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The effects of achievement goals and self-regulated learning behaviors on reading comprehension in technology-enhanced learning environments

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ABSTRACT

Studies examining students' achievement goals, cognitive engagement strategies and performance have found that achievement goals tend to predict classes of cognitive strategy use which predict performance on measures of learning. These studies have led to deeper theoretical understanding, but their reliance on self-report data limit the conclusions that can be drawn. We employed a behavioral approach instead and assessed learning processes by logging learners' behaviors as they used educational technology. We examined the relationship between achievement goals, strategy use, and comprehension scores of 160 undergraduates who studied a hypertext passage in a technology-enhanced learning environment (TELE) equipped with tools that support learning behaviors including highlighting, taking notes, review of annotations, seeking additional information and monitoring understanding. Results of a path analysis indicated that higher mastery goals predicted more information-seeking and note-taking and marginally more monitoring of learning. Performance avoidance goals negatively predicted note-taking and information-seeking. Performance approach goals did not predict the behaviors we traced. Of the behaviors we traced, highlighting and monitoring predicted increases in comprehension scores. A behavioral approach to assessing learning processes confirmed only a subset of paths from achievement goals to learning processes to learning outcomes originally discovered with self-report data.

1. Introduction

A recent literature review (Linnenbrink-Garcia, Tyson, & Patall, 2008) and meta-analysis (Hulleman, Schrager, Bodmann, & Harackiewicz, 2010) indicate that the evidence for relationships between learners' mastery approach and performance approach goals and achievement is mixed; some studies find a relationship and others show none. These syntheses of research suggest a tentative relationship between achievement goals and learning outcomes that needs to be examined further. Though achievement goals have not consistently been found to predict achievement directly, these goals play an important role in the self-regulated learning process. According to theories of self-regulated learning (SRL; Pintrich, 2000a; Winne & Hadwin, 1998, 2008; Zimmerman, 2000, 2011), the goals that learners set motivate the behaviors that are responsible for bringing about learning; if learners adopt goal orientations that motivate them to engage in effective learning strategies, learning is likely to result.

Many prior studies have examined how learning processes mediate the relationship between achievement goals and outcomes, describing these learning processes as instances of cognitive engagement, self-regulation of learning, or strategy use. These studies have tested models of increasingly complex sets of potential mediating processes in order to improve our understanding of the relationship between learner's achievement goals, learning processes and outcomes. A sample of such work can be found in Table 1. The table is by no means exhaustive, but it does provide an example of the area of study and some representative results. Coefficients reflect associative (r) and predictive (β) relationships from correlational, regression and path analyses. Studies examining cognitive strategy use as a mediator of achievement goals' effect on performance found that mastery goals, and to a lesser extents, performance approach goals, predict strategy use, which positively predicts learning. A second set of studies examined types of cognitive engagement and found that the use of meaningful, deep cognitive strategies is both predicted by mastery goals and positively predictive of performance. Performance approach goals predicted the use of both deep and shallow strategies, but these shallow strategies negatively predicted performance. This added distinction led to a more specific understanding of the effect of achievement goals on students' cognitive strategy use, as did additional studies that further differentiate among cognitive, metacognitive or resource management strategies. However, as models increase in complexity, complications emerge. In this paper, we discuss the limitations associated with survey-based representation of constructs like cognitive

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Table 1
Prior studies of achievement goals, cognitive strategy use, and learning.

Type of cognitive engagement strategies examined		MAP		PAP		PAV		Outcome	
		r	*β*	*r*	*β*	*r*	*β*	*r*	*β*
Cognitive engagement									
Nolen and Haladyna (1990)[*]	Strategy value beliefs		.85						
Ablard and Lipschultz (1998)[*]	SRL strategy use	.36	.32	ns	ns				
Nolen (2003)[a]	Deep strategy use	.36		.14				.31	
Greene et al. (2004)[b]	Strategy use	.65	.40	.26				.33	, .15
Lau and Lee (2008)	Strategy use	.63	.51	.38					
Walker and Greene (2009)	Cognitive Engagement	.55		.18					
Deep versus shallow cognitive engagement									
Greene and Miller (1996)[c]	Meaningful cognitive engagement	.67	.53	ns				ns	.31
	Shallow cognitive engagement	ns		.41	.41			ns	−.21
Dupeyrat and Mariné (2005)[*,d]	Deep strategies	.61	.48	.45				ns	
	Shallow strategies	.23		.33	.33			ns	
Phan (2010)[e]	Deep strategies	.19	ns	.19	ns				.32
	Surface strategies	.15		.45	.36	ns	ns		−.12
Additional dimensions of cognitive engagement									
Wolters (2004)[f]	Cognitive strategies	.52		.12		ns		.11	
	Metacognitive Strategies	.53		.12		−.10		.21	
Wolters, Yu, and Pintrich (1996)[#,g]	Cognitive strategies	.55			.24, −.15			ns	
	Regulatory strategies (metacognitive)	.50			.16, −.33			.17	
Vrugt and Oort (2008)[^,h]	Surface cognitive strategies				.10, .20		ns, ns		−.13,−.15
	Deep cognitive strategies		.14, .20		.21, .24		−.09		ns, ns
	Metacognitive strategies		.19, .26		.15, .15				.15, .20
	Resource management strategies		.16		.15, .17		ns, ns		.20, .23

Note. All coefficients listed are significant at $p < .05$, others are denoted "ns" were non-significantly associated or non-significant predictors.
[a] Science exam.
[b] English grade.
[c] Educational psychology exam.
[d] French graduation exam.
[e] Educational psychology grade.
[f] Math grade.
[g] Semester grade.
[h] Psychology exam.
[*] Study employed a measure of goal orientation that did not distinguish between approach and avoidance dimensions of a performance orientation.
[#] Achievement goal measures assessed mastery goals, relative ability goals and extrinsic goals; relative ability and extrinsic goals presented in the performance approach column in that order.
[^] Study examined effective and less effective self-regulators; coefficients presented in this order.

engagement, strategy use and self-regulated learning and propose that tracing learning behaviors may prove to be an informative method of examining how learners' achievement goals prompt the use of specific strategies that impact learning. As we will describe, previous attempts to investigate these relationships are limited by their use of instruments that require learners to self-report general statements describing their strategy use. This practice is complicated by researchers' operational definitions of constructs and the scales they use to represent them and learners ability to accurately characterize their strategy use.

1.1. Varying approaches to representing cognitive strategy use

Across studies examining achievement goals and cognitive strategy use, the scales used to represent a type of cognitive engagement differ. When a researcher conceives of a study, specific hypotheses are to be tested, and the methods used to test these hypothesis shape the design of assessments. This is a productive approach at the level of an individual study, but synthesizing results across numerous studies is difficult when researchers operationally define and assess similarly named constructs using different scales. For instance, Greene and Miller (1996) conducted a study that investigated achievement goals' effect on deep and shallow cognitive strategies and assessed each using items from the Motivation and Strategy Use Scale (Greene & Miller, 1993). Sample items in the study used to represent deep cognitive strategies included language referencing elaboration, organization and metacognitive monitoring. Items representing shallow strategy use included language about memorization strategies like rehearsal. In another study examining deep and shallow strategies, Dupeyrat and Mariné (2005) represented deep cognitive strategies with the Elaboration and Organization scales from the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1991) and scales reflecting memorization strategies like rehearsal to represent shallow cognitive strategies. While their instruments differ, their distinction between strategy classes is analogous. Conversely, a study by Wolters (2004) examined cognitive versus metacognitive strategies, but did not distinguish amongst shallow versus deep strategies. In that study, cognitive strategies were represented by MSLQ Rehearsal (a shallow strategy in the first two studies) and Elaboration (previously a deep strategy) scales. Metacognitive strategies were represented by an MSLQ scale of the same name. A fourth study (Vrugt & Oort, 2008) examined deep, shallow and metacognitive strategies. However, this definition of deep cognitive strategies was reflected by use of Elaboration, Organization and Critical Thinking scales from the MSLQ, while surface cognitive strategies were represented by scores on the Rehearsal scale. Examining the alignment of scales to constructs across these four studies, one can see how a researcher's experimental design decisions make synthesis challenging. Not unexpectedly, findings across these studies are not perfectly aligned.

Looking at the effect of these strategies on performance, Greene and Miller (1996), Dupeyrat and Mariné (2005), and Vrugt and Oort (2008) all found that mastery goals predicted deep strategy use, but only Greene and Miller (1996) found deep cognitive strategies to be predictive of performance. Wolters (2004) found a significant and positive association between cognitive strategies and math grades, which might lead us to believe the additional construct used to assess cognitive strategies, rehearsal, might be responsible for this finding – except that Vrugt and Oort (2008) found that rehearsal, their surface cognitive strategy scale, negatively predicted performance on a psychology exam. It is difficult to determine what to make of these findings given the differences in the way constructs were represented across studies.

A key issue here is the categorization of constructs into groups of strategies that are explicitly deep or shallow. While distinctions between cognitive and metacognitive strategies are rooted in cognitive theory, the theoretical basis for distinguishing between deep and shallow strategies is less robust. As a result, alignment of constructs to deep or shallow categories varies by study. In the absence of a strong, consistent, and theory-driven rationale for categorizing constructs as deep or shallow cognitive strategies, it is probably best to examine constructs and their role as mediators between achievement goals and learning outcomes on an individual basis. By choosing not to assign constructs to larger categories, results of studies can be more easily compared and conclusions about the role of individual strategies can be drawn. These conclusions might also be made more reliably if researchers would use measures that directly assess the strategic behaviors they intend to measure with self-report instruments. A second issue with the use of self-report scales to assess strategy use involves learner's capacity to accurately report the behaviors the scales are designed to assess.

1.2. Calibration and accuracy of self-reported strategy use

It has been demonstrated on more than one occasion that learners, in an attempt to describe their tendencies to self-regulate learning, tend to misrepresent themselves (Bråten & Samuelstuen, 2007; Winne & Jamieson-Noel, 2002). Studies comparing logs of learners' behaviors to measures of their self-reported strategy use show learners' recall of strategy use to be inaccurate, and that they commonly overestimate how frequently they employ strategies.

Some of this inaccuracy may be due to the desire to report the value of a strategy in addition to the frequency it is used. When measured with surveys, students may indicate that they perceive the value of a strategy, but in reality do not employ it because it requires a lot of effort. Prior work examining effort and the perceived value of strategies finds that when a behavioral measure of effort is included with self-reports of value placed on strategies, the behavioral measure is more predictive of learning than are self-ports of strategy use (Dupeyrat & Mariné, 2005). For these reasons, as well as those outlined in Section 1.1, we advocate a different approach to assessing strategy use. We suggest an alternate approach to trusting respondents to accurately report their behaviors. It requires that we examine learners' behaviors ourselves and infer the cognitive processes these behaviors represent. This would eliminate bias stemming from learners' beliefs about the value of strategies and would also avoid misrepresentation of learning behaviors that derive from students' difficulty making accurate assessments about their own learning behaviors.

1.3. A behavioral approach to assessment of strategy use

Given the problems with self-report measures of cognitive strategy use, it may be time to consider assessing students' strategy use by examining behavioral logs that trace the timing and frequency of behaviors indicative of a strategy. When learners conduct a behavior, it indicates both their perceived value of the behavior and their willingness to put forth the effort required to conduct it. The explicit measurement of instances of behavior allows us to determine the frequency of behaviors and infer the strategy or strategies they may reflect.

In this study, we captured evidence of student behavior using log-file analysis and drew inferences from records of their behaviors regarding their use of particular learning strategies. This method provided concrete definitions of learning behaviors that can be inferred as representative of one or more cognitive or metacognitive processes. While behaviors must be interpreted in the context of the learning environment in which they occur, this behavioral approach is free from bias due to learners' inaccurate estimation of their own behaviors common to self-report methods.

1.4. Cognitive measures of learning

In addition to employing a behavioral approach to assess strategy use, we took a cognitive approach to assess learning. Since we are examining how motivational constructs like achievement goals influences cognitive processes, it makes sense to define performance on learning tasks in cognitive terms. By examining the learning process in this way, we were able to appraise a set of authentic behaviors indicative of learners' strategy use and gauge the benefit of each behavior for different types of learning. In the next few sections, we review how self-regulated learning theory and achievement goal theory ground our study, then detail the benefits and early successes of a behavioral approach to measuring learning behavior. First, however, we provide a brief overview of Kintsch's (1998) Construction-Integration Theory of Comprehension, which served as a basis for our measures of textbase and situation model learning.

2. Construction-integration model of comprehension

In this study, prior knowledge and learning were measured in terms of initial comprehension of the reading passage and increases in comprehension using Kintsch's (1998) Construction-Integration Model (C-I). This model describes reading comprehension as a cyclical process of constructing and integrating the propositions that appear in a passage into a *textbase* that readers elaborate upon using prior knowledge and experience to form a *situation model*. The textbase is described as the "elements and relations that are directly derived from the text itself" (Kintsch, 1998, p. 103) and can be equated with declarative knowledge such as facts and definitions. A more complex level of comprehension is the situation model. Learners' situation model comprehension is built by activating prior knowledge, identifying causal linkages between nodes of text, and by creating elaborative inferences based on prior knowledge, individual text pieces, the tone of the text, and so on. In contrast to textbase knowledge, situation model comprehension can be equated with conceptual knowledge. Measurement aligned to the Construction-Integration Model examines two levels of comprehension and allows for the teasing out of effects of motivation and SRL strategies on basic retention and deeper levels of comprehension.

3. Achievement goals

3.1. Achievement goals defined

Over multiple decades of research on achievement goal orientations, both mastery goals and performance goals (Elliot, 1999) have been associated with one's level of performance in academic tasks. Alternate formulations to mastery/performance goal definitions include task/ego goals (Maehr & Nicholls, 1980) and learning/performance goals (Dweck, 1986). Keeping to the mastery/performance framework that has been commonly used in recent reviews of the achievement goal literature (Hulleman et al., 2010; Linnenbrink-Garcia et al., 2008; Senko, Hulleman, & Harackiewicz, 2011), those who adopt mastery goals aim to develop competence by focusing on learning and compare current levels of competence to previous levels. Those pursuing performance goals instead focus on demonstrating their competence, often comparing themselves to others.

Both mastery and performance dimensions can also be investigated along an approach versus avoidance dimension (Elliot & McGregor, 2001). One who adopts a performance approach orientation aims to demonstrate competence by performing better than others whereas the goal of one who adopts a performance avoidance orientation is to avoid performing worse than others. A mastery approach oriented learner seeks to improve competence compared to prior levels. While mastery approach goals have been well documented, research confirming the existence, relevance and appropriate interpretation of mastery avoidance goals within a context is just emerging (Baranik, Stanley, Bynum, & Lance, 2010; Madjar, Kaplan, and Weinstock, 2011). For this reason, we constrain our focus in this study to a trichotomous model including mastery approach, performance approach and performance avoidance goals.

3.2. Multiple goal theory

Research has also revealed that learners' endorsement of achievement goals tend to correlate significantly (Barron & Harackiewicz, 2001). For instance, Murayama, Elliot, and Yamagata (2011) found that, across numerous studies where confirmatory factor analyses demonstrate the constructs are distinct, learners' performance approach and avoidance goals tend to be highly correlated. A theory of multiple goals has emerged to explain findings like this (Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002; Pintrich, 2000b; Senko et al., 2011) and holds that pursuing multiple goals may confer benefits to learners that may be integrative or additive (Senko et al., 2011). In this study, we use path analysis to reflect how individual goals influence strategy use and performance. This technique also allows one to observe any additive effects that occur when a learner endorses more than one achievement goal.

3.3. Relationship with cognitive strategy use and achievement

Recent reviews of the achievement goal literature suggest that both mastery and performance goals are associated with achievement in learning tasks (Hulleman et al., 2010; Linnenbrink-Garcia et al., 2008). Linnenbrink-Garcia et al. (2008) found that both mastery approach and performance approach goals correlated with measures of performance in roughly 40% of studies, while achievement goals were non-significantly related in the remaining sixty percent of studies. When significant correlations were found, the effect sizes associated with these correlations suggest that one's achievement goals have only a modest effect on the outcomes of engaging in a task. Similarly, a meta-analysis conducted by Hulleman and colleagues (2010) found that mastery goals were positively related to achievement. Performance goals, however, were positively related to achievement when measured by items that reflect a desire for normative comparison, but were negatively related to achievement when defined by a concern about one's appearance (i.e. looking smart). These reviews confirm a positive relationship between mastery and performance approach goals and achievement, but the degree to which achievement goals predict achievement is limited. When considering the complexities of the learning process, it makes sense that merely possessing achievement goals should not lead directly to achievement. According to theories of self-regulation, in addition to having a goal, one must conduct some type of cognitive process to achieve competence in a task.

4. Theoretical framework of self-regulated learning

Multiple theorists including Pintrich (2000a), Winne and Hadwin (1998, 2008) and Zimmerman (2000, 2011) have theorized that individuals who approach learning tasks in a thoughtful and strategic way are more likely to increase their knowledge. Pintrich (2000a) identifies this as a tendency to self-regulate learning (SRL) and defines SRL as an "application of general models of regulation and self-regulation to issues of learning, in particular, academic learning that takes place in school or classroom contexts" (p. 451). Winne and Hadwin (1998) offer a description of self-regulated learning as an event-based phenomenon that occurs in weakly sequenced phases. When learners self-regulate, they (1) define the task at hand, (2) set goals that they would like to attain and develop a plan for their attainment, (3) enact those tactics, and (4) monitor their progress towards goal attainment against a preconceived set of internal standards. Within each phase, self-regulatory behaviors are governed by a collection of conditions that describe a context where operations generate products that are evaluated in light of learners' standards. Winne (1997) describes this element of the theory as the COPES architecture. Zimmerman (2000) describes a similar series of phases in the SRL process, which include a period of forethought, performance and self-reflection, and also articulates that SRL processes require an initial and sustained level of motivation (Zimmerman, 2011) to proceed.

5. Measurement of self-regulated learning

Early research on SRL tended to employ questionnaire instruments such as the Motivated Strategies for Learning Questionnaire (Pintrich et al., 1991). More recently, offline measures like questionnaires have been discussed as being less valid indicators of strategy use than online measures that take into account a given context (Zimmerman, 2008). Studies conducted by Winne and Jamieson-Noel (2002) and Bråten and Samuelstuen (2007) provide evidence that offline self-regulated learning measurement has faults and demonstrate a lack of calibration between what learners believe they do when completing tasks and what they actually do. Further, they argue that measuring self-regulated learning using insufficiently contextualized items renders the authenticity and validity of such results suspect. More recent studies of self-regulated learning tend to employ event-based measurement strategies in the form of trace methodologies (Winne, 2006) and think-aloud protocols (e.g. Greene & Azevedo, 2009). These methods capture SRL strategies as they are being employed, which both Zimmerman (2008) and Winne (2010) suggest provide heightened authenticity in their identification of strategy use. Both methods are common among researchers who study SRL in computer-based learning environments, as can be seen by articles detailing the strength of think-aloud methodologies (Greene, Robertson & Costa, 2011) and log analyses (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007) for these contexts.

As compared to the cumbersome process of transcribing think aloud data (Greene & Azevedo, 2009), the development of environments that record learners' actions as they occur has made convenient the process of data collection, allowing for examination of large samples of students' behaviors in technology-enhanced learning environments. Embedded data collection tools compile time-stamped logs of learner actions in the environment, which can be queried to produce indicators of specific *occurrences* (Winne, 2010) or patterns of occurrences. An occurrence is a trace that indicates a learner has conducted a behavior that is inferred to reflect one or more cognitive or metacognitive processes at a specific point in the task. Analysis of this indicator can ensue and research questions that examine how such user actions influence learning can be addressed. This study employs a *log analysis* feature of Winne, Hadwin and Beaudoin's (2009) nStudy browser to trace occurrences of SRL behaviors and examines whether occurrences of SRL behaviors are more common in the presence of an achievement orientation and whether they affect learning.

Prior research has examined individual behaviors representative of self-regulated learning strategies and tested the relationships between these behaviors and learners' achievement goals. Using gStudy (an Internet-based learning environment and precursor to the tool used in this study), Nesbit, Winne, Jamieson-Noel, and colleagues (2006) assessed students' highlighting and note-taking behaviors as a function of their achievement goals. Over the course of studying an educational psychology chapter in the gStudy environment, students had the opportunity to use tools provided by gStudy that included a highlighter and a note-taking feature that allowed for free form and structured note-taking. Data were collected via behavioral logs. Results using traces of students' annotations indicated that Nesbit and colleagues correctly hypothesized that students reporting higher mastery goals demonstrated a greater frequency and sophistication of note-taking and a lower frequency of highlighting terms without using the note tool to elaborate on them. In this study, we examined students' achievement goals and the utilization of these and other features in a different task. We traced the frequency of a larger set of behaviors and analyzed relations between achievement goals, learning behaviors reflective of cognitive strategies, and performance on a posttest measuring comprehension.

6. Hypotheses

We designed the path model in Fig. 1 based on prior findings regarding the relationship between achievement goals, learning behaviors, and performance in achievement tasks. While many of our hypotheses have been previously tested in earlier studies, this study is novel and warranted for three reasons. First, this study reexamines prior work investigating relationships between achievement goals, cognitive strategy use, and performance using behavioral data instead of self-report, thus avoiding the associated susceptibility to inaccuracy of self-reports. Second, we examine the impact of strategies used on two different measures of comprehension, which can provide deeper insight into the kinds of learning that different strategies promote. Third, we simultaneously model learners' mastery approach, performance approach and performance avoidance goals, allowing us to predict the behaviors and outcomes of learners who adopt each goal to a specific degree (Senko et al., 2011) when engaging in a learning task. Because research has shown that learners tend to pursue multiple goals and that pairs of goals can correlate highly, it is important to consider these goals not in isolation, but as a constellation of learner goals, adopted with various strengths that simultaneously impact the behaviors of the learner in the environment. The results we obtain from this approach can refine our conception of the relationships between learners' achievement goals and the specific learning behaviors they motivate, and can also indicate the degree to which these goals and behaviors affect performance in a learning task.

6.1. Predictors of strategy use

In line with Dweck's (1999) descriptions of the behaviors of mastery learners, and Pintrich's explanation that mastery-oriented individuals tend to employ learning strategies (2000b, p. 473), we anticipated that those adopting mastery goals would demonstrate greater tendency towards the cognitive strategies studied previously (Table 1). Mastery learners are apt to report using cognitive and metacognitive strategies (Vrugt & Oort, 2008; Wolters, 2004), but the use of self-report items reflecting classes of strategies and not individual behaviors has precluded examination of more specific actions learners take when engaged in a task. In this study, we expected mastery learners to be more apt to use strategies like taking notes, reviewing notes, accessing elaborated explanations of

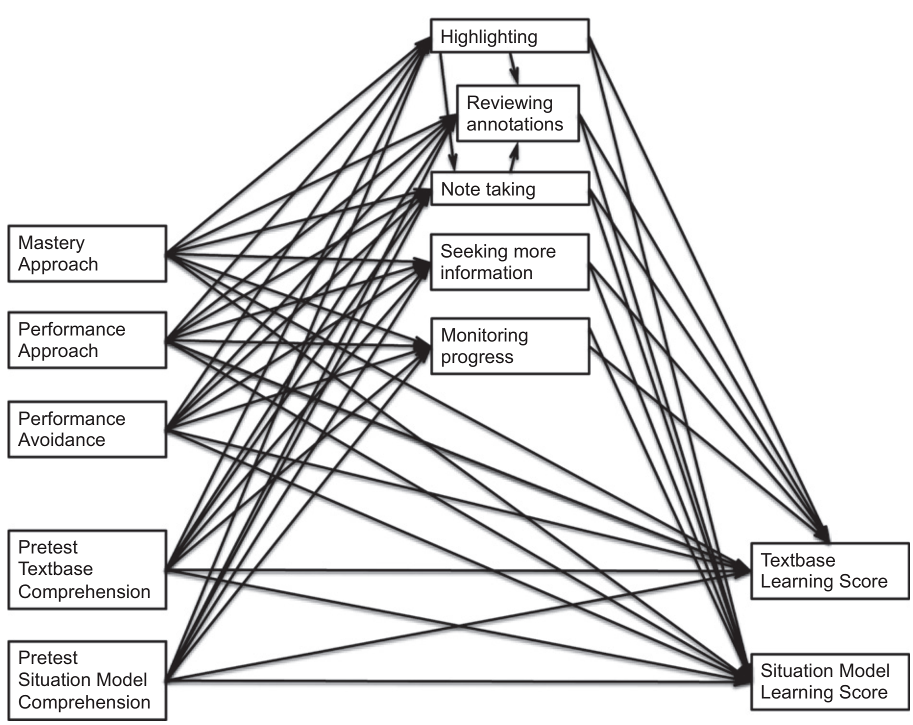

Fig. 1. Hypothesized path model.

the reading topic, monitoring progress using a checklist of learning objectives. Behavioral data provides evidence of these behaviors, which we infer to be reflective of cognitive strategies including organization (some note taking) and elaboration (some note taking, seeking information) and metacognitive monitoring (reviewing annotations, monitoring progress). Our model tested these specific hypotheses by examining paths from mastery goals to each "deep" self-regulated learning strategy that could be traced in the learning task we provided. Additionally, we tested a path from mastery orientation to highlighting, which might be construed as a deep, shallow or metacognitive process.

As a learning strategy, highlighting has been theorized as indicative of a superficial strategy in some cases (Nesbit et al., 2006). Others have theorized that behaviors similar to highlighting might lead to the use of deeper strategies (Greene, Miller, Crowson, Duke, & Akey, 2004). It stands to reason that, if this latter hypothesis is true, highlighting might predict situation model learning, and mastery learners might demonstrate this behavior en route to engaging in deeper learning behaviors. As a result, we tested a path from mastery goals to highlighting, as well as a path from highlighting to other strategies (note-taking and review of annotations).

Because achievement goals have been known to correlate and because multiple goal theory suggests that pursuit of multiple goals might confer benefits, we also examined paths from performance approach goals to strategy use. However, little in the environment should cue students to consider their peers' performance or their perception of their performance; the task was completed on an individual basis and performances were not made public. Since participants were made aware of these features, we made no hypotheses about performance approach or avoidance goals on the grounds of theory, but did attempt to replicate findings from prior research. Performance approach goals have been associated with both deep and shallow cognitive strategies, so we estimated paths from performance approach goals to all learning behaviors. Those with strong performance avoidant goals have been found to self-report lower levels of strategy use (Shih, 2005). To determine what learning strategies these individuals tend to avoid, we estimated paths from performance avoidance to all traced behaviors.

6.2. Predictors of comprehension

Our comprehension measure yields subscores for textbase comprehension, which reflects retention of the text, as well as situation model comprehension, which reflects one's ability to make inferences by drawing on retention of multiple portions the text and prior knowledge (Kintsch, 1998). As a result, we can test hypotheses about the effect of predictors on each type of comprehension. We hypothesized that highlighting, if it is indeed a shallow tactic associated with retention but not deep understanding as Nesbit (2006) and colleagues describe, would predict textbase comprehension. We also tested whether highlighting would predict situation model comprehension since rehearsal practice may strengthen retention of segments of text needed to generate inferences. Based on prior evidence from multiple studies of self-regulated learning (e.g. Azevedo & Cromley, 2004; Greene & Azevedo, 2007, 2009) we tested paths indicating that self-regulated learning strategies would predict comprehension at the textbase and situation model levels. In order to examine relationships between achievement goals and achievement recently summarized by Linnenbrink-Garcia et al. (2008), we also tested direct paths from each achievement goal to each comprehension subscale.

6.3. Role of prior knowledge

In previous research examining the effect of prior knowledge on self-regulated learning behaviors (e.g. Moos & Azevedo, 2008) prior knowledge was found to be a significant predictor of monitoring, but to predict lower amounts of other strategy use. Prior knowledge was also found to predict posttest performance. We include these paths in our model as well, though we do not make any additional hypotheses with respect to relationships between prior knowledge and achievement goals.

Our path model is a fully saturated model in which all paths from exogenous variables (achievement goals and prior knowledge variables) to endogenous learning behaviors and comprehension scores are estimated, as are all paths from these learning behaviors to each comprehension score. We test additional paths from learning behaviors that are theorized to be more superficial than others (highlighting to note-taking) and paths from highlighting and note-taking to review of annotations since one must make an annotation in order to review it. Model identification and model fit are discussed in the results section.

7. Methods

7.1. Participants

One hundred and sixty ($n = 160$) participants enrolled in eight sections of undergraduate education courses from a large Mid-Atlantic public university completed the study. The participants received extra credit for participating in the study. One hundred and eighty-six students out of the 263 who were invited to participate accepted (response rate = 71%). One hundred and sixty of them completed all measures and compose the final sample (adjusted response rate = 61%). For these 160 participants, there was no missing data. Their average age was 21.75 years old ($SD = 3.60$) and they had completed 3.75 semesters ($SD = 1.78$) of post-secondary education. Seventy-two percent were female ($n = 115$) and 81.3% were Caucasian ($n = 130$). Their self-reported mean GPA was 3.17 ($SD = .39$) and their self-reported mean SAT verbal and math scores were 576 ($SD = 74.06$) and 548 ($SD = 81.80$), respectively.

7.2. Measures

Participants completed a battery of measures prior to the learning task including a demographic survey, a pretest knowledge measure (administered again at posttest to measure learning), and the Achievement Goals Questionnaire-Revised (Elliot & Murayama, 2008).

7.2.1. Prior knowledge and learning measures

A knowledge measure was designed specifically for this study and was administered before and after the task to assess textbase (16 multiple choice items) and situation model (four essay items) comprehension as described by Kintsch (1998). Textbase items assessed recall of facts that appear in the reading (Sample item: "The most common medication prescribed for treatment of ADHD is [answer choices: stimulant*; depressant; anti-depressant; anxiolitic]) Situation model items assessed respondents' ability to draw inferences from the reading and to accurately and completely compose an explanation of how multiple portions of the reading relate to a topic. The essay items were coded using a three-point scale (0, 1, and 2) to correspond to learners' answers demonstrating no, partial and complete comprehension of an aspect of the reading passage (Sample Item: "How would you characterize the recent trends in ADHD diagnosis?). Using a holistic rubric, two independent raters scored each response. A Kappa statistic (κ) was calculated for each of four situation model items. Coefficients ranged from $\kappa = .762$ to $\kappa = .918$, with the lower bound of the lowest confidence interval equal to .700.

In order to test hypotheses, scores for *prior knowledge* and *learning* were calculated. Textbase prior knowledge scores were calculated by tallying the number of multiple-choice items answered correctly (out of 16). Situation model prior knowledge scores were calculated by summing the number of points awarded by raters across the four situation model items (out of 8). We defined learning in this task as the degree to which a learner acquired new knowledge that was not previously possessed prior to engaging in the task. Textbase learning scores were determined by calculating the number of items correctly answered on the posttest that were not answered correctly on the pretest. That is, if a learner correctly answered 10 of 16 items on the pretest (prior knowledge score = 10), the learning score was calculated as the proportion of remaining six items correctly answered at posttest (e.g. 0 of 6 correct meaning 0% of potential learning occurred; 6 of 6 = 100%). This percentage represents the extent to which a learner's chosen approach advanced their comprehension of the reading passage towards a criterion of complete comprehension of the reading passage (i.e. mastery).

We acknowledge that for those accustomed to pre-post difference scores, this method requires a different type of interpretation. Whereas difference scores represent straight increases in performance, we sought to examine the proportion of potential learning that resulted from engaging in the learning task. By calculating learning as we did, we changed the way one examines outcomes from a linear increase in performance to a proportion of mastery of new knowledge each learner achieved. In order to help readers gauge the effect that completing the learning task had on comprehension, we included pretest and posttest means and standard deviations in Table 3. The difference between these mean scores on pretest and posttest indicate a large effect of the learning exercise on textbase ($d = 2.92$) and situation model comprehension scores ($d = 1.40$). By that measure, increases in performance are considerable. When examining such increases as measures of learning according to our definition, we found that, for this sample of learners, the mean textbase learning score was $M = .802$ ($SD = .170$). After completing the learning task, the typical participant correctly answered 80% of items that they previously answered incorrectly, or that they learned 80% of the materials that were possible to be learned. The mean situation model learning score was $M = .463$ ($SD = .247$), meaning a typical learner correctly earned 46% of points which were not earned on the pretest essays.

7.2.2. Achievement goal orientation

The Achievement Goals Questionnaire-Revised (Elliot & Murayama, 2008) is a 12-item measure that assesses learners' orientation according to a 2×2 model. Subscales for each achievement goal are composed of three items that are Likert scored from 1 to 7 (Sample items "My aim is to completely master the material presented in this class"; mastery approach; "My goal is to avoid performing poorly compared to others"; performance avoidance). In this study, the coefficient alphas for each scale range from $\alpha = .763$ to $\alpha = .817$ across mastery approach, performance approach and performance avoidance subscales included in the analyses. Items referred to achievement goal statements with respect to "this class." Students were reminded both during recruitment and prior to completion of survey measures that the passage was selected to correspond to course readings, and that they should treat the task as they would any other assignment for their course.

7.3. Materials

7.3.1. Learning task

Learners were given 20 min to study a 1050-word text passage taken from a human development textbook (Berk, 2006) and an additional 307-word passage taken from the webpage of Division 12 of American Psychological Association summarizing a selection of childhood disorders. The topic of the reading passage from the textbook (Berk, 2006) was Attention Deficit Hyperactivity Disorder (ADHD), which was a topic included in the syllabus of all courses from which students were sampled.

The reading passage was broken up across a set of five pages of content with links to an additional ten pages that defined terms in the main reading. Users could navigate to these definition pages via the hyperlinked word in the main passage. In addition to the content pages, a Learning Goals page and a Study Checklist page included a number of specific learning objectives, which appeared alternately as a list of learning goals and as a checklist for review. These were included in order to track planning and monitoring behavior, though no student accessed the Learning goals page prior to visiting the first content page. As a result, planning using the Learning Goals page was not analyzed.

7.3.2. NStudy

The computer-based learning environment employed in this study was nStudy (Winne et al., 2009). NStudy is an Internet-based learning environment through which learners can navigate to any webpage and can browse its contents. The nStudy environment provides students with tools they can use to interact with the webpage such as highlighters, note templates, a glossary, a link creator, and an information panel that records their marks on the webpage content to facilitate review of marks and links made. NStudy then tracks learners' activities within the webpage and creates a time stamped log of learner actions. This log file can be used to analyze the occurrence, frequency, timing and pattern of learner behaviors. Additional tools available in nStudy that were not available to students for this study include a concept map and search tool, as well as collaborative tools like chat and help functions. A screen shot of the nStudy environment appears in Fig. 2. Before participants began their study session, they received a brief (15-slide) tutorial presentation that explained the purpose of the nStudy browser and how to use its tools. This tutorial contained annotated screenshots of the nStudy browser and its functionality as well as a test to ensure they could successfully make a highlight and a note.

7.4. Procedure

The study was introduced to learners during a class visit as an investigation of the impact of computer-based educational materials on different types of learners by the first author. Students were informed that the experiment involved completion of a reading task on a topic to be covered in the course; participation in the study was explained as optional and confidential, requiring less than one hour, and worth extra credit in their education course. Once participants indicated their interest, they were given a consent form and a session was scheduled. With the exception of a written informed consent procedure, all instruments were presented electronically. During each study session, pre-task questionnaire measures were completed, then participants viewed the nStudy tutorial, logged into the nStudy environment, and were given the following directions: "This is the main page for the learning task you are asked to complete. You have 20 min to study its contents in any way you wish. When you decide you are finished or when time expires, you will complete a posttest and the session will be over." Participants completed a session and posttest, were debriefed and dismissed.

7.5. Coding and scoring

The measurement of SRL strategies follows from the assumption of Winne and Perry (2000) that SRL behaviors are best measured as they occur. Logs of learning behavior were analyzed to

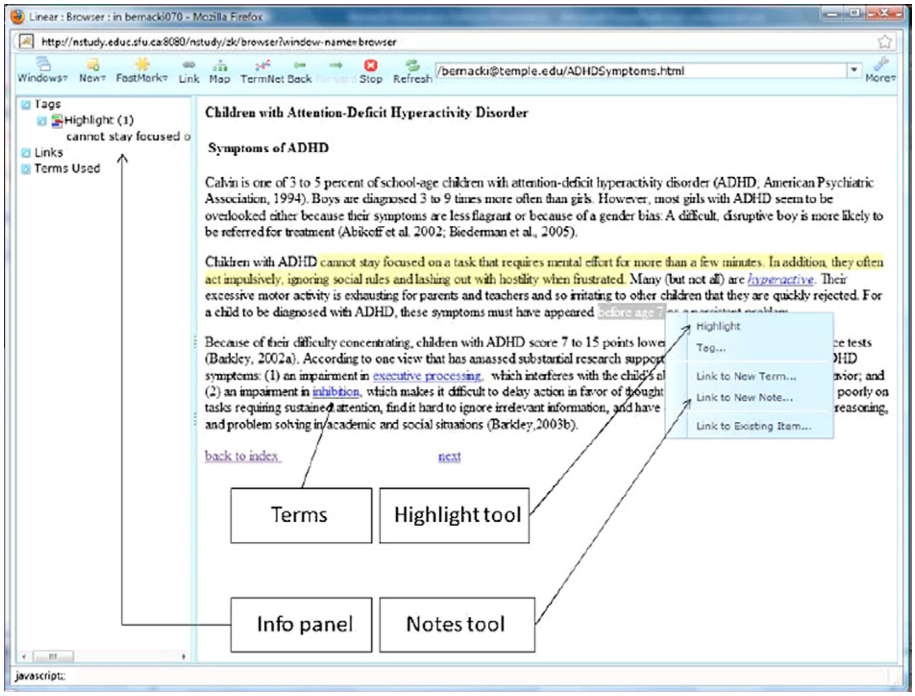

Fig. 2. The nStudy browser.

Table 2
Traced actions, SRL behaviors they represent, and equivalent variables in prior research.

Traced action	SRL behavior	Equivalent traced variable in prior research
Highlighting	Highlight made	Highlight, keeping records[c]
Note-taking[*]	Note taken	Note[a], taking notes[b], monitoring[b], keeping records[c]
Seeking more information	Click on a link to obtain definition of a term	Select new informational source[b]
Monitoring progress	Click on checklist of learning goals	Monitor progress toward goals[b], Self-evaluation[c]
Reviewing annotations	Click in information panel to review highlighted text or open a note	Read notes[b], rehearsal and memorizing[c]

[a] Nesbit et al. (2006).
[b] Azevedo and colleagues (2004).
[c] Zimmerman & Martinez Pons (1986) SRLIS.
[*] Depending on the content of the note, note-taking could be related to multiple metacognitive monitoring codes in the Azevedo codebook including judgment of learning, feeling of knowing, knowledge elaboration, evaluation of content adequacy, and others. The low frequency of each required note-taking to be aggregated.

identify the frequency with which specific behaviors occurred. A set of traceable behaviors indicative of cognitive and metacognitive processes described by SRL theory were conceptualized and captured within nStudy logs. These behaviors align to SRL theories of Winne and Hadwin (1998) and Zimmerman (2000, 2011) as well as to previous methodologies that aim to capture evidence of SRL. Table 2 contains a list of the traceable behaviors under examination in this study, as well as the definition of the action and analogous codes of traces from prior research. The three coding methods used as referents are the logged traces from Nesbit and colleagues' (2006) investigations using gStudy, the micro-level SRL think-aloud codes developed by Azevedo and colleagues (Azevedo & Cromley, 2004; Greene & Azevedo, 2007; Greene & Azevedo, 2009), and categories of SRL actions coded in classrooms using Zimmerman and Martinez-Pons' (1986) Self-Regulated Learning Interview Schedule.

When a learner completes a learning task in nStudy, the browser records every action the user completes. These actions include clicks to access pages, click–and-drags to select text to annotate, or clicks to utilize features of the environment like the highlighter, information panel, note tool, and so on. Each recorded action is stamped with the time it occurred, making it possible to analyze the sequence of actions and the amount of time between actions,

Table 3
Descriptive statistics for achievement goals, self-regulated learning behaviors and comprehension scores.

Variable	Mean	SD	Skewness	Kurtosis
Mastery approach	3.97	0.94	−0.55	−0.53
Performance approach	3.36	1.09	0.01	−0.86
Performance avoidance	3.26	1.16	−0.07	−0.67
Highlighting[*]	11.06	11.16	0.59	−0.78
Note-taking[*]	0.09	0.49	5.89	37.27
Review of annotations[*]	2.09	5.41	3.74	15.23
Seeking more information	1.33	2.12	2.18	5.45
Monitoring progress[*]	0.78	0.69	1.14	3.34
Textbase pretest score	7.37	1.95	−0.39	0.71
Situation Model pretest score	3.60	1.36	−0.41	0.18
Textbase posttest score	13.35	2.152	−2.038	9.179
Situation Model posttest score	5.48	1.327	−.924	1.257
Textbase learning score	0.80	0.17	−1.04	2.12
Situation Model learning score	0.46	0.25	−0.37	−0.57

[*] Behaviors were non-normally distributed. See Section 8.2 for a description of treatment of the data.

or the amount of time spent on a page. As a result, researchers who interpret log data must choose whether to represent behaviors using the number of times an event occurs, the duration of an event, or other metrics. Researchers must also consider whether to treat a behavior as an occurrence (Winne, 2010) of a behavior, as a contingency where the action follows a preceding action, or as a pattern of contingencies. Given the brief duration of the learning task (20 min) and the limited scope of the task environment, it was infrequent that a specific action was consistently preceded by a different specific action (generating a contingency). As such, SRL behaviors were analyzed at the level of occurrences. With the exception of highlighting, which occurred often, SRL behaviors were represented as count variables indicating the frequency of occurrence of a traced behavior across the learning task.

7.6. Data analysis

Replicating the methods employed by other recent studies that model the self-regulated learning behaviors of a similar sized sample of learners in a hypermedia learning environment (e.g. $n = 170$; Greene, Costa & Denlinger, 2011), we estimated a path model (Fig. 1) to address the proposed research questions. The model was composed of five exogenous variables including three achievement goal variables and two prior knowledge variables (score on textbase and situation model subtests). Endogenous variables included five traced SRL behaviors that were anticipated to be predicted by achievement goals and prior knowledge and predictive of the two measures of learning.

8. Results and discussion

8.1. Descriptive statistics

On average, participants spent 11 min and 37 s on the task (*SD* = 5:11). Of the 160 participants, 94% visited all pages containing portions of the hypertext and 71% visited the learning objectives checklist at least once. Forty-four percent followed hyperlinks to seek out definitions of key terms. One hundred out of 160 participants used the highlighter (62.5%) and highlighted 1769 sections of text while 27 used the note-taking tool (16.8%), making a total of 78 notes. Thirty-five of the 100 participants who made annotations reviewed their annotations using the information panel. Others may have also reviewed them during their revisitation of content pages (once text is highlighted, highlights persist). As a result, it is difficult to accurately assess the exact frequency and benefit of review of annotations. The mean number of times each behavior occurred, as well as the skewness and kurtosis of each distribution appears in Table 3. The skewness and kurtosis statistics for the behaviors denoted with an asterisk indicate that the distribution of behaviors was non-normal and that a transformation or different underlying distribution was applied in analyses involving these data to improve model fit.

8.2. The path model

A matrix of correlations between all variables in the model can be found in Table 4. To test hypotheses, a path model was estimated using Mplus 6.11 (Muthén & Muthén, 2010) using a maximum likelihood estimation method. The fit indices of the model suggest an acceptable fit to the data, χ^2 (7) = 13.150, $p = 0.069$ (CFI = .906, SRMR = .030, RMSEA = .074 CI = .000, .135, AIC = 4988.538, BIC = 5182.274, SABIC = 4982.839. The frequency with which learning behaviors occurred tended to be non-normal and, as a result, were modeled as counts. In order to improve the fit of our model to this type of data, a subset of behaviors were re-entered into the model using negative binomial (reviewing annotations, monitoring understanding) and zero-inflated Poisson (note-taking) distributions in order to better represent the distribution of these behaviors (Greene, Costa, et al., 2011). A histogram of highlighting revealed that 60 individuals conducted no highlighting, while the remainder of the distribution was relatively normal (skewness = .265). As a result, we modeled highlighting using an interval scale. Those who did not use the highlighter were assigned a score of zero, while those who made between 1 and 22 highlights (within one standard deviation of 11.056, the mean number of highlights made) were assigned a one, and those making greater than 22 highlights, a two.

When applied concurrently, these adjustments improved the fit of the model (AIC = 1664.963, BIC = 1858.699, SABIC = 1659.264) and yielded the final solution that appears in Table 5 and Fig. 3. Note that the parameter estimates in the model are unstandardized. Standardized coefficients are not available for a model employing count variables as predictors; when modeled as predictors, these types of variables have no variances (Muthén, 2006; Muthén, & Muthén, 2010).

The unstandardized solution for the final path model we estimated to test relationships between achievement goal scores, SRL behaviors and increases in comprehension scores appears in Fig. 3. Paths in black denote statistically significant parameter estimates. Broken lines represent marginal paths. Significance levels are denoted beneath the figure and parameter estimates for all paths and their significance values are provided in Table 5. Because the figure includes unstandardized parameter estimates, comparisons using coefficients to represent the strength of their effect cannot be made. However, the unstandardized model can be used to make practical statements about employment of learning behaviors. For instance, for each additional point a learner indicates on agreement with mastery goals (scaled 1–7), they write an additional 2–3 notes (parameter estimate is 2.751), and that for each time a learner reviews the checklist of learning goals to monitor their learning, their situation model posttest score improves 6%. In terms of the size of these effects, the use of count statistics again precludes calculation of a coefficient of determination (R^2), however the relative

Table 4
Correlation matrix for achievement goals, self-regulated learning behaviors, and comprehension scores.

Variable		1	2	3	4	5	6	7	8	9	10	11	12
1	Mastery Approach	–	.47*	.39*	.08	.09	−.08	.20*	.16*	−.13	.01	.02	−.03
2	Performance Approach		–	.71*	−.03	−.10	−.10	.11	.05	.04	−.07	−.09	−.06
3	Performance Avoidance			–	−.04	−.06	−.08	−.05	.07	.08	−.10	−.21*	−.06
4	Highlighting				–	.19*	.14	.16*	.03	.02	.08	.10	.16*
5	Note−taking					–	.16*	.11	.01	.06	.06	.13	.00
6	Reviewing annotations						–	.07	−.09	.01	.04	.02	−.07
7	Seeking more information							–	.24*	.06	.10	.03	.04
8	Monitoring progress								–	.04	.18*	.06	.14
9	Textbase pretest									–	.20*	.19*	.17*
10	Situation Model pretest										–	.20*	−.15
11	Textbase learning											–	.28*
12	Situation Model learning												–

* $p<.05$.

Table 5
Unstandardized effects among prior knowledge, achievement goals, learning behaviors, and comprehension variables.

Independent variables	Endogenous (dependent variables)						
	Highlighting	Reviewing annotations	Note-taking	Seeking information	Monitoring progress	Textbase learning	Situation model learning
Mastery approach	.088	−.267	2.751*	.432*	.125^	.022	.005
Performance approach	−.046	−.126	1.687	.223	−.036	.017	−.012
Performance avoidance	−.009	−.213	−1.34*	−.311*	.032	−.049*	−.018
Pretest textbase comprehension	.010	.068	−.660	.117	.010	.018*	.028*
Pretest situation model comprehension	.047	−.062	−.790	.009	.086*	.016*	−.046*
Highlighting	–	.812*	3.788*	–	–	.013	.049*
Reviewing annotations	–	–	–	–	–	.000	−.003
Note-taking	–	.255	–	–	–	.030	−.013
Seeking more information	–	–	–	–	–	−.006	.000
Monitoring progress	–	–	–	–	–	.010	.060*

Note:
* $p < .05$.
^ $p = .10$.

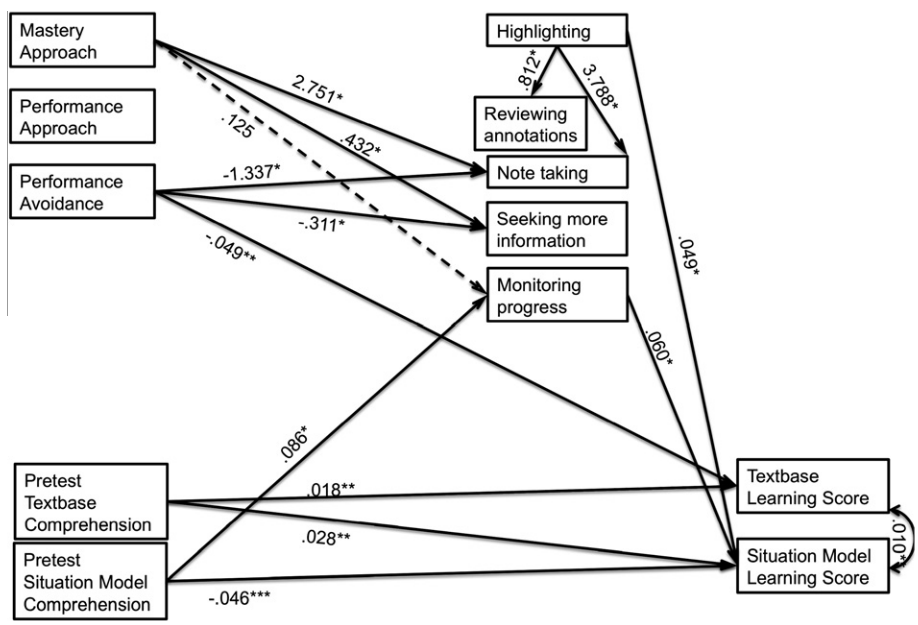

Fig. 3. Unstandardized solution to the final path model. *Notes*: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

strength of an effect of an unstandardized parameter can be inferred by the significance level (the *p* value) associated with each parameter in the model (see Table 5). In this results section, we summarize the estimated strength of hypothesized paths from each achievement goal to SRL behaviors and to comprehension scores, from each SRL strategy to each comprehension score, and from prior knowledge scores to SRL strategies and comprehension scores.

8.2.1. Achievement goals and comprehension scores

Based on prior research, we hypothesized that performance avoidance goals should negatively predict comprehension scores (Senko & Harackiewicz, 2005) and that mastery approach and performance approach goals were only somewhat likely goals to have a direct effect on comprehension (Hulleman et al., 2010; Linnenbrink-Garcia et al., 2008). The final model largely supported these hypotheses. Neither mastery nor performance approach goals had direct effects on comprehension scores; performance avoidance did have a negative effect on learning, but only at the textbase level. While the typical learner was predicted to answer 62% of previously missed items correctly, a 5% decrease was predicted for each unit increase on the performance avoidance score.

Results for performance avoidance conform to the expectations of achievement goal theory; those who sought only to avoid a poor performance in the task were more likely to perform poorly. This raises a question about the adoption of performance avoidance goals in individual learning tasks. In a task condition where no normative reference is available (learners completed the task individually and no normative reference was provided), a set of learners continue to report a performance avoidance orientation and experience the negative effect on learning outcomes that results despite a lack of opportunity to make peer-referenced comparisons. This might suggest that a performance avoidance orientation is a stable individual difference variable attributable to learners that leads to more pervasive negative learning outcomes across tasks. This contrasts with mastery approach and performance approach goals on achievement which were found to not directly effect achievement outcomes in this study, but have been found to be associated with achievement in 40% of studies (Linnenbrink-Garcia et al., 2008).

8.2.2. Achievement goals and SRL

Based on a combination of theory and prior research using self-report measures, we hypothesized that higher mastery approach scores would predict greater amounts of SRL behaviors, higher performance avoidance goals would predict lesser amounts of SRL behaviors, and that higher performance approach goals would not predict the learning behaviors we traced with the potential exception of highlighting (as a shallow processing strategy; Greene & Miller, 1996; Nesbit et al., 2006). These hypotheses, too, were partially confirmed by the model. A set of SRL behaviors emerged based on participants' achievement goal orientations. Learners adopting mastery goals tended to take notes, explore the hypertext using links to seek additional information, and, to a lesser degree, monitor their progress towards goals by referencing a checklist of learning objectives. Performance approach scores did not predict any of these behaviors. Those with high scores on performance avoidance goals took significantly fewer notes and clicked on fewer links to obtain additional information. No achievement goal predicted highlighting or review of annotations.

Interpreting these findings from a multiple goal perspective, we were unable to model additive or integrative effects of pursuing multiple goals on any one behavior. As expected, the direction of effects on behaviors tended to be opposite for mastery approach goals (positive) and performance avoidance goals (negative). We also found no significant paths from performance approach goals to strategies, which confirms our hypothesis about performance goals in a task environment that provided no opportunity for normative referencing. However, because no significant effect of performance approach goals were found on learning behaviors, we could not examine further how mastery and performance approach goals might combine or interact to effect learning behaviors.

On the topic of simultaneous measurement of multiple pathways from goals to strategies, we should also offer a note of caution when interpreting the findings in this study due to potential effects of suppression that may arise when simultaneously modeling multiple paths to a variable. The inclusion of a third variable can influence the relationship between a predictor and a dependent variable (c.f. McKinnon, Krull, & Lockwood, 2000). In instances where this effect is weakened, the third variable acts as a mediator; but in instances where the effect is strengthened, the third variable acts as a suppressor. In this study, SRL behaviors were examined as mediators between achievement goals and performance. However, high correlation among achievement goals increases the risk that including multiple goals in our model might induce a suppression effect on estimated paths, increasing the size of parameter estimates from achievement goal to learning behaviors in the model. Comparing the correlations in Table 4 with the parameter estimates in Table 5, estimation of negative paths from performance approach and performance avoidance goals might reflect a suppression effect caused by the high correlation between performance approach and performance avoidance goals ($r = .71$). Similar effects may have influenced paths from mastery approach to note-taking and from monitoring to situation model learning. Small increases in parameter estimates can turn non-significant or marginal effects into significant ones, which changes the appearance and interpretation of path models. We think that this behavioral approach has potential for finer-grained analysis of effects of achievement goals on students' use of strategies and their effect on learning, but these initial findings should be interpreted with caution until they can be replicated in additional studies.

Assuming for now that the findings are robust, results in this study differ from earlier work that examined how achievement goals influence cognitive engagement strategies. In studies that treated strategy use as a unitary variable self-reported by learners, adoption of mastery goals predicted higher levels of cognitive engagement, and those that separated out strategies into shallow or deep cognitive and metacognitive strategies found that mastery goals promoted deep cognitive and metacognitive strategies, while performance approach goals promoted shallow cognitive strategies. When we assessed strategies using behavioral traces instead of self-report, mastery goals predicted only a subset of the behaviors we traced, and performance approach goals did not predict any behaviors. Mastery goals did predicted two strategies one might conceive of as reflecting cognitive processes like elaboration and organization (note-taking, information-seeking) and were a marginal predictor of a behavior reflecting metacognitive monitoring.

8.2.3. SRL and situation model comprehension

The third dimension of our research question focused on the relations between self-regulated learning behaviors and textbase and situation model comprehension. As can be seen in the model, learning behaviors did not affect textbase comprehension. However, participants' tendency to highlight and to monitor their progress towards learning goals both predicted increases in the amount comprehension would increase on the situation model subtest. These findings align closely to self-regulated learning theory, which suggests that a task must be sufficiently difficult for a self-regulated learning behavior to be relevant to successful performance (Greene & Azevedo, 2009). Given that the typical participant in the study learned 80% of the available material regardless of their SRL behaviors, acquiring textbase comprehension was not a sufficiently difficult task to require SRL to ensure success. At the situation model level, however, the typical learner improved comprehension only 46%. This subtest was considerably more difficult and results indicate that learners who conducted specific SRL behaviors learned more than their peers. Identification of important segments of text (as evidenced by increased rates of highlighting) predicted increases in comprehension. Similarly, evaluation of progress towards learning goals, as evidenced by repeated visitation to a learning goals checklist, may have supported inference generation, a key to the development of situation model comprehension, according to Construction-Integration Theory (Kintsch, 1998).

8.2.4. Prior knowledge, SRL and learning outcomes

Our model also accounted for the effect of prior knowledge on strategy use and learning. Our hypothesis that prior knowledge would predict increased monitoring, decreased strategy use and increases in learning was partially confirmed. Pretest situation model comprehension scores predicted monitoring scores (replicating Moos & Azevedo, 2008), however no effect was found on any of the other behaviors we examined. Higher pretest textbase comprehension scores predicted larger increases in both textbase and situation model comprehension, suggesting that increased amounts of prior knowledge made it easier to acquire new knowledge within the task. Higher pretest situation model scores predicted lower amounts of learning. This was due to the inclusion of some less difficult items and a particularly difficult item. Those with high prior knowledge correctly answered the easier items at pretest and their learning score reflects difficulty mastering the additional challenging item. Situation model learning scores of those with lower prior knowledge indicate their mastery of easier items in addition to their mastery of the more difficult item. Having examined each component of the model, we now consider the results of the study at a higher level, compare the findings to prior research, and discuss implications of the findings.

8.3. Implications

A primary purpose of this study was to use behavioral data to reexamine the previous finding that learners' achievement goals predict the cognitive strategies they use, which in turn predict their performance on learning tasks. In addition to producing a model based on behavioral assessments of strategy use, this study prompts discussion of some next steps towards reconciling behavioral measures with the cognitive, metacognitive and self-regulatory processes that they and self-report measures are intended to reflect.

The final model we estimated revealed that mastery goals predicted two (note-taking, seeking additional information) of the five self-regulated learning behaviors we traced, and a third path from mastery to monitoring was marginally significant. Of these predicted behaviors, only monitoring was a significant predictor of increases in comprehension, and only at the situation model level. If we compare this model to prior research using self-reported strategy use to investigate the same relationships, we find that a generalized pathway from mastery goals to cognitive strategy use to learning is maintained. However, direct observation of learners' behavior demonstrates that cognitive engagement is not evenly distributed across the set of strategies typically characterized as deep cognitive strategies in the literature. Instead one's mastery goals predict the use of a subset of cognitive strategies, only one of which is predictive of learning.

Of the behaviors we measured, highlighting had a significant and stronger effect on learning than all but one of the strategies associated with self-regulated learning and cognitive engagement that we traced (monitoring). Highlighting has been alternately conceived of as a shallow cognitive strategy (Nesbit et al., 2006), and as a type of behavior that may lead to deeper cognitive engagement (Greene et al., 2004). Highlighting was predictive of note-taking and of review of annotations. Based on these findings, we can partially confirm Greene and colleagues' hypothesis. What we cannot say is what type of cognitive processes occurred as learners highlighted text. Were they simply conducting rehearsal, akin to the shallow strategies reported in prior studies? Did highlighting reflect a metacognitive judgment that specific passages were important? Was the highlighter a tool used to select passages for further elaboration or a method of identifying passages to be organized with prior knowledge or other important segments of the text?

These unanswered questions reflect the current challenge associated with the use of behavioral evidence of learning processes. Using behavioral traces eliminates biases associated with self-reports and can help researchers avoid potential mischaracterizations of strategies as reflecting a particular type of cognitive process that may not have occurred. However, the cognitive processes that are occurring while the behavior is being logged are not known. In the case of highlighting, further investigation, perhaps using eye tracking and think-aloud protocols, might be in order to investigate how learners attend to text when highlighting and what mental processes occur as they do so.

For now, we have identified a behavior (highlighting) that promoted learning. Interestingly, we found that highlighting predicted situation model comprehension increases but not textbase increases. One would expect a strategy described as shallow to predict textbase learning and not the deeper learning reflected by situation model learning scores. However, since the opposite was true we must consider that the act of highlighting may reflect a deeper consideration of the text than previously thought.

8.4. Limitations

The limitations unique to this study include the validity of log data, the comprehensiveness of the behaviors traced, and the task context in which the study was conducted. While the use of behavioral logs eliminates bias and inaccuracy associated with self-report measures, log analyses are not without limitation themselves. Using log data to represent SRL variables introduces a new limitation in that indicators have yet to be validated to learners' self-reported cognitive processes that traces are intended to represent. Conclusions can be drawn only about a specific behavior as a predictor of learning, and connection made to cognitive or metacognitive operations are tentative until a trace can be validated. As suggested by Greene and Azevedo (2009), future research needs to be conducted to pair think-aloud data with log analyses in order to assess the validity of inferences regarding the cognitive processes behavioral traces reflect.

In addition to requiring validation to ensure that the behaviors we observed reflected the strategies learners intended to employ, our list of traceable behaviors ($n = 5$) is short in comparison to number of constructs assessed by self-report measures of cognitive engagement or by think aloud codes of SRL processes ($n > 30$). Increasing the amount and type of information in a log file and the sophistication with which we interpret it can yield an expanded list of traceable behaviors. These can better approximate the type and frequency of cognitive strategies learners employ. Environments with features that capture these self-regulated learning behaviors are emerging (e.g. MetaTutor; Azevedo, Witherspoon, Chauncey, Burkett, & Fike, 2009), as are more complex interpretations of log data (Aleven, Roll, McLaren, & Koedinger, 2010). It is possible that, were we able to trace additional behaviors that are self-reported in other studies, these behaviors might have been associated with mastery goals and learning outcomes as found in prior research. Being able to trace any learning behaviors is a step up from asking students to recount them, but our methods and predictive models will need to improve so we can increase the number of strategies we can capture and model.

Learning environments differ in their affordances and restrictions as well as the content of the task and the type of performance used to assess learning. As a result, all findings need to be considered in light of a task context. Our task involved learning from hypertext in a web-based environment stocked with tools meant to support specific learning behaviors. Other environments may support different behaviors and each set of tools and traced behaviors may predict different outcomes depending upon the content of the task and the way learning is assessed. Researchers should consider this when interpreting findings, and any generalization of these findings to new contexts should be limited to instances where populations and environments are similar.

One final limitation to our study that bears mentioning concerns subjects' interpretation of the items used to assess their achievement goals. We used the original wording of the AGQ-R items, which refer to one's goals for "this class." We did so because we chose a topic that would be discussed later in the class and told students to treat the task as they would any other course reading. Subjects were reminded of this upon recruitment and at the beginning of the session. However, because sessions were conducted separate from class instruction, subjects may not have interpreted the reading task as affiliated with readings to be done for their course, which might have influenced the achievement goals they reported.

8.5. Summary and conclusions

Specific achievement goals motivated individual self-regulated learning behaviors, and some of these behaviors affected comprehension of a hypertext reading. Mastery learners were more apt to take notes and seek information and marginally more likely to monitor learning. Monitoring predicted higher levels of comprehension at the situation model level. This confirmed prior evidence that mastery goals were the most beneficial achievement orientation for motivating enactment of learning strategies that lead to learning, however not all of the strategies that mastery goals motivated were optimal strategies for performance on the measures of learning we administered. Additionally, other strategies not motivated by mastery goals (highlighting) were significant predictors of increased comprehension. In addition to fostering mastery goals to promote deep strategy use, it would be beneficial to teach learners to consider the task conditions and the utility of different learning strategies that are supported by the learning environment. If students' mastery goals compel them to take notes, seek additional information and monitor their learning process, they might also be taught to monitor their environment and adapt their strategies in light of the context. Monitoring both one's learning process and the learning environment would increase the likelihood that students would attend to task conditions and select optimal strategies for the task and achieve the greatest level of comprehension as a result.

8.6. Future directions

Moving forward, it is important to continue to develop the methods by which we capture evidence of learning behaviors so that we might better approximate the cognitive and metacognitive processes that constitute self-regulated learning. Behavioral data is more robust against the bias and error associated with self-report data. If we can develop behavioral traces that reflect SRL strategies, our models of the learning process will support better investigations into the links between motivational constructs, learning behaviors and learning outcomes. It will be important to examine these relationships in additional learning environments, both in traditional classrooms where trace data can be collected and in multiple technology-enhanced learning environments where different task conditions (e.g. tool provision, task structure, domain, measures of learning) are present. Further investigation will allow us to determine the degree to which relations between achievement goals, learning behaviors and learning outcomes are robust across contexts or are dependent on features of a learning task.

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