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Helping students help themselves: Generative learning strategies improve middle school students' self-regulation in a cognitive tutor

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A B S T R A C T

The current study investigated whether prompting students to engage in generative learning strategies improves students' subsequent judgments of learning and self-regulation. Seventy-eight middle school students in a pre-algebra class completed worksheets in between problem-solving sessions in a computer-based cognitive tutor. Some students were prompted to engage in a generative learning strategy (i.e., writing a summary or writing an explanation for a peer) followed by a judgment of learning (generative group), whereas other students were only asked to make a judgment of learning (control group). Results indicated non-significant levels of judgment accuracy in both groups; however, students in the generative group showed better-calibrated help-seeking behaviors when solving subsequent problems in the tutor. These results suggest that self-regulation can improve in the absence of accurate learning judgments, and that generative learning strategies can facilitate such an improvement. This may be especially true for younger students, who generally demonstrate lower metacognitive awareness.

1. Introduction

The ability to make accurate metacognitive judgments, including judgments of one's own understanding, is a critical skill for effective self-regulation and learning (Dunlosky & Hertzog, 1998; Son & Metcalfe, 2000; Thiede, Anderson, & Therriault, 2003). Unfortunately, students' judgments of their own comprehension are often inaccurate (Dunlosky & Lipko, 2007; Lin & Zabrucky, 1998), especially in younger students (Brown, 1978). These inaccurate judgments likely contribute to suboptimal self-regulated learning behaviors (i.e., selecting, implementing, and evaluating strategies for learning) and poor learning outcomes. Thus, it is important to develop instructional methods that improve students' metacognitive calibration (i.e., judgment accuracy) and self-regulation (e.g., help seeking).

One promising approach to improve metacognitive calibration and learning outcomes is to prompt students to engage in generative learning strategies before making a knowledge judgment. Generative learning strategies encourage students to actively make sense of the material by reorganizing it and fitting it with their existing knowledge (Fiorella & Mayer, 2015; Fiorella & Mayer in press; Wittrock, 1990). There is a large research base indicating that generative learning strategies such as summarizing, self-explaining, and self-testing can be used to improve learning outcomes (Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013; Fiorella & Mayer, 2015, in press). Further, a variety of generative strategies have been shown to increase metacomprehension accuracy (i.e., judgments about comprehension), including summarizing (Thiede & Anderson, 2003), generating key words (Thiede et al., 2003), making concept maps (Redford, Thiede, Wiley, & Griffin, 2012), and practicing completion problems (Mihalca, Mengelkamp, Schnotz, & Paas, 2015). The current study extends this research by testing the effects of generative learning strategies on judgments of learning, as well as subsequent self-regulation behavior.

The effect of generative strategies on metacomprehension accuracy is usually explained by *cue validity* theory (Koriat, 1997; Thiede, Griffin, Wiley, & Anderson, 2010). Cue validity theory posits that individuals will make accurate learning judgments to the extent that they have valid cues (i.e., cues related to their true level of comprehension) on which to base their judgments. Therefore, generative learning strategies may improve metacomprehension accuracy because they help learners access and utilize valid cues as a basis for comprehension judgments (Thiede et al., 2010).

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In line with cue validity theory, standard models of the relationship between metacognition and learning in authentic learning situations (e.g., academic learning) generally contain four main steps, as indicated by Fig. 1. The basic schematic is as follows: cue utilization leads to metacognitive judgments, which in turn lead to self-regulation, which in turn leads to learning outcomes. Many studies of metacognitive calibration manipulate the cues participants access, such as by having them engage in a generative strategy (Step 1), and measure metacognitive judgments via self-report judgments of learning (Step 2). These studies are often conducted under the theoretical assumption that metacognitive judgments predict later self-regulation (Step 3), and further, that self-regulation predicts learning outcomes (Step 4). Some empirical work supports such inferences (e.g., Thiede et al., 2003; Thomas & McDaniel, 2007); however, studies that explicitly establish the connections between more than two of these steps are uncommon in the literature, especially with children as the population of interest.

Children demonstrate especially poor metacognitive awareness (Brown, 1978). For example, in one experiment with seventh graders, students in a control condition demonstrated metacognitive calibration that was marginally negative, while students who created concept maps (a generative strategy) demonstrated metacognitive calibration that was positive but not significantly different from zero (Redford et al., 2012, Exp. 1). In other words, using a generative strategy took students from being systematically wrong in their learning judgments to generating learning judgments with no relationship to their performance—technically, a significant improvement. Needless to say, there is much room for improvement in promoting metacognitive awareness in younger students.

Further, studies relying solely on self-report learning judgments may underestimate younger children's actual metacognitive awareness. Metacognitive judgments are typically measured by self-report judgments of learning, such as by rating one's understanding on a 10-point scale (Pilegard & Mayer, 2015a). Younger students may have difficulty translating internal metacognitive judgments into self-reported ratings. Measuring other indicators of metacognitive awareness, such as self-regulation, can offer a more comprehensive understanding of students' metacognitive abilities.

1.1. Current study and predictions

The current study tested the effects of asking students to engage in generative learning strategies on subsequent judgments of learning and self-regulation behavior. Middle school pre-algebra students completed a unit on converting fractions, decimals, and percents within a computer-based cognitive tutor. In between sections of the unit, students were asked to complete worksheets that either asked students to make a judgment of learning (control group), or to engage in a generative learning strategy and then make a judgment of learning (generative group). Students assigned to the generative group either wrote a summary of the material they learned from the tutor (generative summary group) or wrote an explanation to teach a peer the material (generative explanation group)—two learning strategies that are generally supported by previous empirical research (e.g., Doctorow, Wittrock, & Marks, 1978; Fiorella & Mayer, 2013, 2014; Wittrock & Alesandrini, 1990). The primary aim of this study was to test the prediction that generative learning strategies would lead to better-calibrated judgments of learning (based on performance during the preceding section in the tutor), and ultimately to better self-regulated learning behaviors (based on help-seeking behaviors during the following section in the tutor; Aleven, Stahl, Schworm, Fischer, & Wallace, 2003; Newman, 1994).

2. Method

2.1. Participants and design

Participants were 78 students at a middle school located near Pittsburgh, PA. Participants were enrolled in one of seven Bridge to Algebra Cognitive Tutor classes with one of three different teachers. Bridge to Algebra is a pre-algebra class that focuses on requisite knowledge needed for later algebra classes, such as learning to converting between fractions, decimals, and percents. Cognitive Tutor classes involve a mix of traditional instruction (i.e., standard lessons and problem-solving) and computer-based cognitive tutor instruction (i.e., solving problems while receiving targeted hints and feedback). Participants were randomly assigned to the generative summary group, the generative explanation group, or the control group. Fifty students served in the generative condition (25 in the generative summary group and 25 in the generative explanation group) and 28 students served in the control condition. Although specific demographics data is unavailable, all students were sampled from the same course level (i.e, pre-algebra) and random assignment took place on an individual basis across the different classes and teachers.

2.2. Materials

2.2.1. Cognitive tutor

The cognitive tutor is an individually paced, intelligent tutoring system that provides step-by-step feedback, allows students to seek help (i.e., by asking for hints), and logs student behavior at a fine-grained level (see Ritter, Anderson, Koedinger, & Corbett, 2007). The current study took place during Unit 17 of the Bridge to Algebra Cognitive Tutor, entitled "Fraction, Decimal, and Percent Conversions." This unit consists of 5 sections. Sections 1 and 2 focus on converting between fractions, decimals, and percents into each other. Section 3 focuses on converting fractions, decimals, percents, improper fractions, and mixed numbers into each other. Sections 4 and 5, which are the focus of our analyses, focus on converting fractions, decimals, percents, decimal percents and fractional percents into each other. Specifically, the subject of Section 4 is *Converting with Percents Less than 1* (sample question: "Enter the number 0.03% as a percent written with a decimal, a percent written with a fraction, a decimal, and a fraction."). The subject of

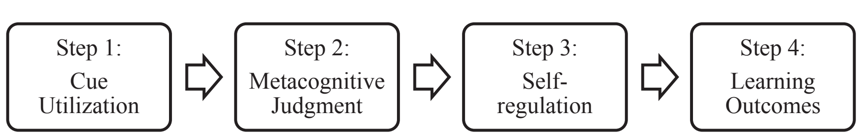

Fig. 1. Schematic of metacognition and learning, including inferred causal relationship between cue utilization, metacognitive judgments, self-regulation, and learning outcomes. While reciprocal relationships are likely to exist between these steps (Butler & Winne, 1995; Dunlosky & Hertzog, 1998; Zimmerman, 2002), this simplified schematic demonstrates the standard inferential logic in metacognition research.