38$)	$F(2,87)$	Multiple comparisons[1]
Learn	0.21 (0.18)	0.15 (0.12)	0.27 (0.21)	3.383*	H, L > A
Guess	0.12 (0.13)	0.18 (0.20)	0.22 (0.18)	2.173	H = L = A

[1]Significant at a 0.05 level, Tukey's HSD tests.
*$P < 0.05$.

who were rated by teachers as average or low in motivation.

Second, prior work indicates that students' math self-concept varies with math achievement (Leder *et al*. 2002). Here, a one-way ANOVA with math achievement (high, average, low) as the grouping factor and students' math self-concept scores as the outcome measure showed that students who were performing very well in math had higher math self-concept scores than students who were meeting grade-level expectations, who in turn had higher self-concept scores than students who were at risk of failing their math class, $F(2,87) = 18.253$, $P < 0.001$. Thus, students' self-reports of their math motivation were consistent with the perceptions of their classroom teachers, and with their actual performance in math class.

Procedure

Students came to their school computer lab for two 50-min math class periods under the supervision of their math teacher. On the first day, they were provided with user names and passwords and directed to the Wayang Outpost website. Students logged in, completed the survey of math motivation, and then entered the tutoring module of the website and worked on math problems for the rest of the class period. Students returned a second day and worked on additional problems. Behavioural data were automatically recorded by the software and then machine-classified to produce five interaction pattern proportion scores for each student (*Solve*, *Solve-errors*, *Learn*, *Guess*, *Skip*). Skipping rates were very low (under 1%) and are not considered here. Primary analyses focus on instances of inappropriate guessing (*Guess* scores) and appropriate help-seeking (*Learn* scores).

Results

The first research question was to learn if students' achievement in math was related to instances of inappropriate guessing and appropriate help-seeking. A one-way ANOVA with students' math achievement (high, average, low) as the grouping factor and the proportion of math problems machine-classified as *Guess* as the outcome measure indicated that the effect of achievement was not significant. Mean scores are shown in Table 2.

A similar ANOVA was conducted with mathematics achievement (high, average, low) as the grouping factor and problems classified by the software as indicating effective use of multimedia help (*Learn*) as the dependent measure. There was a significant effect of math achievement, $F(2,87) = 3.38$, $P < 0.005$. *Post hoc* comparisons (Tukey's HSD tests, $\alpha = 0.5$) indicated that both low-achieving and high-achieving students had significantly higher *Learn* scores than students with average achievement. Mean scores are included in Table 2.

The second research question focused on the possible relation of math self-concept with guessing and appropriate help-seeking, as suggested by prior work on expectancy-value theory (Eccles *et al*. 1993). Students' math self-concept scores were significantly correlated with the proportion of math problems that were classified by the software as *Guess*, 0.36, $P < 0.001$. However, students' math self-concept scores were not correlated with their *Learn* scores.

Because students' math self-concept scores varied with math achievement, we also explored the relative contribution of these factors to inappropriate guessing and appropriate help-seeking. Students' achievement level (high, average, low) and their math self-concept scores were entered in a standard least squares regression model to predict GUESS scores. The results indicated that the overall model was significant, $r^2 = 0.134$, $F(3,86) = 4.455$, $P < 0.01$. The independent effect of math self-concept was also significant, $F(1,85) = 8.638$, $P < 0.01$. Solving for power indicated a value of 0.82 ($\alpha = 0.05$). The math achievement factor did not account for significant variance in *Guess* scores.

Students' math self-concept scores and math achievement ratings were also entered into a standard least squares regression model to predict their *Learn* scores. However, the overall model was not significant, $F(3,89) = 2.35$, $P = 0.077$, $r^2 = 0.759$. Rates of appropriate help-seeking were relatively low overall, possibly making it difficult to evaluate the independent contributions of self concept and achievement.

General discussion

The present study was conducted to investigate the relation of math achievement and math motivation to inappropriate guessing and appropriate help-seeking with instructional software. Mathematics teachers provided ratings of the students as high, average or low in math achievement. Students completed a self-report survey designed to assess two components of mathematics motivation defined by expectancy value theory: math self-concept beliefs, and beliefs that math is important to learn. Students then worked with software that provided multimedia instruction in geometry problem solving, with instances of inappropriate guessing and appropriate use of the integrated multimedia help resources automatically classified by the software.

The first research question was whether students' math achievement was related to inappropriate guessing and appropriate help-seeking while working with instructional software. The results showed that guessing rates did not vary with math achievement. However, math achievement was significantly related to students' appropriate help-seeking from the instructional resources in the software. Interestingly, the low-achieving students engaged in as much appropriate help-seeking behaviour (27%) as the high-achieving students (21%), whereas students with average achievement had the lowest rates of help-seeking (15%). Prior work suggests that students who are performing poorly in math tend to avoid seeking help in a traditional classroom setting, possibly out of embarrassment at not understanding the material (Newman 2002; Turner *et al*. 2002). The present results provide an initial demonstration that low-achieving students may be willing to seek instructional help from the computer, whereas they may often be reluctant to do so from a peer or teacher in the classroom (Ryan *et al*. 2005).

The second research question was whether students' behaviour with instructional software might also be related to their mathematics self-concept. The results indicated that students who did not feel confident in their math ability, did not expect to do very well in math, and reported that math was difficult were more likely to guess while working with the software than students who held more positive beliefs about their ability in math. Previous work has shown a strong relation between mathematics self-concept and students' learning behaviours in traditional classroom settings (Leder *et al*. 2002). The present results also demonstrate this relation in the context of computer-assisted instruction.

To summarize, the results demonstrated that students' math achievement was related to their appropriate help-seeking from software, whereas math self-concept was related to inappropriate guessing behaviour. Conclusions from the study are limited by the relatively brief assessments of mathematics self-concept and achievement, necessitated by math teachers' reluctance to give up instructional time for the research. Even so, the findings suggest that brief assessments of math self-concept could be used to identify the students who may be most likely to guess while working with software. Interventions that are integrated into software with the goal of detecting and reducing guessing might be especially helpful when directed specifically to these students (Walonski & Heffernan, 2006b; Roll *et al*. 2007). Such interventions might also directly address students' poor math self-concept beliefs, for example, by indicating that successful students do well because they take advantage of instructional resources and avoid guessing, and suggesting that the student who doubts his or her ability can succeed by adopting similar behaviours.

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Supplementary Material

The following supplementary material is available for this article online:

Table S1. Items and response options for mathematics motivation survey

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