Improving self-regulation, learning strategy use, and achievement with metacognitive feedback

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Published online: 24 February 2010
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Abstract Comprehension of science topics occurs when learners meaningfully generate relationships and conceptions about what they read. In this generation process, learners’ cognitive and metacognitive regulation is one of the most critical factors influencing learning. However, learners are not always successful in regulating their own learning, especially in computer-based learning environments (CBLEs) where they are alone. Based on this rationale, the present study was designed to examine the effects of two scaffolding strategies—generative learning strategy prompts and metacognitive feedback—on learners’ comprehension and self-regulation while learning the human heart system in a CBLE. Participants were 223 undergraduate student volunteers. Structural Equation Modeling (SEM) was employed to conceptualize and empirically test a model that explains mediating processes among variables. Results revealed that the combination of generative learning strategy prompts with metacognitive feedback improved learners’ recall and comprehension by enhancing learners’ self-regulation and better use of highlighting and summarizing as generative learning strategies.

Keywords Generative learning strategy · Self-regulation · Metacognitive feedback · Structural Equation Modeling (SEM)
Introduction

Are scaffolds necessary to help learners comprehend complex science topics in computer-based learning environments (CBLEs)? If so, what kinds of scaffolds are necessary? To answer these questions, insights were drawn from generative learning theory. According to generative learning theory, to comprehend a complex topic, learners need to “...selectively attend to events and generate meaning for events by constructing relations between new or incoming information and previously acquired information, conceptions, and background knowledge” (Wittrock 1992, p. 532).

The essence of this theory is that learners need to make their own meaning by integrating new information with current existing knowledge (Grabowski 2004). In this regard, learning strategies that learners choose to use should result in the actual creation of personally meaningful relationships and meaning. Learning strategies employed in the name of generative learning are simple coding strategies such as underlining, note taking, and adjunct questions; complex coding strategies such as creating hierarchies and headings, summarizing and concept mapping; and elaborative integration strategies such as imaging and creating examples, interpretation, or analogies (Doctorow et al. 1978; Rickards 1979; Rickards and August 1975; Wittrock 1990; Wittrock and Carter 1975). Although both learning theory and many studies support the effectiveness of these generative learning strategies (Barnett et al. 1981; Davis and Hult 1997; King 1992; Rickards and August 1975; Shrager and Mayer 1989), the effects are not always consistent in every learning environment.

Problems with computer-based learning environments

Computer-based learning environments such as hypermedia and web-based instruction, have been widely used with high expectation of enhancing students’ understanding of complex and challenging topics, because rich resources and various learning strategies can be incorporated easily. In CBLEs, learners are assumed to be active participants in the learning processes and have the potential to regulate their own learning. However, research has shown that learners are not always successful controlling their own learning in CBLEs. Consequently, the prediction that the use of hypermedia will lead to significant learning gains has inconsistent support (Azevedo et al. 2004a, b; Dabbach and Kitsantas 2005). Characteristics of CBLEs, such as freedom of navigation or sequencing of instruction, may be interfering with rather than supporting the learners’ learning processes (Hmelo-Silver and Azevedo 2006; Winne et al. 2006).

Scaffolds in computer-based learning environments

So, how can learners be supported while learning in CBLEs? The answer to this question may be found from examining one key assumption of generative learning theory—learners need to control their learning process. Thus, learners’ self-regulation, especially cognitive and metacognitive control, is critical for knowledge generation. Learners must be accountable and responsible for how they generate their own knowledge (Barab et al. 1999; Wittrock 1991). Cognitive control refers to how learners regulate the use of cognitive strategies to accomplish learning goals; metacognitive control refers to how learners monitor and modify their cognitive strategies in order to make any adaptive changes while they are learning (Schunk 1996; Zimmerman 2000). Therefore, support and guidance to improve learners’ cognitive and metacognitive control in CBLEs may be necessary. Two
questions arise regarding support and guidance: What should support and guidance help learners do? And, how should support and guidance be given to learners?

First, considering the generative learning processes, learners should selectively attend to events, meaningfully generate their own knowledge, and monitor the knowledge they have generated. By underlining or highlighting, learners select relevant information and integrate the information with their own preconceptions (e.g., Rickards and August 1975). Learners, also, can create headings, organizations, or summaries (e.g., Peper and Mayer 1986). Adjunct questions provide learners with a opportunity to review their learning and create personally meaningful understanding (e.g., Anderson and Biddle 1975). Thus, support and guidance can assist learners in their use of these learning strategies, which help them to selectively attend to events and create meaningful understanding from the events.

Second, this facilitation may be accomplished by prompting learners to use generative learning strategy tools more frequently. For example, asking learners to highlight important sentences, summarize their understandings, or respond to given adjunct questions may be suggestive enough to increase their use of these learning strategies.

Third, simple prompting may be sufficient to motivate learners to use the generative learning strategy, but fail to help them monitor, be aware of, or adjust their learning processes according to how well they are learning from the chosen learning strategy (Azevedo and Cromley 2004; Kramarski and Mevarech 2003; Shapiro 2008). Thus, one potential solution is to provide metacognitive feedback about which cognitive strategies to use and how to use them (Butler and Winne 1995; Winne 1997; Wittrock 1992). Metacognitive feedback is the communication that makes a learner conscious of the learning strategies being used and their degree of success. Metacognitive feedback can remind learners to assess the suitability of cognitive strategies employed to continue or change their strategy use (Jacobs and Dempsey 1993; Narciss 2008).

Several studies investigated the effect of metacognitive feedback that used self-questioning or prompting. Mevarech and Fridkin (2006) examined the effects of self questions on students’ mathematical knowledge, mathematical reasoning, and metacognition. The study included four types of self questions: comprehension questions (e.g., What is the problem all about?), connection questions (e.g., What are the similarities and differences between the given problem and problems you have solved in the past, and why?), strategic questions (e.g., What strategies are appropriate for solving the problem, and why?), and reflection questions (e.g., What am I doing here?). Learners using self questions significantly outperformed the students who were not using them on mathematical knowledge and reasoning tests and metacognition. Kramarski and Gutman (2006) also tested the effectiveness of self questioning on metacognition. They found that students prompted to self-question on metacognition in e-learning environments achieved significantly more and used significantly more self-monitoring strategies than students who were not.

Veenman et al. (1994) examined the effect of metacognitive prompts on the use of learning strategy, learning performance, and the interaction effect between metacognitive prompts and learners’ intelligence. Using think-aloud protocols, they found that metacognitive prompts, which prompted learners to paraphrase the question, generate a hypothesis, or evaluate outcomes, increased the occurrence and improved the quality of orientation strategies, systematic orderliness, and evaluation learning strategies. Accordingly, metacognitive prompts enhanced learning performance. Kauffman (2004) tested the effects of self-monitoring prompts in his investigation of students’ use of self-regulated learning strategies in a web-based setting. The students who received self-monitoring prompts, which prompted students to post a confidence judgment about the completeness of their learning, had higher achievement than the control group.
In sum, learners’ cognitive and metacognitive regulation is a critical process in knowledge generation. Theoretically, learners are assumed to be active participants in the learning process and they have the potential to monitor, control, and regulate their own cognition. However, this does not mean learners will or can accomplish this regulatory process in all contexts or at all times. Therefore, scaffolds, which support and guide learner’s self-regulatory process, are necessary. There is empirical evidence for providing learning strategy prompts and metacognitive feedback to increase the frequency and quality of using those learning strategies.

Conceptual framework and hypothesis

Based on a theoretical understanding and empirical research, a generative learning conceptual framework was created and is shown in Fig. 1.

Learners’ generative activities help them create relationships among or between new information and their prior knowledge. In the process of integrating new and existing knowledge, learners self-regulate and control their generative activities (Lee et al. 2008; Wittrock 1974, 1990, 1991, 1992). In addition to the well-studied processes as represented by solid lines in Fig. 1, two proposed, hypothesized mechanisms are represented by dotted lines. First, it was hypothesized that generative learning strategy prompts and metacognitive feedback would enhance learners’ regulation of their learning, and accordingly, improve their use of generative strategies. Second, we predicted that as learners’ use of generative strategies improves, their knowledge generation would also improve due to actively creating meaning while learning.

Based on the conceptual understanding provided in Fig. 1, we focused the study on answering two primary research questions: (1) Do generative learning strategy prompts or generative learning strategy prompts with metacognitive feedback positively affect learners’ self-regulation, the quality of overt use of generative learning strategies, and learning performance? (2) If, the answer to the first question is yes, do those treatments

Fig. 1 Generative learning conceptual framework
indirectly affect learners’ learning performance through their self-regulation and the quality of overt use of generative learning strategies?

Method

Participants

Participants in this study were 261 undergraduate students recruited in the spring, 2008 from two general education courses in a large land grant university in northeastern United States. Participation was voluntary and they received extra points from their instructors. Of the participants, 238 of 261 completed all parts of the study. The participants were freshmen through seniors enrolled in a variety of majors from throughout the campus. The majority (n = 177) were female. Among the 238 participants, 15 failed to complete all items on the measurement instruments. Little’s Missing at Completely Random (MCAR) test examined the pattern of the missing data (Cohen et al. 2003). The test indicated that the nature of the missing data was random (χ² = 237.855; df = 235; p = .811). Listwise deletion of missing data resulted in 15 incomplete data points being eliminated from further analysis. The final data set for analysis represented 223 students (94% of the original sample).

Instructional materials

Paper-based text materials, developed by Dwyer and Lamberski (1977) about the human heart, were adapted for this study. The original script for the instructional content about the human heart contained approximately 1,800 words divided into three sections: the parts of the heart, the circulation of blood, and the cycle of blood pressure. These were converted into self-paced computer-based instruction consisting of 20 screens developed using Adobe Acrobat 8.0 Professional® interactive form fields with static graphics.

Treatments

Treatment 1: static visualized instruction with generative learning strategy tools

This treatment was used as the control condition. The materials for it consisted of one page of introduction and 20 pages of PDF screens with instructional content on the left and corresponding graphics on the right. Two navigational buttons, “previous” and “next,” appeared at the bottom of each screen. Participants were allowed to navigate at a self-regulated pace. Participants were able to highlight sentences using a ‘highlight text tool’ and type their notes on note-taking fields provided on each page. Four tutorial pages regarding how to use highlighting and note-taking tools were added at the beginning of the instruction to minimize participants’ frustration from lack of familiarity with the software.

Treatment 2: static visualized instruction with generative learning strategy prompts

The instructional scripts and graphics for this treatment were the same as the control group (T1). Additionally, 16 instructional screens contained embedded generative learning strategy prompts asking participants to highlight important sentences in the instructional script (e.g., “Highlight one or more sentences that you think are important in this
section.”), and then prompted them to summarize or organize their understanding in the provided note-taking field (e.g., “Summarize the sequence of a wave of muscular contraction of the heart in your own words.”). Also, 10 additional instructional screens with an adjunct question were inserted on succeeding screens. Simple knowledge-of-correct-response feedback (right or wrong) was provided. The instruction proceeded regardless of the correctness of the learner’s response or if the respondent ignored the question.

Treatment 3: static visualized instruction with generative learning strategy prompts and metacognitive feedback

This treatment was the same as the second treatment (T2) except that metacognitive feedback was added to knowledge-of-correct-response feedback for the ten adjunct questions. If a participant selected an incorrect answer, the following feedback appeared: “Incorrect! Now would be a good time to ask yourself if you have learned all the important information. If you haven’t, it would be a good idea to return to the previous page to revise your highlighting or note.”

Measurement instruments

All of the observed variables and their latent variables which are inferred by the properties of the observed variables are summarized in Table 1. All scores achieved an acceptable alpha higher than .7, except prior knowledge test score. Even though the prior knowledge test score was associated with a low reliability score, it was acceptable to employ it since it was a covariate in this study.

Prior knowledge test

The prior knowledge test, used to measure basic understanding about human physiology, consisted originally of 27 multiple-choice question items. The Cronbach’s alpha of all 27-item test scores was .42 ($n = 223$). In order to improve the internal consistency of the test

<table>
<thead>
<tr>
<th>Variables Assessed by</th>
<th>Measure description</th>
<th>Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prior knowledge</td>
<td>Human physiology</td>
<td>20 items</td>
</tr>
<tr>
<td>Self-regulation</td>
<td>MSLQ survey</td>
<td>25 items</td>
</tr>
<tr>
<td>Cognitive control</td>
<td>15 items: 7-point Likert</td>
<td>.82</td>
</tr>
<tr>
<td>Metacognitive control</td>
<td>10 items: 7-point Likert</td>
<td>.74</td>
</tr>
<tr>
<td>The quality of overt use of GLS</td>
<td>Generative activity score</td>
<td>Total 90 points</td>
</tr>
<tr>
<td>Highlighting</td>
<td>15 tasks: 4-point rubric</td>
<td>.96</td>
</tr>
<tr>
<td>Note taking</td>
<td>14 tasks: 4-point rubric</td>
<td>.97</td>
</tr>
<tr>
<td>Recall</td>
<td>Criterion test</td>
<td>20 items</td>
</tr>
<tr>
<td>Terminology</td>
<td>10 items</td>
<td>.74</td>
</tr>
<tr>
<td>Fact</td>
<td>10 items</td>
<td>.73</td>
</tr>
<tr>
<td>Comprehension</td>
<td>Criterion test</td>
<td>19 items</td>
</tr>
<tr>
<td>Concept</td>
<td>8 items</td>
<td>.75</td>
</tr>
<tr>
<td>Relationship</td>
<td>11 items</td>
<td>.75</td>
</tr>
</tbody>
</table>
score, seven items were deleted based on a careful review of ‘corrected-item-total correlations’ and ‘scale-if-item-deleted.’ For the 20 items, Cronbach’s alpha was .55 (n = 223).

Self-regulation survey

The self-regulation survey was adapted from the Motivated Strategies for Learning Questionnaire (MSLQ) developed by Pintrich et al. (1991). The survey was used to measure “college students’ motivational orientations and their use of different learning strategies” (p. 3). The researchers selected two of the 15 original constructs measured by the entire MSLQ. The first construct was cognitive control measuring four facets of college students’ cognitive strategy use: rehearsing, elaborating, organizing, and critical thinking. The second construct was metacognitive control measuring two facets of college students’ metacognitive strategy use: regulating and monitoring.

Original items were revised slightly to measure the learners’ level of self-regulation while they studied the treatment material. “This material” replaced the words “this class” or “this course” in the revised questions.

The survey consisted of 25 items with a seven-point Likert-type scale ranging from 1 (not at all true of me) to 7 (very true of me). Cronbach’s alphas of the items for cognitive control and metacognitive control were .82 and .74, respectively. Most of items indicated a modest positive item-total correlation, above .3, suggesting these items measure the same theoretical constructs (Nunnally and Bernstein 1994).

The quality of learners’ overt use of generative learning strategy

The quality of learners’ overt use of generative learning strategies was operationally defined as a learner’s overt demonstration of the degree of attention to important information and the positive degree of creating relationships and meanings. To illustrate, each highlighted sentence and notes taken by a learner were indicators of this construct. An example page of the collected material appears in Fig. 2.
The rubric for accessing the quality of learners’ overt use of generative learning strategies for this study was developed by following the generic guidelines of developing rubrics suggested by Nitko and Brookhart (2007). It was reviewed further by an educational psychology professor for validation. This rubric, shown in Table 2, identifies four different levels of quality of overt use of generative learning strategies with descriptive evidence provided for each level.

Each page was assessed based on the rubric, and Cronbach’s alphas of the scores were .94 (n = 223) for highlighting tasks and .96 (n = 223) for note taking tasks.

Recall test

The recall test, adopted from the terminology test developed by Dwyer (1978), measured specific facts, terminology, and definitions. Participants answered 20 multiple-choice questions by selecting responses that best describe different parts of the heart. Each correct test item was awarded one point making the maximum score 20 points.

The test measured two subtypes: terminology and facts. Cronbach’s alpha and the corrected item-total correlation were used to examine the internal consistency of the measure. The reliability coefficient of the whole instrument was .84 (n = 223). Cronbach’s alpha of the terminology subtype was .74, and of the fact subtype was .73. Most items indicated a modest positive item-total correlation, above .3, suggesting these items measure the same theoretical constructs (Nunnally and Bernstein 1994).

Comprehension test

The comprehension test, adopted from the criterion test developed by Dwyer (1978), measured the participants’ comprehension of the human heart. The test consisted of 20 multiple-choice questions. This test measured understanding of complex procedures and/or interactive functions of each component. A high score indicates that participants thoroughly understand the heart, its components, its internal functioning, and the simultaneous processes that occur during the systolic and diastolic phases. The test measured two subtypes of the higher-level cognitive task: concepts—whether the participant understood what was being communicated—and relationships—whether the participant could use it to explain some other phenomenon (Dwyer 1978). Each correct test item was awarded one point making the maximum score 20 points.

Cronbach’s alpha and the corrected item-total correlation were used to examine the internal consistency of the measure. The Cronbach’s alpha reliability coefficients of the concept subtype, the relationship subtype, and the whole instrument were .75, .73, and .85 (n = 223) respectively. Most of items indicated a modest positive item-total correlation above .3 except for item # 15. A careful review of the test item suggests that this item did not function as it should have. Thus, the reliability coefficient of the instrument was re-examined with 19 items, excluding item #15. The reliability coefficient and item-total correlation of most items slightly improved, suggesting these items measure the same theoretical constructs.

Experimental procedures

The participants were asked to come to a university computer lab where they had access to the research treatments presented on the university’s course management system. All had
Table 2  Rubric for assessing the quality of learner’s overt use of generative learning strategies

<table>
<thead>
<tr>
<th>Screen #</th>
<th>Main idea</th>
<th>Type of activity</th>
<th>Not manipulated</th>
<th>Manipulated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>No generation</td>
<td>Incorrect generation</td>
</tr>
<tr>
<td>Designated instructional material page</td>
<td>Key ideas that learners need to study in the page</td>
<td>Highlighting</td>
<td>No highlighted sentence on the page</td>
<td>Highlighted all of the paragraph on the page</td>
</tr>
<tr>
<td>Note taking</td>
<td>No note on the note field</td>
<td>Note taking</td>
<td>No note on the note field</td>
<td>Copied and pasted instructional scripts</td>
</tr>
</tbody>
</table>

0 1 2 3
been randomly pre-assigned to one of the three treatment groups. After logging onto the research site, the participants completed an online pretest about human physiology. They were then instructed to download the instructional material and study it. Afterwards, the participants completed a survey of self-regulation while they studied the treatment material and took two criterion post-tests about the human heart.

Results

Analysis of the data collected to answer the research questions attempted to explain how generative learning strategy prompts and metacognitive feedback affect learning. Of interest were learners’ self-regulation such as cognitive and metacognitive control and their actual use of generative learning strategies as mediating variables. Also of interest was the order of mediating impact metacognitive feedback had on self-regulation, use of strategies, and learning. Thus, we employed a latent variable Structural Equation Modeling (SEM) approach to take into account multiple measures of constructs and possible causal orderings among constructs, which cannot be accomplished with traditional MANCOVA design (Bagozzi and Yi 1989).

Three accepted steps for SEM were followed (Bagozzi and Yi 1989): (1) data screening examines the basic assumptions of SEM; (2) a one-way MANCOVA model with a latent variable Structural Equation Model is specified and tested; and (3) to assess the hypothesized mediating processes, an alternative model is proposed and then tested using the Satorra-Bentler statistic (Satorra and Bentler 1994).

Data screening

To examine the basic assumptions of SEM, means, standard deviations, skewness, and kurtosis of the composite score of each observed variable were screened to check outliers, normality, and multicollinearity (see Table 3). The data collected from 223 participants satisfied all three key examinations; thus, further analyses were conducted with this data.

Modeling one-way MANCOVA with a latent variable structural model

To answer the first research question, effects of treatments—providing generative learning strategy prompts only versus providing generative learning strategy prompts with metacognitive feedback—were compared after controlling for learner’s prior knowledge. A Multiple Indicators and Multiple Causes (MIMIC) model, where factors are regressed on one or more dichotomous causal indicators that represent group membership (i.e., coded 0 = control and 1 = treatment), allowed testing for multiple group differences on latent variables (Kaplan 2000). Figure 3 presents a specified structural equation model adopting Kühnel’s (1988) one-way MANCOVA design applying the LISREL notation (Jöreskog and Shörbom 1984). The present model includes two independent variables (represented by two dummy variables for three levels of generative learning strategy treatments), one covariate (prior knowledge), and four latent dependent variables (self-regulation, the quality of overt use of generative learning strategy, recall, and comprehension).

The two causal indicators in the structural model of Fig. 3 are two dichotomies using the group code (dummy code) approach (Aiken et al. 1994). One dummy variable, Dummy 1, coded as 1 = generative learning strategy prompts group (T2) and 0 = control group.
as well as generative learning strategy prompts with metacognitive feedback group (T3). This dummy variable represents the comparison of generative learning strategy prompts group (T2) with control group (T1). The other dummy variable, Dummy 2, coded $1 = \text{generative learning strategy prompts with metacognitive feedback group (T3)}$ and $0 = \text{control group (T1) as well as generative learning strategy prompts group (T2)}$. This dummy variable represents the comparison of generative learning strategy prompts with metacognitive feedback group (T3) and control group (T1).

As shown in Fig. 3, to analyze the means of the observed dependent variables as a function of the categorical independent variables, a pseudovariable ("CONST") is added to the initial structural model. This reparameterization is done by adding a constant to the sample moment matrix as another variable having 1.0 in the diagonal and the means of all other variables as off-diagonal elements (Bagozzi and Yi 1989). That is, the first set of regression coefficients, $\gamma_{11}^*, \gamma_{12}^*, \gamma_{13}^*$ and $\gamma_{14}^*$, are the differences in the means of four dependent latent variables between the generative learning strategy prompts group and the control group, and, in the same way, the second set of regression coefficients, $\gamma_{21}^*, \gamma_{22}^*, \gamma_{23}^*$ and $\gamma_{24}^*$, are the differences in the means of the four dependent latent variables between the generative learning strategy prompts with metacognitive feedback group and the control group.

In simpler terms, the examination of the paths from the dummy exogenous variables to the dependent latent variables tested the null hypothesis that the means of the multiple dependent variables (e.g., note-taking, concepts, and relationships) did not differ across groups. These tests, therefore, performed the same function as the omnibus test commonly used in traditional MANCOVA analyses (e.g., the Pillai’s Λ or Wilks’ Λ). That is, if all regression coefficients from the dummy variables equal 0, then the null hypothesis retained, supporting the conclusion that the dependent variables are equivalent across groups. In order to test the null hypothesis of equal means across groups, a $\chi^2$ difference test between a full model and the other restricted model (i.e., $\gamma_{11}^* = \gamma_{12}^* = \gamma_{13}^* = \gamma_{14}^*$ and $\gamma_{21}^* = \gamma_{22}^* = \gamma_{23}^* = \gamma_{24}^*$).

<table>
<thead>
<tr>
<th>Latent variables and observed variables</th>
<th>Total</th>
<th>Mean</th>
<th>SD</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prior knowledge</td>
<td>20</td>
<td>11.722</td>
<td>2.687</td>
<td>.210 (.194)</td>
<td>-.392 (.166)</td>
<td>6</td>
<td>19</td>
</tr>
<tr>
<td>Self-regulation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cognitive control</td>
<td>7</td>
<td>4.182</td>
<td>.867</td>
<td>-.266 (.102)</td>
<td>-.099 (.853)</td>
<td>1.73</td>
<td>6.13</td>
</tr>
<tr>
<td>Metacognitive control</td>
<td>7</td>
<td>3.887</td>
<td>.852</td>
<td>.100 (.534)</td>
<td>-.388 (.172)</td>
<td>1.90</td>
<td>5.80</td>
</tr>
</tbody>
</table>

The quality of overt use of generative learning strategy

<p>| | | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Highlighting</td>
<td>45</td>
<td>24.955</td>
<td>12.384</td>
<td>-1.011 (.0001)</td>
<td>-.270 (.401)</td>
<td>0</td>
<td>42</td>
</tr>
<tr>
<td>Note taking</td>
<td>42</td>
<td>26.363</td>
<td>14.106</td>
<td>-.954 (.0001)</td>
<td>-.563 (.022)</td>
<td>0</td>
<td>42</td>
</tr>
<tr>
<td>Recall</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Terminology</td>
<td>10</td>
<td>4.623</td>
<td>2.690</td>
<td>.467 (.005)</td>
<td>-.872 (.0001)</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>Fact</td>
<td>10</td>
<td>5.991</td>
<td>2.556</td>
<td>-.075 (.641)</td>
<td>-.898 (.0001)</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>Comprehension</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Concept</td>
<td>8</td>
<td>4.368</td>
<td>2.378</td>
<td>.140 (.385)</td>
<td>-1.269 (.0001)</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Relationship</td>
<td>11</td>
<td>5.233</td>
<td>2.871</td>
<td>.401 (.015)</td>
<td>-.914 (.0001)</td>
<td>0</td>
<td>11</td>
</tr>
</tbody>
</table>

Note: $p$-values are in parentheses
The quality of overt use of GLS

Recall

The quality of overt use of GLS

The quality of overt use of GLS

Prior Knowledge

GLS Prompts with Meta-cognitive Feedback (Dummy 2)

Generative Learning Strategy Prompts (Dummy 1)

Self-Regulation

Concepts

Note Taking

Highlighting

Relationships

Fig. 3 Structural equation model specification of one-way MANCOVA with four latent dependent variables of multiple measures, three groups, and a covariate. Note: CONST = Pseudovariable for mean structure

Table 4 $\chi^2$ statistics of the structural model for one-way MANCOVA

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2_{\text{NT}}$</th>
<th>p-value</th>
<th>$\chi^2_{\text{SB}}$</th>
<th>p-value</th>
<th>df</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full model</td>
<td>78.10</td>
<td>.001</td>
<td>78.26</td>
<td>.001</td>
<td>30</td>
</tr>
<tr>
<td>Restricted model</td>
<td>220.77</td>
<td>.001</td>
<td>227.36</td>
<td>.001</td>
<td>38</td>
</tr>
</tbody>
</table>

Note: $\chi^2_{\text{NT}}$, normal theory weighted least squares $\chi^2$; $\chi^2_{\text{SB}}$, Satorra-Bentler scaled $\chi^2$

The $\gamma_{14} = 0$ and $\gamma_{21} = \gamma_{22} = \gamma_{23} = \gamma_{24} = 0$) was conducted (Kaplan 2000). The $\chi^2$ statistics of the full model and the restricted model appear in Table 4.

The Satorra-Bentler scaled $\chi^2$ difference test ($\chi^2 (8) = 164.00; p < .001$) suggests rejecting the null hypothesis of equal means across groups. After rejecting the null hypothesis, a significant test of each regression coefficient linking the dummy variables to the dependent latent variables examined which group affected which variables. This test is analogous to the univariate ANOVA on the dependent variables but holding other variables in the model constant. Thus, the regression coefficients of each path from the dummy
variables to the latent variables were inspected. Table 5 presents the unstandardized regression coefficient, standard error, and $t$-value.

According to the previous results, five significant paths, linking treatments to four dependent variables including from dummy 1 (g1) to USE and from dummy 2 (g2) to four dependent variables, were identified (see Fig. 4).

![Fig. 4 Structural model with significant paths. Note: g1 dummy code for T2 group, g2 dummy code for T3 group, pre prior knowledge, SR self-regulation, cog cognitive control, meta metacognitive control, USE the quality of overt use of generative learning strategies, highl highlighting, note note taking, REC recall, fact fact, termi terminology, COM comprehension, conc concept, relat relationship](image)

**Table 5** Path coefficients, standard error, and $t$-value of treatments

<table>
<thead>
<tr>
<th>Latent variable</th>
<th>Dummy 1 (g1): Control versus generative learning strategy (GLS) prompts group</th>
<th>Dummy 2 (g2): Control versus GLS prompts with metacognitive feedback group</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Path coefficient</td>
<td>$t$-value</td>
</tr>
<tr>
<td>Self-regulation</td>
<td>.12 (.14)</td>
<td>.87</td>
</tr>
<tr>
<td>The quality of overt use of GLS</td>
<td>20.69 (1.40)</td>
<td>14.83*</td>
</tr>
<tr>
<td>Recall</td>
<td>.48 (.37)</td>
<td>1.31</td>
</tr>
<tr>
<td>Comprehension</td>
<td>.66 (.38)</td>
<td>1.76</td>
</tr>
</tbody>
</table>

*Note: Standard errors are in parenthesis

* $p < .05
Conversely, three paths, linking dummy 1 to self-regulation, recall, and comprehension, were not significant. Thus, these nonsignificant paths were removed and the modified structural model was estimated with only statistically significant paths, as recommended by Kline (2005) and Kaplan (2000) (see Fig. 4). The modified model obtained acceptable model fit indices ($\chi^2_{SB} = 82.17$; df = 33; $p < .0001$, the CFI = .95; the RMSEA = .082, and the SRMR = .016). Even though, the $\chi^2$ was significant and RMSEA is slightly greater than the criteria (.06), other fit indices satisfied the criteria suggesting acceptable model fit.

Alternative model to test mediating effects

The second research question examined whether learners’ self-regulation or overt use of generative learning strategies mediate the effects of the treatments on learners’ performance. To test these mediating effects as a result of a causal ordering among the dependent variables, three paths, linking self-regulation to learners’ use of generative learning strategies and learners’ use of generative learning strategies to recall and comprehension, replaced error covariances between them, as hypothesized (see Fig. 5).

To test the mediational hypothesis, the scaled $\chi^2$ difference comparing the model that includes direct effects of generative learning strategy prompts with metacognitive feedback (g2) on recall and comprehension (i.e., $\gamma^2_{23} \neq \gamma^2_{24} \neq 0$) to the model that does not include these direct paths (i.e., $\gamma^2_{23} = \gamma^2_{24} = 0$), was tested. The $\chi^2$ statistics of these two models appear in Table 6.

![Fig. 5 Structural equation model with hypothesized causal paths](image-url)
The Satorra-Bentler scaled $\chi^2$ difference test ($\chi^2 (2) = .95, p > .05$) suggests retaining the null hypothesis of no direct effects of generative learning strategy prompts with metacognitive feedback on recall and comprehension, thus supporting the indirect effects of self-regulation and learners’ use of generative learning strategies.

**Discussion**

This study employed generative learning strategy prompts and metacognitive feedback to enhance learners’ ability to regulate, monitor, and refine their strategy use, and in turn, improve their use of generative learning strategies. Generative learning strategy prompts with metacognitive feedback improved learners’ self-regulation and use of generative strategies and, accordingly, their learning performance. In contrast, generative learning strategy prompts without metacognitive feedback improved only learners’ use of generative strategies. Based on the results, the generative learning conceptual framework was revised as shown in Fig. 6. Discussion on the relationships follows.

**Effects of generative learning strategy prompts and metacognitive feedback**

*Self-regulation and generative activity*

Our findings revealed that generative learning strategy prompts with metacognitive feedback significantly increased learners’ self-regulation while they were studying over the control group, but generative learning strategy prompts without metacognitive feedback did not. This result was inconsistent with the prediction that learners who received...
generative learning strategy prompts would also use more cognitive strategies and control metacognition than the learners who did not receive them. Cognitive development theory may explain this inconsistency. According to cognitive development theory, college students have better capabilities for self-regulation than elementary students. The older students have an already established way of using cognitive strategies based on prior experiences (Hofer et al. 1998; Wigfield et al. 1996). Thus, in this study, the learners who were in the control group might have had some degree of self-regulation ability already to regulate their own learning without any prompts. Consequently, the difference between the control group versus generative learning strategy prompts group would be minimal.

However, adding metacognitive feedback to generative learning strategy prompts did increase learners’ cognitive and metacognitive self-regulation over the control group. Metacognitive feedback reminded learners to monitor and refine their cognitive strategy use after they answered a question. In a post-survey, learners who were given generative learning strategy prompts with metacognitive feedback agreed significantly more ($M = 4.97$ of 7) than the learners who were only given generative learning strategy prompts ($M = 4.067$ of 7) that they reviewed previous pages. That is, the learners who received metacognitive feedback tended to go back, and in doing so may have refined their understanding more. This result suggests that college students’ self-regulation can possibly be improved by combining strategy prompts with metacognitive feedback.

Our findings also revealed that both generative learning strategy prompts and generative learning strategy prompts with metacognitive feedback significantly improved the quality of learners’ generative learning strategy use over that of the control group. Interestingly, the two treatments were equally effective in improving the quality of learners’ generative learning strategy use, even though the generative learning strategy prompts alone were not effective in improving learners’ self-regulation. This result may be explained by results on the two post-survey items that asked whether or not learners changed their highlighting or revised their notes after they were given feedback to the adjunct questions. Those two groups were not significantly different on either item. The low mean scores for both groups indicated that learners were not more likely to revise their notes or what they had already highlighted.

The previous discussion indicates that metacognitive feedback enhanced learners’ monitoring and refinement of their learning more in covert way, thus the learners who were given generative learning strategy prompts with metacognitive feedback achieved higher scores on their self-regulation survey. But these cognitive processes were not necessarily represented as overt behavior which was measured as the quality of overt use of generative learning strategies.

**Learning achievement**

The findings of this study also revealed that learners who received generative learning strategy prompts with metacognitive feedback performed better in recall and comprehension over the control group. In contrast, there were no difference between learners who received just the generative learning strategy prompts alone and the control group in recall and comprehension scores. In this regard, simple prompting may not be enough instructional help for learners in computer-based learning environments, because learners need to monitor, be aware of, and adjust their learning processes according to how well they did. Thus, metacognitive feedback is one strategy to remind learners to regulate their learning and enhance the function of the generative learning strategy prompts to improve learners’ achievement.
Mediating processes

Another important result, as predicted, was that generative learning strategy prompts with metacognitive feedback improved learners’ achievement in recall and comprehension by enhancing their self-regulation and the use of generative learning strategies. Many previous studies found that learners’ self-regulating skills related to academic achievement (Az-cervedo and Cromley 2004; Kramarski and Gutman 2006; Pintrich and De Groot 1990; Zimmerman 1998; Zimmerman and Schunk 2001). However, little research attempted to identify mediation effects of learners’ self-regulatory processes and their actual use of learning strategies.

The results of this study supported the mediation effects of learners’ use of generative learning strategies on recall and comprehension and of learners’ self-regulation on their use of generative learning strategies. It is implied that learners’ covert self-regulation refines the learning outcomes from their overt use of learning strategies, and this refinement positively affects learning. Therefore, instructional strategies should take into account learners’ overt use of strategies and learners’ covert self-regulation.

Conclusion

Students’ learning processes involve various cognitive as well as behavioral processes in technology-enriched learning environments. Accordingly, instructional designers should identify intermediate processes between instruction and learning, which mediate the effect of instructional interventions on learning. The present results indicate that learning can be enhanced effectively by dealing with mediating variables of self-regulation and quality of use of generative learning strategies by providing generative learning strategy prompts and metacognitive feedback. These strategies facilitate learners’ regulation, monitoring, and refinement of their use of learning strategies. Current technologies allow for incorporating generative learning strategy tools such as highlighting and summarizing. Thus, instructional designers or instructors need to design computer-based learning environments that help learners regulate and monitor their learning processes and allow learners using generative learning strategies in better way.

Moreover, learners have different levels of self-regulatory skills and prior domain knowledge. Thus, perhaps an even more effective technique may involve support with adaptive metacognitive feedback (Aleven et al. 2006). Therefore, a worthwhile future investigation would test an adaptive metacognitive feedback system and its effects on learners’ cognitive and metacognitive processes, and, accordingly, on learners’ knowledge generation processes and outcomes. In addition, Structural Equation Modeling is strongly recommended for analyzing results of such system, because it allows identifying underlying mediating processes, diagnosing individual or situational conditions, and testing the effects of the various adaptive metacognitive feedback.

References


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