Spring 2011

Three elements of self-regulated learning: Metacognitive functioning, self-efficacy, and study behavior

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Three elements of self-regulated learning: Metacognitive functioning, self-efficacy, and study behavior

Abstract
Individuals' metacognitive insight regarding their own performances -- what people think they know about what they know -- is often flawed. Students' metacognitive functioning was examined in two studies. In Study 1, exam performance estimates compared with actual scores were assessed across three in-class exams. Results demonstrated a systematic tendency for lower performers to overestimate their exam performances. Top performers underestimated their performance. In Study 2, an incentive to be as accurate as possible in exam performance estimations ($50 gift card) did not reduce estimation miscalculations for either bottom or top performers.

In Study 1, higher levels of students' self-efficacy (one's confidence that they can successfully complete a given task) were associated with higher levels of academic performance. Additionally, students with higher self-efficacy tended to use more cognitively based ("active") study strategies. Further analysis of study behavior demonstrated a positive correlation between reported use of active study behaviors and exam score and a negative correlation between reported use of passive study behaviors and exam score. Students who were both high on the active study behavior measure and low on the passive study behavior measure scored highest on the exam. Implications for successful self-regulated learning were discussed.

Keywords
Psychology, Social, Education, Educational Psychology

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THREE ELEMENTS OF SELF-REGULATED LEARNING:
METACOGNITIVE FUNCTIONING, SELF-EFFICACY, AND STUDY BEHAVIOR

BY

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DISSERTATION

Submitted to the University of New Hampshire
In Partial Fulfillment of
The Requirements for the Degree of

Doctor of Philosophy
In
Psychology

May, 2011
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Date: April 14, 2011
ACKNOWLEDGEMENTS

This dissertation was supported by a grant from the Davis Educational Foundation, Victor A. Benassi, Principal Investigator. The Foundation was established by Stanton and Elisabeth Davis after Mr. Davis's retirement as chairman of Shaw's Supermarkets, Inc.
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ABSTRACT

THREE ELEMENTS OF SELF-REGULATED LEARNING:
METACOGNITIVE FUNCTIONING, SELF-EFFICACY, AND STUDY BEHAVIOR

by

Catherine E. Overson

University of New Hampshire, May, 2011

Individuals’ metacognitive insight regarding their own performances – what people think they know about what they know – is often flawed. Students’ metacognitive functioning was examined in two studies. In Study 1, exam performance estimates compared with actual scores were assessed across three in-class exams. Results demonstrated a systematic tendency for lower performers to overestimate their exam performances. Top performers underestimated their performance. In Study 2, an incentive to be as accurate as possible in exam performance estimations ($50 gift card) did not reduce estimation miscalculations for either bottom or top performers.

In Study 1, higher levels of students’ self-efficacy (one’s confidence that they can successfully complete a given task) were associated with higher levels of academic performance. Additionally, students with higher self-efficacy tended to use more cognitively based (“active”) study strategies. Further analysis of study behavior demonstrated a positive correlation between reported use of active study behaviors and exam score and a negative correlation between reported use of passive study behaviors and exam score. Students who were both high on the active study
behavior measure *and* low on the passive study behavior measure scored highest on the exam. Implications for successful self-regulated learning were discussed.
INTRODUCTION

Academic achievement presupposes that students have an overall understanding of their knowledge and learning needs, that they effectively manage study time allocation and that they are reasonably confident they can succeed on required tasks. These elements may lay the foundation for self-regulated learning, and each can be enhanced by the use of study strategies that advance learning. For some students, however, difficulties with one or more of these essential elements of learning may lead to disappointing academic performance. For example, difficulties can arise because people misallocate study time (Kornell & Bjork, 2008; Metcalfe & Kornell, 2005), lack confidence in their ability to succeed (Bandura, 1993; Pajares, 1996), are mistaken about what they think they know (Kruger & Dunning, 1999; Ehrlinger, Johnson, Banner, Dunning, & Kruger, 2008), or employ study strategies that are not favorable to academic performance (Thomas & McDaniel, 2007).

One model of self-regulated study, posited by Metcalfe and Kornell (2005), suggests that students allocate their study according to their “region of proximal learning.” That is, students set aside already mastered items and begin their study by first attending to those items that they perceive are easier to learn and proceed, incrementally, toward the study of items deemed by them to be more challenging. It follows, therefore, that in order for the occurrence of adequate study regulation, a faithful appreciation of one’s degree of learning is crucial. In other words, students should be able to distinguish items they have learned from those they have not.
The length of time students are willing to remain in a state of little or no learning may be related to circumstantial elements (for example, time constraints) or individual differences. One possible individual difference variable related to a person’s capacity for self-regulated study is self-efficacy.

The degree of confidence – that is, the self-efficacy – a student has regarding the successful completion of a task in question can affect academic performance (Bandura, 1993; Pajares, 1996). Variations in levels of confidence tend to be reflected in task perseverance. High degrees of confidence are associated with optimism and continued effort, and low degrees of confidence are associated with pessimism and diminishing efforts of perseverance (Bandura, 1993). Whereas high efficacious individuals generally outperform their low-efficacious counterparts (Bandura, 1993; Pajares, 1996), the implication is that perseverance is reflected in outcome performance. The manner in which levels of self-efficacy affect judgments of performance is uncertain, and may provide some insight into metacognitive functioning.

One way researchers can examine metacognitive functioning is by asking individuals to judge their performance at a given task and then compare their estimations to objective measures of assessment (Kruger & Dunning, 1999; Ehrlinger et al., 2008). A singular drawback to performance estimations is that, with the exception of the top performers, individuals systematically tend to overestimate, sometimes dramatically, how well they have done on a performance task (Kruger & Dunning, 1999; Ehrlinger et al., 2008).

A particular concern for educators is that unwarranted optimism can negatively affect students’ study behaviors, leading to inadequate and ineffective study patterns.
Thomas & McDaniel, 2007). Individual differences in study patterns are strongly related to academic performance, with some study methods producing better learning outcomes than others. For example, when compared to merely studying and massed practice (Carpenter & Pashler, 2007; Johnson & Kiviniemi, 2009; McDaniel, Anderson, Derbish, & Morisette, 2007; Roediger & Karpicke, 2006), self-testing and spaced practice (spreading studying over time) have been empirically demonstrated to be superior with regards to learning and retention of academically meaningful material (Metcalf et al., 2007).

In this program of research, I examine three elements related to students’ academic performance: metacognitive functioning, self-efficacy, and study behavior. Working to unravel the phenomena interlacing these elements may help researchers and educators to better understand the circumstances that give rise to – at times – ill-advised choices students make in their efforts toward self-regulated learning.
CHAPTER 1

THREE ELEMENTS OF SELF-REGULATED LEARNING

Judgment of Performance

“What’s especially difficult about being ignorant is that you are content with yourself . . . If you don’t think you need anything, of course you won’t want what you don’t think you need.” Plato.

People often manifest biases and illusions about their abilities and performances, and about what they think they know. That is, the degree of metacognitive insight regarding their abilities and performances—what people think they know about what they know—is often flawed. One way this flawed thinking is expressed is through self-evaluation.

People’s evaluations of themselves are often self-serving (e.g., Alicke, 1985; Dunning, Meyerowitz, & Holzberg, 1989). One manifestation of self-serving evaluations is noted in the “above average effect”—that is, a tendency for people to rate themselves as being above average in abilities and performances. For example, people tend to rate themselves as being above average in having desirable traits (Alicke, 1985), knowledge of humor and grammar, and skill at computing logic problems (Kruger & Dunning, 1999), and performance on exams (Dunning et al. 2003; Ehrlinger et al., 2008). Alicke suggested that people think about themselves in this way because of a desire to feel good about themselves—that is, they strive to maintain a positive self-concept. It is through
this esteem bolstering, Alicke argued, that people develop a sense of personal control, competence, and efficacy.

Flawed self-assessments are also observed among average and lower performers who tend to hold biases that lead them to overestimate their performances on tasks in a variety of social and intellectual domains. The lower these individuals perform, the greater is the observed disparity between belief and actual performance. These people tend to possess an inflated self-assessment, that is, they have an illusion of competence (Kruger & Dunning, 1999; Dunning, Johnson, Ehrlinger, & Kruger, 2003; Ehrlinger et al., 2008).

In a laboratory setting, Kruger and Dunning (1999) examined participants’ performances and judgments of performance in a variety of domains, including ability to recognize humor, logical reasoning, and grammar. In each of these domains, the authors found a consistent pattern of overestimation among the average and lower performers. They argued that lower performers not only lack necessary skills to perform the given task, they are generally unaware that errors have occurred at all. That is, their lack of metacognitive skills renders them incapable of recognizing their own incompetence and accurately predicting their performance relative to their peers. In addition, they found that this pattern of performance misestimation on a logic task persisted even after viewing performances of their more competent peers. The authors suggested that this finding demonstrates that lower performers not only have an inability to recognize their own incompetence, they also lack ability to recognize – and to veridically compare themselves with – competent others. Conversely, high performing students, relative to their low performing peers, tend to underestimate their performance. Further, when provided
evidence of their true standing on the logic task, higher performers are able, according to Kruger and Dunning, to make corrective adjustments by raising their self-assessments. Thus, high performers’ corrective reassessments reflect evidence of appropriate metacognitive skills; theirs is a misperception of peer performance rather than metacognitive error, in contrast to lower performers.

The above studies were conducted in a laboratory setting. Educators might ask whether these patterns of under- and over-estimations manifest in real educational contexts. For lower performers, the concern is the real possibility that chronic faulty self-assessments may negatively impact future academic achievement. If lower performers are unable to recognize their own incompetence and fail to accurately compare themselves with — and to recognize — competent others, they may not seek the additional learning opportunities they need. This is a challenge for educators who are generally motivated to help the incompetent to become competent.

Dunning and colleagues (2003) investigated whether the familiar laboratory patterns of performance misestimations would occur in a natural academic setting. They examined student participants in an undergraduate psychology course. After taking an in-class exam, students were asked to estimate their raw score (absolute scores), mastery of course material, and their performance relative to other students taking the exam (percentile). As expected, in general, students reported that they mastered course material better than average relative to their peers; further, students in the bottom quartile grossly overestimated their scores and relative standing, and those at the top quartile underestimated their scores and relative standing, albeit not dramatically.
In a replication of the above study, psychology students taking an in-class exam (reported as challenging by the authors) showed the familiar pattern of misestimation in both absolute score estimates and percentile ranking estimates (Ehrlinger et al., 2008). A second in-class exam, used statistically to provide estimates for test-to-test reliability and correcting for measurement error, did not substantially reduce the pattern of student misestimation. For the lowest performing students, correcting for unreliability reduced the 49-point percentile ranking overestimates by 5 points. For the highest performers, however, correcting for unreliability was more impressive (given that the level of misestimation for this group was small to begin with); the correction reduced raw-score underestimation from 1.7 points to .2 points. An additional analysis of this second exam, not performed by the authors, might have facilitated analysis for a possible persistence of these misestimations across exams. In particular, additional analysis might reveal whether students who consistently perform poorly, or those who consistently perform well across two or more exams, persist in making the same erroneous performance estimates.

One can imagine that the notion of misestimation persistence, especially for the lowest performers, might compound educators’ concern for student success. Assuming that educating these students in appropriate skills and strategies for task success can facilitate academic competency, might there also be a change for the better in these students’ metacognitive functioning? Kruger and Dunning (1999) would argue “yes.” In a laboratory setting, the authors first had students complete a logic task followed directly by their judgments of performance. They then provided these students with requisite skills for logical reasoning and asked them to reassess the work they had done prior to the skills session. They found that these now competent students, after having reviewed their
work prior to their skills sessions still overestimated their relative performance; however, their re-estimates of their percentile ranking were significantly more accurate when compared to estimates prior to training. Conversely, students without logic skills training continued to show metacognitive miscalculation when reassessing their performances. Kruger and Dunning argued that achieving competence had altered students’ metacognitive functioning, effectively improving their metacognitive skills. These results suggest that identifying the sources of lower performers’ faulty self-assessments may be the first step toward improving academic performance.

Caputo and Dunning (2005) explored the possibility that metacognitive deficit does not account for all faulty self-assessments. They proposed that in some instances, judgments of performance reflect an ignorance regarding the breadth and scope of required response to a question, problem, or task. That is, imperfect self-evaluations could occur when individuals lack some of the information necessary for accurate self-judgment. In these cases, faulty self-assessments might sometimes reflect “errors of omission.” In their study, participants were asked to assess their ability to find all possible words in a Boggle puzzle. Initially, they were not informed of the actual number of possible solutions, and their judgments of their own performance were based on solutions accomplished rather than on words that might have been missed. Unaware of the actual number of word possibilities, participants’ self-evaluations did not take into account all possible word omissions. They simply did not have all the important pieces of information relating to the task environment (see also Carter & Dunning, 2008). Metacognitive competency was demonstrated when, after feedback regarding the total number of word solutions, participants were given a second opportunity to judge their
performance. They now gave weight to omitted words and their self-assessments more closely matched their actual performance.

As noted above, accurate and timely feedback can be a powerful strategy that informed others (e.g. educators) might provide to help students improve self-insight. Feedback, thus given, must be delivered with forethought and candor. Feedback that is ambiguous, biased, misleading, or for any reason withheld can itself contribute to faulty self-assessments by heightening recipient confusion, and relieving students of opportunities for self-reflection necessary for accurate metacognitive judgments (Carter & Dunning, 2008).

Errors of omission and feedback particularly speak to environmental elements as possible contributors to misleading self-estimates of performance. Additional sources may stem from internal, personal cues, such as chronically held self-views regarding preexisting knowledge and abilities (Ehrlinger & Dunning, 2003). In one study, psychology students systematically rated their performance on tests as higher if they believed the tests measured an ability they possessed (abstract reasoning) rather than one in which they felt deficient (computer programming), independent of actual performance.

Critcher and Dunning (2009) found that these chronically held self-views (top down – preconceived notions of ability) shaped phenomenological experiences (bottom-up – concrete testing cues), providing the psychological mechanism for performance estimates. Students interpreted their testing experiences as less demanding when they were lead to believe they were tested on a task on which they believed themselves to be competent rather than incompetent (abstract reasoning vs. computer programming). This knowledge, in turn, informed estimates of performances – but only when students were
informed of testing domain prior to taking the test, when bottom-up experiences could be contaminated. Students’ performance estimates were not affected by knowledge of testing domain if informed after taking the test, phenomenological experience already having been set.

**Self-Efficacy**

One potentially powerful individual difference related to students’ engagement with academic performance tasks involves their sense of self-efficacy. According to Bandura (2001), the overarching concept of self-efficacy is personal agency – the capacity “to intentionally make things happen by one’s actions” (p. 2). He went on to explain that intentional behavior involves a plan for action that is motivated and shaped by our goals and outcome expectations. In an academic setting, for example, a student given a logic task plans a series of behavioral strategies designed to help solve the problem. As the student engages in the logic task, the goal of solving the problem gives past and future actions (particular implementation of rules and strategies) purpose and meaning. Once the problem solving has begun, the student’s personal agency fosters self-reflective comparisons of distinct behaviors with goals (i.e., metacognitive evaluation). These evaluations help to shape future actions.

At the core of personal agency are efficacy beliefs. Because these beliefs reflect one’s confidence in the capability to effect change (e.g., solve a logic problem), they can profoundly impact decisions regarding whether to engage, level of engagement, and persistence of engagement in the task. More specifically, self-efficacy refers to an individual’s degree of confidence that he or she possesses the ability and skills to accomplish a particular task in a given domain (Pajares, 1996; Zimmerman, 2000).
Self-efficacy should be distinguished from a related construct, one’s self-concept. Self-concept comprises a series of cognitive components, which Markus (1977) calls self-schemata. These self-schemata are beliefs that people have about themselves, and they can be based on specific or general experiences. For example, people may have developed self-schemas related to personal experiences regarding gender, career, family, and academics. According to Zimmerman (2000), our various experiences are combined to produce a self-concept that is a global construct comprised of many forms of self-knowledge. In addition, self-concept has an affective, evaluative element associated with “competence and the feelings of self-worth associated with the behaviors in question. Self-concept judgments can be domain specific but are not task specific” (Pajares, 1996, p. 561). In contrast, self-efficacy reflects the degree to which individuals believe they have the capacity to effect specific change within themselves and/or over their environments (Pajares, 1996).

The degree of confidence a student has regarding the successful completion of a particular academic task in the face of obstacles can affect performance (Bandura, 1993; Pajares, 1996). High degrees of confidence are associated with optimism and continued effort and perseverance, whereas low degrees of confidence are associated with pessimism and diminishing efforts and perseverance. Bouffard-Bouchard (1989), for example, examined a group of students with equal ability in a verbal concept-formation task. The students were randomly assigned to either a high or low self-efficacy group, within which efficacy levels were experimentally manipulated. They found that, although the students equally possessed the skills needed to complete a verbal concept-formation task, those with high self-efficacy persisted longer on the task and completed
significantly more problems when compared with their low-efficacy counterparts who also possessed the requisite skills.

Goal achievement, as Bandura (2001) indicated, can be a particularly motivating factor driving students’ desire for successful academic outcomes. Educators might naturally presume that mastery of course material is the goal toward which their students aspire. However, Liem, Lau, and Nie (2008) found that students’ academic goals might not always be as straightforward as acquiring mastery in a given course. They discussed two complementary goal theories that contribute to understanding student achievement behaviors. According to achievement goal theory, some students are oriented toward demonstrating a successful performance and elevated competence relative to their peers, that is, they adopt a “performance-approach” to goal achievement. Expectancy-value theory takes into account a student’s self-efficacy along with the value a student places on whether the material to be learned is instrumental – or necessary – for the achievement of future goals. For example, a college might require the successful completion of preliminary courses prior to registration and entry into advanced courses.

Liem and colleagues (2008) found Singaporean students’ self-efficacy scores for learning the English language correlated with “instrumentality,” or practical use that the knowledge of English might afford. Higher self-efficacy also predicted the adoption of the performance-approach to goal achievement. Both higher self-efficacy and adoption of the performance-approach goal were associated with deep learning strategies. Deep learning strategies, the authors describe, are cognitive strategies associated with “elaborating ideas, thinking critically, and linking as well as integrating one concept with another” (Liem et al. 2008, p. 489). Conversely, their lower efficacious counterparts, less
oriented toward success than their more confident peers, tended to move toward goals that would disengage them from the task. In other words, the low-efficacy students behaved as predicted by Bandura (1993) and others. They gave up. Because students who adopt the performance-approach are concerned with demonstrating an elevated competence relative to their peers, an empirical question raised by the current study inquires whether high efficacious students make larger errors when judging their performances on an academic task.

In addition to goal-achievement, self-efficacy has been widely examined with regard to academic performance. In a literature review, Pajares (1996) reported on multiple investigations demonstrating that self-efficacy in general and academic self-efficacy in particular are associated with self-regulated learning, use of metacognitive strategies, and academic performance. For example, Pajares reported that a meta-analysis demonstrated a correlation (mean $r = .38$) between self-efficacy and academic performance. Of the few studies Pajares’ reviewed that reported participants’ educational level, the majority involved students in elementary, middle and high school. My research adds to the relative small number of studies examining college-age students’ levels of academic self-efficacy and academic performance.

Zimmerman and Kitsantas (2005) examined the relation of self-efficacy to academic achievement. They investigated whether self-efficacy mediated the relation between homework practices (time spent on homework and quality of homework [regulating time, completing assignments, etc.]) and grade point average (GPA). The participants in this study were enrollees of a private all-girls high school. Path model analysis confirmed a mediating role of self-efficacy. The zero-order correlation between
self-efficacy and GPA was also highly correlated ($r = .68$). Although these results look promising with regard to the positive effects of self-efficacy on academic performance, readers should note that participants in this study were enrolled in a parochial school known for high achievement and the valued role of homework.

An additional critique of the above research concerns the use of GPA for academic achievement; GPA is not a pure measure of objective academic performance. Auxiliary elements, such as attendance, participation, extra-credit opportunities, etc., are often included in the course grades on which GPA is based. Amalgamated over time, these auxiliary elements can potentially contribute to measurement error regarding the construct of academic achievement. Moreover, GPA is a more global measure of academic achievement. Efficacy beliefs are better assessed – are more predictive – when they correspond to specific tasks and goals (Pajares, 1996). Use of a more objective and discrete measure of academic performance may more accurately define the associations between academic self-efficacy and academic performance. In his review, Pajares (1996) reported on correlations between academic self-efficacy and more specific academic performances such as in-class work, homework, exams, etc. In the current study, self-efficacy is measured in relation to a particular course and to major course examinations rather than the more global measure of GPA and to performance on major course examinations.

Alternatively, a researcher might use GPA as a general measure of ability. Other measures of ability might include, for instance, SAT scores and nationally standardized specialty exams. A systematic pattern develops when performance outcomes are measured with respect to self-efficacy, independent of students’ ability (Bandura, 1993).
Collins, for example (1982, as cited in Bandura, 1993), found in a lab-based study, that students with high academic self-efficacy performed better on a mathematics task than their low belief counterparts, and this result occurred at each of the three levels of mathematics ability (low, moderate, high) (see also Pajares, 1996). Bandura (1993) speculated that “people who perform poorly may do so because they lack the skills or they have the skills but the lack the sense of efficacy to use them well” (p.119). However, it might be that academic self-efficacy is also correlated with background knowledge, in which case the higher performance for high self-efficacy students might be due to a positive relation between self-efficacy and mathematical ability. For example, for those students falling in the lowest third of mathematical ability, perhaps those in the high self-efficacy group also are those who have the highest mathematical ability in that bottom third. This possibility was examined in the present research.

Research has shown that self-efficacy is related to behavioral strategies for studying (e.g. Pajares, 1996; Prat-Sala & Redford, 2010). Leim et al. (2008), as described above, distinguished between “deep learning strategies” (cognitive-based processes including elaboration, critical thinking, and concept integration) and “surface learning strategies” (e.g., memorization and rote learning). Singaporean students with higher self-efficacy, as well as those who had adopted a performance-approach goal to achievement were more likely to use deep learning strategies. The following chapter section explores the various study strategies in which students engage, and identifies many of the cognitive-based study strategies that have been empirically demonstrated to improve learning.
Study Behaviors

A student's ability to resolve metacognitive errors and accurately distinguish the known from the unknown is an important component of effective learning. Learning is also likely to be promoted by students' confidence in their academic strengths insofar as this leads to expanded effort and perseverance in study. These factors, discussed in the prior two sections of this chapter, are central to a student's development as a self-regulated learner. Another potentially powerful contributor to academic success is the adoption of study behaviors that have been empirically demonstrated to promote learning (e.g., see McDaniel & Calendar, 2008).

Students vary dramatically in the ways they study, but they are often not aware that some study behaviors produce better learning outcomes than others. For example, students may engage in study behaviors that lead both to an illusion of competence and illusory learning, they may misallocate study time, or they may resist cognitively-based study behaviors associated with effective learning, choosing instead practices that are inconsistent with effective self-regulated learning. Following is a brief survey of study behaviors that are not hallmarks of effective self-regulated learning.

Ineffective Learning Behaviors

Cognitive psychologists posit that metacomprehension during learning is a cognitive process whereby students engage in ongoing assessments of their levels of understanding and make predictions about their potential to remember the material at a later time. Effective metacomprehension involves thinking about and monitoring one's overall comprehension, as well as the ability to make appropriate, necessary adjustments in order to facilitate understanding (Thomas & McDaniel, 2007). However, people
sometimes have biases about what they think they know. This can lead lower performing students to markedly overestimate their abilities and performances (Kruger & Dunning, 1999), lessening their motivation to pursue further study. In addition, lower performing students may engage in ineffective study strategies. Examining the relation between academic performance and study behavior is one of the objectives in the current dissertation.

Metcalfe (1998) proposed that people sometimes fall prey to metacognitive miscalculations that give rise to unwarranted cognitive optimism. She posited that phenomena such as the overestimation of skills at problem solving, experiences of hindsight bias (the “I knew it all along” phenomenon), and tip-of-the-tongue events are the result of cognitive biases and heuristics likely to produce faulty, inflated self-assessments. Kornell and Bjork (2008) reported that students’ ubiquitous practice of prematurely dropping flashcards from further study, those that students believed to be the “learned” content from a larger stack of yet-to-be-learned cards, results in a learning deficit. They proposed that the premature termination of study in this manner results from lack of knowledge about effective study behaviors. That is, students are largely unaware of the benefits of additional study of already learned material.

People can also be misled by an illusion of effective learning through massed allocation of exposure to study materials, especially when the massed learning occurs just prior to an examination (i.e., cramming), when memory of the studied material is fresh and when performance is likely to be high (e.g. Cepeda, Vul, Rohrer, Wixted, & Pashler, 2008; Kornell & Bjork, 2008; Kornell, 2009). Massed study, however, is a less effective technique for long-term retention of learned material compared to spacing study events
over time. Considerable lab-based research has documented that spacing of study maintains an advantage in long-term retention over massed study even when the two methods allowed equivalent time for study (e.g., Cepeda, et al., 2008). Nevertheless, many learners remain unconvinced of the benefits of spaced learning, keeping a resolute hold of their faulty judgments.

Another kind of overconfidence in learning was identified by Koriat and Bjork (2005)—the “foresight bias.” They described this bias as a common scenario played out in typical study behaviors in which individuals have concurrent access to both questions and answers (flashcards, questions and answers within a textbook, etc.). Given this circumstance, learners tend to exhibit overconfidence in predicted future recall on memory tests of material to which they had been previously exposed. That is, when making their predictions, people have difficulty in disengaging from their concurrent exposure to questions and answers, giving rise to a “tendency to overgeneralize from present processing to future processing” (p. 193). This faulty judgment can bring about specious impressions of mastery result in reduced study.

Potential adverse consequences of faulty self-assessments are substantial in the academic arena. Learners are influenced by their metacomprehension in the decisions they make about what study behaviors to adopt and how to employ them (Kornell, 2009; Kornell, & Bjork, 2008; Koriat & Bjork, 2005). Overconfidence in this setting can lead to inadequate – or premature cessation of – effortful study. Uncovering possible mechanisms underlying metacognitive misjudgments could have a profound impact on academic performance.
Cognitively-Based Learning Behaviors

In order to facilitate the development of effective self-regulated learning, students must make appropriate study decisions and adopt study behaviors that have been demonstrated to contribute to learning. For example, students must decide how to allocate their study time, when to start studying an item and when to stop and move on, and how to organize materials to be studied. In addition, students must determine which strategies to use while engaging in study.

Allocating Study Time.

The fundamental decision of how to allocate time for study can be problematic for some students, oftentimes with unfortunate academic consequences. Studies have demonstrated that misallocation of study time can be detrimental to learning (Kornell & Bjork, 2008; Metcalfe & Kornell, 2005).

When given a choice of how to allocate study time, students are likely to report a preference for massed practice, for example cramming, over distributed – or spaced – practice involving spreading studying episodes over time, reflecting their belief that massed practice is more effective than spaced practice (Kornell, 2009; Kornell & Bjork, 2008). In fact, however, there is a demonstrated advantage of distributed practice regarding learning and long-term retention of academically meaningful material (Cepeda, Vul, Rohrer, Wixted, & Pashler, 2008; Kornell, 2009; Kornell & Bjork, 2008; Metcalfe et al., 2007) when compared to massed practice (Carpenter & Pashler, 2007; Johnson & Kiviniemi, 2009; Kornell, 2009; Kornell & Bjork, 2008; McDaniel, Anderson, Derbish, & Morrisette, 2007; Roediger & Karpicke, 2006).
Massed versus Spaced Practice.

In an example of the learning advantage of spaced versus massed practice, Kornell (2009) examined a familiar method of study for most students: flashcards. In one condition, participants studied twice through an entire deck of cards, using the same full deck on each of one of four days (representing the spaced condition). In the second condition, the same participants studied a separate divided deck of cards, split into 4 equal smaller stacks, and studied one stack each day, reviewing each stack eight times per day (representing the massed condition). The same amount of time was spent studying in each of these conditions. A test was given on the fifth day. Kornell found that the spaced study condition was the more effective study strategy, with students averaging 54% accuracy (compared to 21% accuracy in the massed condition).

Metcalfe and Kornell (2005; see also Metcalfe, 2009) proposed a systematic approach to study in which students rely on their metacognition to guide their study of particular items. That is, in this approach they must engage in self-regulated study. Students must decide, for example, whether to study an item (is it already learned?), when to start studying an item (ordered by degree of difficulty, easiest to learn, first), and when to stop studying an item (when it is learned, or when they judge that their rate of learning has stopped – that is, no further learning is taking place),

One model of self-regulated study, posited by Metcalfe and Kornell (2005), suggests that students allocate their study according to their “region of proximal learning” (RPL). In a series of studies, they found that students were able to identify those items that they knew from those they did not know. After then setting aside those items that they believed they had already mastered, students launched into their study by first
attending to those items that they perceived were easier to learn. Once they decided that this new material had been learned, they proceeded, incrementally, toward the study of items deemed more challenging. It follows, therefore, that in order for the occurrence of adequate study regulation, a faithful appreciation of one’s degree of learning—that is, one’s accuracy in metacognition, or thinking about one’s thinking—is crucial. In other words, students should be able to distinguish items they have learned from those they have not.

Once students prioritize items to be studied, they must then engage in the study. Some strategies produce better learning outcomes than others. Cognitively-based study strategies that have been demonstrated through empirical studies to improve learning and performance outcomes include generation and self-testing.

Generative study activity.

Learning is enhanced when people generate their own answers to questions rather than being told the answers or simply reading the answer (Fonseca & Chi, 2011; Metcalfe & Kornell, 2007; Thomas & McDaniel, 2007). In one form of generative study, called self-explanation, the student summarizes presented material out loud and then relates elements of that summary to existing knowledge (Fonseca & Chi, 2011). Two advantages to this strategy are that it is just as effective with very young children (age 5) as with older learners and in cases where the learner has little or no prior knowledge on the topic. The authors reported that this strategy produces successful outcomes in a wide range of academic domains and activities such as computer programming, physics, algebra, and word problems.
Thomas and McDaniel (2007) reported on a number of studies that investigated the long-term retention benefit of generative activities during study. Generative activities—such as summarizing the material, generating keywords, and reinserting deleted letters into word passages—are thought to improve processing at the encoding level by giving rise to cognitive work beyond that of simple reading. In a series of studies, Thomas and McDaniel had participants engage in one of three study conditions: a letter reinsertion task (detail processing), a sentence-sorting task (conceptual processing), or just reading the text. Manipulating the kind of testing question asked, the authors found that learning was improved when the type of generative activity engaged in during learning was congruent with the kind of assessment questions given to the students (questions requiring details versus questions requiring conceptual responses). Learning was poorer (compared to the congruent condition and to the just reading condition) when generative activity and type of testing questions were incongruent, Students motivated to succeed should be advised to use generative study techniques, and also to tailor their techniques of generative study strategies to the kind of questions they will be asked on exams.

Test-enhanced Learning.

Testing is not only useful in assessing knowledge; testing can be instrumental in the learning process itself. The so-called testing effect refers to a phenomenon utilizing sequences of testing — in-classroom or student self-testing — throughout the learning phase, resulting in improved student performance on final tests when compared to merely studying (Carpenter & Pashler, 2007; Johnson & Kiviniemi, 2009; Karpicke & Roediger, 2007; McDaniel, Anderson, Derbish, & Morrise, 2007; Roediger & Karpicke, 2006).
Self-testing has been demonstrated to reduce metacognitive illusions and to improve learning and retention of academically meaningful material (Metcalf et al., 2007). In a study investigating the benefits of testing over repeated study, Karpicke and Roediger (2007) found that students who studied a list of unrelated words repeatedly before taking the test (15 times: SSST condition) recalled fewer words one week later when compared to students who studied once and had repeated testing (STTT condition) prior to the final evaluation. The authors suggested that working to retrieve the items during testing is the mechanism that facilitates long-term retention.

Framework for Learning.

One way researchers and educators can think about study behaviors is to classify behaviors into categories. Fonseca and Chi (2011) identified four categories as a framework for classifying types of learning activities and identifying expected outcomes:

*Passive* involvement includes no physical activity. Examples are reading, listening to a lecture, and watching a movie. Passive involvement produces minimal learning.

*Active* involvement includes some form of physical activity – highlighting is provided as an example. Active involvement produces greater learning than passive involvement.

*Constructive* involvement includes generating self-explanations of concepts, asking questions, and diagramming material. Constructive involvement leads to greater learning than active involvement.
Interactive involvement includes, for example, engaging in exploratory dialogue and debating with an informed other. Learning outcome for this classification is the highest.

Fonseca and Chi (2011) suggested that the key for educators is to engage students’ learning behaviors throughout the framework, moving students toward opportunities for increasing levels of learning. Modeling framework-specific learning behaviors during class, and providing students with in-class opportunities to engage in more constructive and interactive study behaviors, may go far to move students along as self-regulated learners.
CHAPTER 2

RESEARCH AIM AND HYPOTHESES FOR STUDY 1

Research Aim

For some students, difficulties with one or more essential elements related to self-regulated learning may lead to disappointing academic performance. For example, students may be mistaken about what they think they know (Kruger & Dunning, 1999; Ehrlinger et al., 2008), lack confidence in their ability to succeed (Bandura, 1993; Pajares, 1996), or employ study strategies that are not favorable to academic performance (Kornell & Bjork, 2008; Metcalfe & Kornell, 2005; Thomas & McDaniel, 2007). The purpose of the present research is to investigate possible links between the occurrence of metacognitive functioning, academic self-efficacy, and study behaviors as they relate to academic performance.

Study 1 is divided into three parts. Part 1 is a replication and significant extension of the studies conducted by Dunning et al. (2003) and Ehrlinger et al. (2008), showing that low performing students tend to overestimate and high performing students tend to underestimate their score and percentile rank on an in-class exam. The current study adds an important extension to existing studies by examining students’ performance estimations and actual performances across three in-class exams conducted throughout the semester. One advantage of evaluating successive exams is that the second and third exams can be used as replications of prior exams taken within the same course.
Additionally, examinations of the patterns of estimations and actual performances over time will demonstrate whether students’ estimations change over time in the same testing environment.

In the second part of Study 1, I assessed students’ reported levels of self-efficacy in relation to exam performance. Because efficacy beliefs are more predictive when they correspond to specific tasks and goals (Pajares, 1996), such as in-class work, homework, exams, etc., my study evaluates self-efficacy in relation to students being in a particular course and taking major course examinations in that course rather than using the more global measure such as grade point average.

In the third part of Study 1, I investigated the relation between self-reported study behaviors and academic performance. People are sometimes biased about what they think they know, that is, they think that they know some information when they do not (Kruger & Dunning, 1999; Metcalfe, 1998; Koriat and Bjork, 2005). The concern is that if students think they already know the information, they may not be motivated to pursue further study. In addition, students are often unaware of the distinctions between effective and ineffective study strategies. Thus, even if they do study, they may be using strategies that have not been documented to promote learning, I investigated whether students who performed higher on a major course exam reported using strategies that have been empirically demonstrated to facilitate learning, and whether the lower performing students reported using other, less effective methods.

Overview of Study

In Study 1, I evaluated the statistical relation between exam-related self-assessments, perceived academic self-efficacy, study behaviors, and academic
performance on course exams. An additional strength of this study (apart from evaluating students’ performance estimates on successive exams, as described above) is that my hypotheses were tested with students enrolled in college courses, representing two distinct academic fields and disciplines, rather than the laboratory setting of most previous studies.

During the second week of the semester, students completed a measure of academic self-efficacy (Clark & Benassi, 1997) See Appendix A. Immediately following completion of each of the three course exams, students were asked to estimate their exam performance and to provide an estimate their performance relative to others in the course (Dunning et al., 2003; Ehrlinger et al., 2008; Kruger & Dunning, 1999). After students received instructor-provided feedback on their first exam score, including score distributions and the overall mean score on the exam, students completed a study behavior inventory, adapted from Gurung, Jeske, and Weidert (2009). This inventory asks students questions about the study methods they used to prepare for the exam.

**Hypotheses for Study 1**

**Hypothesis 1: Illusion of Competence.**

Consistent with laboratory-based (Kruger and Dunning’s (1999) and in-class (Ehrlinger et al., 2008; Dunning et al, 2003) research, I predict that bottom and average performers on each of the course exams will estimate that they performed better than they actually did, and that they will estimate that they performed better relative to their peers. I also predict that the lower the actual performance, the greater the disparity between estimated and actual exam scores. Conversely, relative to their poorer performing peers, I
predict that the highest performing students will underestimate both the score they obtained on the exam and their percentile rank.

Kruger and Dunning’s (1999) study demonstrated that high performers (those in the fourth quartile) revised their estimations of their own performance after being provided evidence of their true standing (by grading five tests from other less competent students in their cohort). They increased their estimates of both their ability and percentile rank, which resulted in a more accurate reflection of their true standing. Kruger and Dunning posited that these top performers were able to make the appropriate adjustments to their estimations because they have adequate metacognitive skills to recognize their own competence. Conversely, Kruger and Dunning’s participants in the bottom quartile made no corresponding corrective adjustment in their estimations after the grading portion of the study.

My study builds upon the above studies and adds an important extension. I examined students’ performance estimations and actual performance in their courses across three exams throughout the semester. Evaluation of the patterns of estimations and actual performances should provide information on whether students’ estimations change across exams. In addition, students received detailed instructor-provided feedback, including class distributions and the overall mean score, after each of their exams. This feedback informed students of their true standing, information that could be used by them to compare with their prior performance estimations. Kruger and Dunning (1999) reported that students in the top quartile adjusted their performance estimates after viewing the work of five others in their cohort who were less competent. This adjustment brought top performers’ estimations in closer correspondence with actual performance.
The authors attributed this corrective adjustment to a metacognitive skill that enables top performers to recognize competence in themselves and others. If, as Kruger and Dunning argued, top performing students are able to veridically compare their performance with those of others, then in my study, when students are informed by exam feedback regarding an entire class distribution of scores, and they are made aware of their own true percentile rank, top performers should make more accurate estimations on following exams. Because students can move between quartiles from one exam to another, I examined only those students who remained in the top quartile for all three exams.

Therefore, I predict that those students who performed well on all three exams will reduce the degree to which they underestimate their performance after they received explicit feedback regarding their and their classmates’ performance on their exams.

In addition, Kruger and Dunning’s (1999) theory of illusory competence posits that poor performers, when informed that they performed less well than they had estimated, fail to make corrective adjustments to their faculty self assessments. Therefore, I predict that, students who performed poorly on all three exams will not systematically reduce their degree of overestimation.

Hypothesis 2: Self-efficacy and Academic Performance.

Bandura’s (1993, 2001) and Pajares’ (1996) theories of academic self-efficacy predict that students who report high levels of academic self-efficacy will perform better on exams than their low self-efficacy counterparts. In addition, Bandura (1993) argued that an association between self-efficacy and academic performance should be found at all levels of academic ability. That is, even among the lowest ability students, those students with relatively high academic self-efficacy should perform better than their low
self-efficacy counterparts. I know of no academic course-based studies that have tested this hypothesis.

I predict that students with relatively higher academic self-efficacy beliefs pertaining to the course they are in (assessed in the second week of the semester) will perform better on the first major exam of the semester than their low self-efficacy counterparts. I further predict that this relation will be found at all levels of academic ability, measured in this study as chemistry background knowledge (The Toledo Chemistry Placement Exam, Study 1a; or SAT-Verbal scores, Study 1b).

In addition, Bandura (1993) and Pajares (1996) posited that high degrees of confidence are associated with optimism and continued effort and perseverance, and low degrees of confidence are associated with pessimism and diminishing efforts and perseverance. Goal achievement, as Bandura (2001) indicated, can be a motivating factor driving students’ desire for successful academic outcomes. According to achievement goal theory, some students are oriented toward demonstrating a successful performance and elevated competence relative to their peers, that is, they adopt a “performance-approach” to goal achievement (Liem, Lau, and Nie, 2008). Liem and colleagues (2008) found Singaporean students’ self-efficacy scores for learning the English language correlated with “instrumentality,” or practical use that the knowledge of English might afford. Higher self-efficacy found in Liem et al.’s Singaporean students learning English predicted the adoption of the performance-approach to goal achievement.

Liem and colleagues (2008) found that higher self-efficacy predicted the adoption of the performance-approach to goal achievement. Both higher self-efficacy and adoption of the performance-approach goal were associated with deep learning strategies. Deep
learning strategies, the authors describe, are cognitive strategies associated with
“elaborating ideas, thinking critically, and linking as well as integrating one concept with
another” (Liem et al. 2008, p. 489). Conversely, their lower efficacious counterparts, less
oriented toward success than their more confident peers, tended to move toward goals
that would disengage them from the task. Therefore, based on the findings of Liem et al.
(2008) I predict that students who measure higher in self-efficacy will use more active
study behaviors when preparing for their exams and students who measure lower on self-
efficacy will use more passive study behaviors when preparing for their exams.

Goal-oriented students may be motivated to demonstrate achievement in a task
insofar as it “announces” their competency and readiness to move to the next level in
their course/education goals. Because students who adopt the performance-approach are
concerned with demonstrating an elevated competence relative to their peers, I predict
those students’ higher self-efficacy scores will be positively correlated with
overestimation of exam scores and percentile ranks.

Hypothesis 3: Study Behaviors.

Consistent with prior laboratory and classroom based research (e.g., Fonseca &
Chi, 2011; Metcalfe & Kornell, 2007; Metcalfe, Kornell, and Son, 2007; Thomas &
McDaniel, 2007) documenting the superior effect of cognitive-based study behaviors on
academic performance, I predict that students who report using cognitively-supported
behaviors to prepare for an exam perform better on that exam.
CHAPTER 3

STUDY 1

General Method for Studies 1a and 1b

Participants.

Participants were undergraduate volunteers from a moderate-sized United States public northeastern university. Student volunteers were enrolled in two lower-division university courses, representing fields of chemistry and nursing. Course structure for each of the courses included lecture, demonstrations, clickers, etc.

Assessments and Measures. This project was part of a larger series of studies under which University of New Hampshire institutional review board approval has been granted to Victor A. Benassi (Appendix B). Data from these studies included collection of a variety of data using a variety of measures; only those measures directly related to the present dissertation are described herein. For the nursing course, SAT-Verbal scores were secured with students’ permission from a university database. For the chemistry course, The Toledo Chemistry Placement Exam was administered by the course instructor in laboratory sections during the first week of the semester. Each of the courses had three regularly scheduled 80-minute in-class exams given across the semester, each of which totaled 100 possible points.

1. Relative Academic Self-efficacy Scale (after Clark & Benassi, 1997) (Appendix A)

During the second week of the semester and prior to the first exam, participating students completed the measure of academic self-efficacy related to their current course.
\[ \alpha = .92 \] for Chemical Principles for Engineers

\[ \alpha = .93 \] for Making Babies: Technology, Nature, and Social Context

2. Judgment of Performance questionnaire

Immediately after finishing each exam, and prior to receiving performance feedback, students answered two questions about their estimation regarding their own and other students’ performance on the exam. (These estimates were made before students had any direct knowledge of scores on the exam – their own or those of other students.)

The wording of the questions was:

1. Your exam had a total of 100 possible points. How many points do you think that you will receive on this exam? _____ points.

2. How well do you think you performed on this exam compared to other students in the course? I think I performed better than ______ percent of students in the class.

After exams were scored, teachers provided for the students detailed feedback on both their performance and performance of all students in the course (mean and distribution of scores with associated grade equivalence)

3. Study behavior inventory

Students completed this inventory after Exam 1. On this measure, adapted from Gurung, Jeske, and Weidert (2009), students reported on various study strategies they had used to prepare for the exam. In order to statistically evaluate students’ use of cognitive based study behaviors, I created two composite measures from the study behavior inventory. One of the composite measures comprised behaviors that have been empirically demonstrated to promote learning of academic material (for heuristic
purposes, I have named these behaviors “Active”). The second composite variable comprised behaviors that have been demonstrated to be less facilitative of learning of academic material (for heuristic purposes I have named these behaviors “Passive”). Items from each inventory and reliability for each course are below:

Active study behaviors

\[ \alpha = .69 \] for Chemical Principles for Engineers

\[ \alpha = .60 \] for Making Babies: Technology, Nature, and Social Context Course

Items included were:

- I tested myself without referring to my notes
- I took notes during class
- I related what I was reading to what occurred during class sessions
- Use of practice questions
- Use of practice problems

Passive study behaviors

\[ \alpha = .57 \] for Chemical Principles for Engineers

\[ \alpha = .47 \] for Making Babies: Technology, Nature, and Social Context Course

Items included were:

- I highlighted or underlined the most important information in my reading
- To what extent did you ask the professor or TA to help you understand course material?
- To what extent did you ask a classmate/friend to help you understand course material?
To what extent did you ask the professor or TA to provide you with additional materials?

**Study 1a: Chemistry Course**

**Participants**

Participants included 191 students who were enrolled in Chemical Principles for Engineers. Among these participants, not everyone completed every measure used in the studies, so the Ns for each analysis depend on the number of students who completed all the measures for each analysis. With just a few exceptions, students in this course were second semester freshmen.

**Results and Discussion**

**Hypothesis 1: Estimated Exam Scores Compared to Actual Score.** Mean exam scores for exams 1, 2, and 3 were 65.49, 61.65, and 65.63 respectively. I analyzed the data using one within-subjects factor (estimated exam score and actual exam score) and one between-subjects factor (an exam performance grouping variable). Students were assigned to one of four quartile groups based on their score on the exam. Hypothesis 1 predicts significant interaction effects, and I focus on these effects below. The interaction effects were significant for estimated Exam 1, Exam 2, and Exam 3 scores, $F(3, 176) = 30.82, p < .001, \eta^2_p = .34, F(3, 182) = 23.41, p < .001, \eta^2_p = .28, F(3, 177) = 24.20, p < .001, \eta^2_p = .29$, respectively. Inspection of Figures 1, 2, and 3 illustrate the nature of the interaction, which was the same for each of the exams. As predicted, on average, students in the bottom quartile (and those in the second quartile) overestimated their exam score, whereas those in the top quartile underestimated their score. For the bottom and the top quartiles, the mean difference between estimated and actual scores was reliable across all
exams (all $ps < .001$). Students in the third quartile provided, on average, accurate estimates of their performance on the exams.
Figure 1. Exam 1. Students' mean estimated and raw score estimates as a function of their actual exam performance quartile. (Chemistry)
Figure 2. Exam 2. Students' mean estimated and raw score estimates as a function of their actual exam performance quartile. (Chemistry)
Figure 3. Exam. 3 Students’ mean estimated and raw score estimates as a function of their actual exam performance quartile. (Chemistry)
Hypothesis 1: Estimated Exam Percentile Rank Compared to Actual Percentile Rank. As above, I analyzed the data using one within-subjects factor (estimated percentile rank and actual percentile rank) and one between-subjects factor (an exam performance grouping variable). Students were assigned to one of four quartile groups based on their score on the exam. Hypothesis 1 predicts a significant interaction between these two factors, and I focus on interaction effects below. The interaction effects were significant for estimated Exam 1, Exam 2, and Exam 3 scores, $F(3, 176) = 45.74, p < .001, \eta^2_p = .44$, $F(3, 182) = 54.38, p < .001, \eta^2_p = .47$, $F(3, 177) = 46.64, p < .001, \eta^2_p = .44$, respectively. Inspection of Figures 4, 5, and 6 illustrate the nature of the interaction, which was the same for each of the exams. As predicted, on average, students in the bottom quartile (and those in the second quartile) overestimated the percentage of students whom they believed they outperformed on the exam, whereas those in the top quartile underestimated their relative standing. For the bottom and the top quartiles, the mean difference between estimated and actual relative standing was reliable across all exams (all $ps < .001$).
Figure 4. Exam 1. Students’ mean estimated and percentile as a function of their actual exam performance quartile. (Chemistry)
Figure 5. Exam 2. Students’ mean estimated and percentile as a function of their actual exam performance quartile. (Chemistry)
Figure 6. Exam 3. Students’ mean estimated and percentile as a function of their actual exam performance quartile. (Chemistry)
The overall pattern is clear across the three exams. Bottom and top performers tended to overestimate and underestimate their exam scores and percentile ranking, respectively, across all three exams. Further, there was no evidence that the degree to which students in these groups overestimate and underestimate their performance decreased over the three exams. However, the results in Figures 1-6 may not reflect what occurs with individual students because they may move in or out of a particular quartile on different exams. For example, a student in the bottom quartile on Exam 1 might score in the second quartile on Exam 2. Therefore, I performed a more refined analysis on the performance estimates of students who either scored in the bottom quartile or the top quartile on each of the three exams.

**Consistent Poor Performers.** I examined the “difference scores” between estimated and actual exam scores for the subset of students who performed in the bottom 25th percentile on all three exams (N = 14). A positive difference score means that a student estimated her/his exam score would be higher than the score the student actually received on the exam. The mean difference scores and standard deviations for the three exams are provided in Table 1. There was no reliable difference among the means $F(2, 26) = .53, p < .59, \eta^2_p = .04$. These results show that consistently poor performing students did not show, on average, a reliable change in the degree to which they overestimated their exam score.
Table 1
Mean Difference Scores (Estimated Exam Score Minus Actual Exam Score) and Standard Deviations for Consistent Poor Performers on All Three Exams

<table>
<thead>
<tr>
<th>Exam</th>
<th>M</th>
<th>SD</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>13.29</td>
<td>14.94</td>
</tr>
<tr>
<td>2</td>
<td>17.71</td>
<td>12.62</td>
</tr>
<tr>
<td>3</td>
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<td>16.09</td>
</tr>
</tbody>
</table>

Consistent High Performers. I also examined the difference scores between estimated and actual exam scores for the subset of students who performed in the top 25\textsuperscript{th} percentile on all three exams ($N = 23$). The mean difference scores and standard deviations for the three exams are provided in Table 2. There was no reliable difference among the means $F (2, 44) = .73$, $p < .49$, $\eta^2_p = .03$. These results show that consistently high performing students did not show, on average, a reliable change in the degree to which they underestimated their exam score.

Table 2
Mean Difference Scores (Estimated Exam Score Minus Actual Exam Score) and Standard Deviations for Consistent High Performers on All Three Exams

<table>
<thead>
<tr>
<th>Exam</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-3.57</td>
<td>5.11</td>
</tr>
<tr>
<td>2</td>
<td>-6.00</td>
<td>9.04</td>
</tr>
<tr>
<td>3</td>
<td>-4.22</td>
<td>6.84</td>
</tr>
</tbody>
</table>

Consistent Poor Performers. I also examined the difference between students’ estimated percentile rank on the exams and actual exam percentile rank for the subset of students who performed in the bottom 25\textsuperscript{th} percentile on all three exams ($N = 13$). The mean difference scores and standard deviations for the three exams are provided in Table 3. There was no reliable difference among the means $F (2, 24) = .06$, $p < .94$, $\eta^2_p = .005$. These results show that consistently poor performing students did not show, on average, a
reliable change in the degree to which they overestimated their test score.

Table 3
*Mean Difference Scores (Estimated Percentile Minus Actual Percentile) and Standard Deviations for Consistent Poor Performers on All Three Exams*

<table>
<thead>
<tr>
<th>Exam</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>19.98</td>
<td>25.52</td>
</tr>
<tr>
<td>2</td>
<td>22.17</td>
<td>18.17</td>
</tr>
<tr>
<td>3</td>
<td>20.21</td>
<td>22.99</td>
</tr>
</tbody>
</table>

**Consistent High Performers.** I also examined the difference between students’ estimated percentile rank on the exams and actual exam percentile rank for the subset of students who performed in the top 25th percentile on all three exams (N = 23). The mean difference scores and standard deviations for the three exams are provided in Table 4.

There was no reliable difference among the means $F(2, 44) = 1.66, p < .20, \eta_p^2 = .07$.

These results show that consistently high performing students did not show, on average, a reliable change in the degree to which they underestimated their relative percentile rank on the exam.

Table 4
*Mean Difference Scores (Estimated Percentile Minus Actual Percentile) and Standard Deviations for Consistent High Performers on All Three Exams*

<table>
<thead>
<tr>
<th>Exam</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-14.49</td>
<td>10.77</td>
</tr>
<tr>
<td>2</td>
<td>-16.09</td>
<td>14.78</td>
</tr>
<tr>
<td>3</td>
<td>-11.30</td>
<td>12.22</td>
</tr>
</tbody>
</table>

**Hypothesis 2:** Confirming hypothesis 2, there was a significant correlation between academic self-efficacy and Exam 1 performance, such that higher self-efficacy was associated with higher exam scores, $r (N = 169) = .31, p (1-tailed) < .001$. I also predicted that the positive relation between self-efficacy and exam performance would be
found at all levels of academic ability. As my measure of academic ability, I used the Toledo Chemistry Placement Exam, a nationally-normed chemical background knowledge test widely used to assess students’ background knowledge of chemistry upon entering the first chemistry course in college.

I partitioned students into one of three groups based on their score on the Toledo Chemistry Placement Exam (low [low - 33 percentile], moderate [34 – 66 percentile], and high [67 – high percentile] groups). To generate distinct categories of high and low self-efficacy students, I created two groups consisting of students who scored in either the top third or bottom third of the self-efficacy measure. Exam 1 performance varied as a function of both chemical background knowledge and academic self-efficacy as shown in Figure 7. There was a main effect for chemistry background knowledge such that higher levels of knowledge were associated with higher exam performance, $F (2, 108) = 6.42, p < .002, \eta^2 = .09$. There was also a main effect for academic self-efficacy, such that students who scored in the upper third of the measure performed better on the exam than their counterparts who scored in the bottom third $F (1, 108) = 13.61, p < .001, \eta^2 = .10$. Most important, there was not a significant background knowledge by academic self-efficacy effect $F (2, 108) = .001, p < .99$. 
Figure 7. Exam 1. Performance as a function of both chemical background knowledge and academic self-efficacy. (Chemistry)
In support of my hypothesis, at each level of chemistry background knowledge, high self-efficacy people performed better than low self-efficacy people. The question is whether the high efficacy ratings for each of the levels are confounded by underlying ability.

A straightforward interpretation of these results is that people, in fact, with high self-efficacy perform better on the exam of ability because, as Bandura and others have suggested, high self-efficacy is associated with behaviors that lead to academic success (e.g., persistence in the face of obstacles). However, it might be that academic self-efficacy is also correlated with background knowledge, in which case the higher performance for high self-efficacy students in the figure above might be due to a positive relationship to academic self-efficacy and chemical background knowledge, at each level of background knowledge. For example, for students in the bottom quartile, perhaps those in the high self-efficacy group also are those who have the highest chemical background among the students in that quartile. Related to this point, for the overall sample, the correlation between chemical background knowledge scores and academic self-efficacy was .22 ($p < .002$).

To assess whether the significant relation reported for hypothesis 2 (above) is partially or totally explained by the significant relation between self-efficacy and chemical background knowledge, I regressed exam 1 performance on self-efficacy and chemistry background scores. At step 1, self-efficacy as expected, was significantly related to Exam 1 performance ($\beta = .30, t = 4.10, p < .001$). At step 2, the self-efficacy effect remained significant ($\beta = .21, t = 3.05, p < .003$) when chemical background knowledge was entered into the equation ($\beta = .42, t = 6.07, p < .001$). Therefore, the
observed relation between self-efficacy and exam performance cannot be attributed to the correlation between self-efficacy and chemistry background knowledge.

Also, in hypothesis 2, I examined whether students with higher self-efficacy scores had a tendency to overestimate performance both in actual score estimates and percentile estimates. To do this, I examined the correlation between self-efficacy with both the exam score difference scores (estimated exam score minus actual exam score) and with the percentile difference scores (estimated percentile rank minus actual percentile rank). I then examined the correlations at each quartile of exam performance. Consistent with my prediction, there was a significant correlation between academic self-efficacy and a tendency to overestimate both exam scores and percentiles; the correlations were stronger when controlling for actual scores (Table 5).

<table>
<thead>
<tr>
<th>Exam Quartiles</th>
<th>n</th>
<th>Self-efficacy and Exam 1 Score Difference Score Correlation (p)</th>
<th>Self-efficacy and Exam 1 Percentile Difference Score Correlation (p)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bottom</td>
<td>44</td>
<td>.27 (&lt; .08)</td>
<td>.52 (&lt; .001)</td>
</tr>
<tr>
<td>Second</td>
<td>38</td>
<td>.33 (&lt; .04)</td>
<td>.33 (&lt; .05)</td>
</tr>
<tr>
<td>Third</td>
<td>38</td>
<td>.17 (&lt; .31)</td>
<td>.35 (&lt; .03)</td>
</tr>
<tr>
<td>Top</td>
<td>46</td>
<td>.14 (&lt; .35)</td>
<td>.27 (&lt; .06)</td>
</tr>
</tbody>
</table>

*Note: Difference score for exam score = estimated score – actual score; difference score for percentile score = estimated percentile – actual percentile.*

I also predicted that students who report higher levels of self-efficacy will also report using more active study behaviors when preparing for their exams and that students who report higher levels self-efficacy will also report using passive study behaviors to a lesser extent when preparing for their exams. To test this hypothesis, I examined the relation between self-efficacy and active study behaviors, controlling for
reported use of passive study behaviors ($r_{141} = .17, p < .04$; partial $r_{140} = .24, p < .004$). I also examined the relation between self-efficacy and passive study behaviors, controlling for reported use of active study behaviors ($r_{141} = -.26, p < .001$; partial $r_{140} = -.31, p < .001$). The direction and statistical significance of the effects support my hypothesis. Students who reported higher levels of academic self-efficacy also reliably reported the greater use of active study behaviors and the lesser use of passive study behaviors.

**Hypothesis 3**: I examined the relation between self-reported study behaviors and exam 1 performance for both the active and passive study behavior measures. Supporting Hypothesis 3, the correlation between the active study behavior measure and the exam score was $.29 (150), p (1-tailed) < .001$; the partial correlation (controlling for reported passive study behavior use) was $.36 (149), p (1-tailed) < .001$. In further support of Hypothesis 3, the correlation between the passive study behavior measure and the exam score was $-.20 (150), p (1-tailed) < .008$; the partial correlation (controlling for reported study behavior use) was $-.29 (149), p (1-tailed) < .001$. These results clearly show that greater reported use of active study behaviors is positively and significantly related to exam 1 performance, while controlling for reported passive study behaviors use. Also, the results show that greater reported use of passive study behaviors is negatively and significantly related to exam 1 performance, while controlling for reported active study behaviors use.

To further explore the relation between active and passive study behaviors and exam performance, I created high and low categories for each of the study behaviors measures. For the active study behaviors measure, I formed high and low categories
based on students who scored in the upper third (high active) and bottom third (low active) on the measure. For the passive study behaviors measure, I formed high and low categories based on students who scored in the upper third (high passive) and bottom third (low passive) on the measure. The results are shown in Table 6. Most noteworthy is that students who were both high on the active study behavior measure and low on the passive study behavior measure scored highest on the exam ($M = 80.97$). Students who scored low on the active study behavior measure scored the lowest on the exam whether they were low ($M = 67.65$) or high ($M = 65.39$) on the passive measure. Because of the relatively small $ns$ in the individual cells, I am not reporting inferential statistics.

Table 6

*Study Behavior Use and Mean Exam Scores (Chemistry)*

<table>
<thead>
<tr>
<th>Study Behavior</th>
<th>$M$</th>
<th>$SD$</th>
<th>$N$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Low</td>
<td>67.65</td>
<td>19.90</td>
<td>15</td>
</tr>
<tr>
<td>High</td>
<td>65.39</td>
<td>13.14</td>
<td>7</td>
</tr>
<tr>
<td>High Low</td>
<td>80.97</td>
<td>15.03</td>
<td>8</td>
</tr>
<tr>
<td>High High</td>
<td>73.02</td>
<td>14.30</td>
<td>15</td>
</tr>
</tbody>
</table>

**Study 1b: Nursing Course**

I followed the same general approach described at the beginning of this chapter for the following study.

**Participants**

Participants included 307 students who were enrolled in a general education nursing course: Making Babies: Technology, Nature, and Social Context. Among these participants, not everyone completed every measure used in the studies, so the $Ns$ for each analysis depend on the number of students who completed all the measures for each
analysis. Of the 307 students, 302 students were freshmen, one was a sophomore, and two were juniors (two missing information).

Results and Discussion

Hypothesis 1 Estimated Exam Scores Compared to Actual Score. Mean exam scores for exams 1, 2, and 3 were 82.86, 83.23, and 88.33 respectively. As with Study 1a, I analyzed the data using one within-subjects factor (estimated exam score and actual exam score) and one between-subjects factor (an exam performance grouping variable). Students were assigned to one of four quartile groups based on their score on the exam. Hypothesis 1 predicts significant interaction effects, and I focus on interaction effects below. The interaction effects were significant for estimated Exam 1, Exam 2, and Exam 3 scores, $F(3, 296) = 110.26, p < .001$, $\eta^2_p = .53$, $F(3, 285) = 76.63, p < .001$, $\eta^2_p = .45$, $F(3, 290) = 28.39, p < .001$, $\eta^2_p = .23$, respectively. Inspection of Figures 8, 9, and 10 illustrate the nature of the interaction, which was the same for each of the exams. The overall pattern of results is the same as found in Study 1a. What is different is that in this class, for exam 3, the degree of overestimation for the bottom quartile was relatively small compared to exams 1 and 2. This result will be addressed more fully below.
Figure 8. Exam 1. Students’ mean estimated and raw score estimates as a function of their actual exam performance quartile. (Nursing)
Figure 9. Exam 2. Students’ mean estimated and raw score estimates as a function of their actual exam performance quartile. (Nursing)
Figure 10. Exam 3. Students’ mean estimated and raw score estimates as a function of their actual exam performance quartile. (Nursing)
Hypothesis 1 Estimated Exam Percentile Rank Compared to Actual Percentile Rank. As above, I analyzed the data using one within-subjects factor (estimated percentile rank and actual percentile rank) and one between-subjects factor (an exam performance grouping variable). Students were assigned to one of four quartile groups based on their score on the exam. Hypothesis 1 predicts a significant interaction between these two factors, and I focus on interaction effects below. The interaction effects were significant for estimated Exam 1, Exam 2, and Exam 3 scores, \( F(3, 297) = 152.68, p < .001, \eta_p^2 = .61, F(3, 282) = 120.63, p < .001, \eta_p^2 = .56, F(3, 292) = 105.14, p < .001, \eta_p^2 = .52 \), respectively. Inspection of Figures 11, 12, and 13 illustrate the nature of the interaction, which was the same for each of the exams. As predicted, on average, students in the bottom quartile (and those in the second quartile) overestimated the percentage of students whom they believed they outperformed on the exam, whereas those in the top quartile underestimated their relative standing. For the bottom and the top quartiles, the mean difference between estimated and actual relative standing was reliable across all exams (all \( ps < .001 \)). For all three exams, students reported, on average, that they were above average.
Figure 11. Exam 1. Students’ mean estimated and percentile estimates as a function of their actual exam performance quartile. (Nursing)
Figure 12. Exam 2. Students’ mean estimated and percentile estimates as a function of their actual exam performance quartile. (Nursing)
Figure 13. Exam 3. Students’ mean estimated and percentile estimates as a function of their actual exam performance quartile. (Nursing)
The overall pattern is clear across the three exams. Bottom and top performers tended to overestimate and underestimate their exam scores and percentile ranking, respectively, across all three exams. However, the results in these figures may not reflect what occurs with individual students because they may move in or out of a particular quartile on different exams. Therefore, as in Study 1a, I performed a more refined analysis on the performance estimates of students who either scored in the bottom quartile or the top quartile on each of the three exams.

**Consistent poor performers.** I examined the difference scores between estimated and actual exam scores for the subset of students who performed in the bottom 25th percentile on all three exams ($N=23$). The mean difference scores and standard deviations for the three exams are provided in Table 7. There was a reliable difference among the means $F(2, 44) = 7.03, p < .002, \eta^2_p = .24$. These results show that consistently poor performing students did not show, on average, a reliable difference between exam 1 and exam 2 ($t(22) = -.91, p < .37$). However, the mean difference between exams 1 and 3 ($t(22) = 2.95, p < .007$) and between exams 2 and 3 ($t(22) = 3.11, p < .005$) were reliably different. This decrease for exam 3 in this study did not occur in Study 1a. What might account for this difference between the studies?

<p>| Table 7 |
| Mean Difference Scores (Estimated Exam Score Minus Actual Exam Score) and Standard Deviations for Consistent Poor Performers on All Three Exams |</p>
<table>
<thead>
<tr>
<th>Exam</th>
<th>$M$</th>
<th>$SD$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>14.61</td>
<td>9.03</td>
</tr>
<tr>
<td>2</td>
<td>17.04</td>
<td>16.14</td>
</tr>
<tr>
<td>3</td>
<td>6.35</td>
<td>13.08</td>
</tr>
</tbody>
</table>
Because quartile placement is relative to performance on a given exam, and scores on exam 3 in this class as a whole are high ($M = 88.5$), I computed a difference score (estimation minus actual scores) on those individuals who were, in fact, actual poor performers ($< 70\% \ n = 11$, with mean difference score $= 17.73$). Then, I computed another difference score (estimated minus actual scores) for those individuals who were still in the bottom quartile yet on the upper end, and who performed between 70% and 83%, ($n = 66$, with mean difference score $= 2.14$). These results show that, although the exam 3 mean difference score is reliably lower than the mean difference scores of exams 1 and 2, those students who actually performed the poorest in the bottom quartile did, in fact, overestimate their performance to a substantial degree (by 11.73 points), consistent with the results in Study 1a.

**Consistent High Performers.** I also examined the difference scores between estimated and actual exam scores for the subset of students who performed in the top 25\textsuperscript{th} percentile on all three exams ($N = 25$). The mean difference scores and standard deviations for the three exams are provided in Table 8. There was a reliable difference among the means, $F (2, 48) = 4.42, \ p < .02, \ \eta^2_p = .16$. These results show that consistently high performing students did not show, on average, a reliable difference between exam 1 and exam 2 ($t (24) = -.107 \ p < .58$). However, the mean difference between exams 1 and 3 ($t (24) = 3.05 \ p < .005$) was significant. The difference between exams 2 and 3 ($t (24) = 1.07 \ p < .06$) did not achieve $p < .05$. These results show that, if anything, high performing students increased the extent to which they underestimated their exam performance.
Table 8
*Mean Difference Scores (Estimated Exam Score minus Actual Exam Score) and Standard Deviations for Consistent High Performers on All Three Exams*

<table>
<thead>
<tr>
<th>Exam</th>
<th>( M )</th>
<th>( SD )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-4.12</td>
<td>3.07</td>
</tr>
<tr>
<td>2</td>
<td>-4.50</td>
<td>4.42</td>
</tr>
<tr>
<td>3</td>
<td>-6.32</td>
<td>3.87</td>
</tr>
</tbody>
</table>

**Consistent Poor Performers.** I examined the difference between students’ estimated percentile rank on the exams and actual exam percentile rank for the subset of students who performed in the bottom 25\(^{th}\) percentile on all three exams \( N = 23 \). The mean difference scores and standard deviations for the three exams are provided in Table 9. There was no reliable difference among the means \( F (2, 44) = 1.48, p < .24, \eta^2_p = .06 \). These results show that consistently poor performing students did not show, on average, a reliable change in the degree to which they overestimated their test score.

Table 9
*Mean Difference Scores (Estimated Percentile Minus Actual Percentile) and Standard Deviations for Consistent Poor Performers on All Three Exams*

<table>
<thead>
<tr>
<th>Exam</th>
<th>( M )</th>
<th>( SD )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>46.20</td>
<td>18.48</td>
</tr>
<tr>
<td>2</td>
<td>46.08</td>
<td>12.79</td>
</tr>
<tr>
<td>3</td>
<td>39.72</td>
<td>22.54</td>
</tr>
</tbody>
</table>

The degree of overestimation in relative standing for poor performers in this class, when compared to that of the chemistry class, is notably larger. This finding may be related to the relatively high scores noted on the exams for this class among the poor performers. It is possible that because mean scores for students in this class who scored in the bottom quartile in each of the exams \( M = 67\%, M = 65\%, \) and \( M = 74\% \), respectively) are relatively higher than for their counterparts in the chemistry class \( M = \)
47.7%, $M = 42.6\%$, and $M = 44.19\%$, respectively), their judgments of their relative performance may have reflected this fact.

**Consistent High Performers.** I also examined the difference between students’ estimated percentile rank on the exams and actual exam percentile rank for the subset of students who performed in the top 25\textsuperscript{th} percentile on all three exams ($N = 26$). The mean difference scores and standard deviations for the three exams are provided in Table 10. There was no reliable difference among the means $F (2, 50) = .98, p < .38$, $\eta_p^2 = .04$. These results show that consistently high performing students did not show, on average, a reliable change in the degree to which they underestimated their relative percentile rank on the exam.

Table 10

<table>
<thead>
<tr>
<th>Exam</th>
<th>$M$</th>
<th>$SD$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-17.51</td>
<td>20.92</td>
</tr>
<tr>
<td>2</td>
<td>-13.58</td>
<td>16.68</td>
</tr>
<tr>
<td>3</td>
<td>-19.17</td>
<td>21.39</td>
</tr>
</tbody>
</table>

**Hypothesis 2:** Confirming hypothesis 2, there was a significant correlation between academic self-efficacy and exam 1 performance, such that higher efficacy was associated with higher exam scores, $r (N = 264) = .25, p (1\text{-tailed}) < .001$. I further predicted that the positive relation between self-efficacy and exam performance would be found at all levels of academic ability. Because I did not have access to a background-knowledge measure pertinent to this course, I used students’ SAT-Verbal scores as my measure of academic ability.
I partitioned students into one of three groups based on their score on the SAT-Verbal test (low [low - 33 percentile], moderate [31 – 50 percentile], and high [51 – high percentile] groups). As in Study 1a, to generate distinct categories of high and low self-efficacy students, I created two groups consisting of students who scored in either the top third or bottom third of the self-efficacy measure. Exam 1 performance varied as a function of both SAT-Verbal scores and academic self-efficacy as shown in Figure 14. There was a main effect for SAT-Verbal scores such that higher SAT-Verbal scores were associated with higher exam performance, $F (2, 164) = 3.83, p < .02, \eta^2 = .04$. There was also a main effect for academic self-efficacy, such that students who scored in the upper third of the measure performed better on the exam than their counterparts who scored in the bottom third, $F (1, 164) = 10.14, p < .002, \eta^2 = .05$. Most important, there was not a significant SAT-Verbal score by academic self-efficacy interaction effect, $F (2, 164) = .29, p < .75$. As with the chemistry class, the relation between background ability (SAT-V) and academic self-efficacy was significant, $r = .34, p < .001$.

To assess whether the significant relation reported for hypothesis 2 (above) is partially or totally explained by the significant relation between self-efficacy and SAT-V scores, I regressed exam 1 performance on self-efficacy and SAT-V scores. At step 1, self-efficacy, as expected, was significantly related to Exam 1 performance ($\beta = .22, t = 3.57, p < .001$). At step 2, the self-efficacy effect remained significant ($\beta = .13, t = 2.07, p < .04$) when SAT-V scores were entered into the equation ($\beta = .27, t = 4.12, p < .001$). Therefore, the observed relation between self-efficacy and exam performance cannot be totally attributed to the correlation between self-efficacy and SAT-V scores.
Figure 14. Exam 1. Performance as a function of both SAT-Verbal and academic self-efficacy. (Nursing)
Also in hypothesis 2, I examined whether students with higher self-efficacy scores had a tendency to overestimate performance both in actual score estimates and percentile estimates. To do this, I correlated self-efficacy with the exam score difference scores (estimated exam score minus actual exam score) and with the percentile difference scores (estimated percentile rank minus actual percentile rank). I then examined the correlations at each quartile of exam performance. As predicted, there was a significant correlation between academic self-efficacy and a tendency to overestimate both exam scores and percentiles; the correlations were stronger when controlling for actual scores (see Table 11).

Table 11
Correlation: Self-Efficacy and Difference scores (Nursing)

<table>
<thead>
<tr>
<th>Exam Quartiles</th>
<th>Self-efficacy and Exam 1 Score Difference Score</th>
<th>Self-efficacy and Exam 1 Percentile Difference Score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correlation</td>
<td>Partial Correlation</td>
</tr>
<tr>
<td>Bottom</td>
<td>.15 (p &lt; .24)</td>
<td>.31 (p &lt; .01)</td>
</tr>
<tr>
<td>Second</td>
<td>.41 (p &lt; .003)</td>
<td>.38 (p &lt; .008)</td>
</tr>
<tr>
<td>Third</td>
<td>.22 (p &lt; .05)</td>
<td>.31 (p &lt; .005)</td>
</tr>
<tr>
<td>Top</td>
<td>.22 (p &lt; .08)</td>
<td>.20 (p &lt; .12)</td>
</tr>
</tbody>
</table>

Note: Difference score for exam score = estimated score – actual score; difference score for percentile score = estimated percentile – actual percentile.

I also predicted that students who report higher levels of self-efficacy will also report using more active study behaviors when preparing for their exams and that students who report higher levels self-efficacy will also report using passive study behaviors to a lesser extent when preparing for their exams. These results were not significant for the nursing course; therefore the results will not be presented.

Hypothesis 3: I examined the relation between self-reported study behaviors and exam 1 performance for both the active and passive study behavior measures. Supporting
Hypothesis 3, the correlation between the active study behavior measure and the exam score was .19 (143), \( p \) (1-tailed) < .001; the partial correlation (controlling for reported passive study behavior use) was .23 (142), \( p \) (1-tailed) < .001. In further support of Hypothesis 3, the correlation between the passive study behavior measure and the exam score was -.25 (143), \( p \) (1-tailed) < .001; the partial correlation (controlling for reported study behavior use) was -.28 (142), \( p \) (1-tailed) < .001. Consistent with my hypothesis and with the results of Study 1a, these results clearly show that greater reported use of active study behaviors is positively and significantly related to exam 1 performance, while controlling for reported passive study behaviors use. Also, the results show that greater reported use of passive study behaviors is negatively and significantly related to exam 1 performance, while controlling for reported active study behaviors use.

To further explore the relation between active and passive study behaviors and exam performance, I created high and low categories for each of the study behavior measures. For the active study behavior measure, I formed high and low categories based on students who scored in the upper third (high active) and bottom third (low active) on the measure. For the passive study behavior measure, I formed high and low categories based on students who scored in the upper third (high passive) and bottom third (low passive) on the measure. The results are shown in Table 12. Most noteworthy is that students who were both high on the active study behavior measure and low on the passive study behavior measure scored highest on the exam \( (M = 89.09) \). Students who scored low on the active study behavior measure and high on the passive measure scored the lowest on the exam \( (M = 79.33) \). Because of the relatively small \( ns \) in the individual cells, I am not reporting inferential statistics.
### Table 12

*Study Behavior Use and Mean Exam Scores (Nursing)*

<table>
<thead>
<tr>
<th>Study Behavior</th>
<th>Active</th>
<th>Passive</th>
<th>M</th>
<th>SD</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low and</td>
<td>Low</td>
<td></td>
<td>84.57</td>
<td>10.42</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td></td>
<td>79.33</td>
<td>8.64</td>
<td>6</td>
</tr>
<tr>
<td>High and</td>
<td>Low</td>
<td></td>
<td>89.09</td>
<td>8.17</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td></td>
<td>82.91</td>
<td>12.37</td>
<td>11</td>
</tr>
</tbody>
</table>

As with the chemistry class, Study 1b showed that there was no change in the degree to which consistently low- and high-performing students overestimated or underestimated both their performance and relative standing on the three exams. Students’ judgments of performance were obtained immediately upon completion of their exams, only with the request that they do the best that they could to accurately estimate their exam score and their performance on the exam relative to their classmates. That is, there was no external incentive for students to be accurate. The results for Studies 1a and 1b were strikingly consistent. Whether an external incentive might motivate students’ accuracy is a notion worth investigating. Study 2 addressed this issue.
CHAPTER 4

STUDY 2: MONETARY INCENTIVE

In a variety of domains, researchers have reported the consistent finding that the highest performing people tend to underestimate their performance, and the poorest performing people tend to dramatically over-predict their performance (Kruger & Dunning, 1999; Dunning, Johnson, Ehrlinger, & Kruger, 2003; Ehrlinger et al., 2008). Kruger and Dunning (1999) proposed that because poor performers lack domain specific knowledge (that is, they are unskilled or “incompetent”), they are not in a position to recognize their own incompetence; they lack metacognitive skills for accurate self-assessments. A possible alternative is the notion of motive. Perhaps people do not care enough to take the time to give their estimations much thought, or they are perhaps reluctant to report that they are incompetent. If students are sufficiently motivated to be as accurate with their estimations as they can, might estimations be more in line with their actual performances?

Ehrlinger et al. (2008, Study 4) examined students’ estimations of performance in the laboratory on a logic-reasoning test. Participants, randomly assigned to an incentive or control condition completed a multiple choice test. For each test question, students reported their confidence on a scale from 20% to 100% that their response was accurate. Those in the incentive condition were offered $100 for complete accuracy in prediction of how many of the questions they answered correctly, and $30 for accuracies that fell within 5% of actual test scores. Results showed that the incentive did not improve
estimate accuracy. No participant got the $100 prize. Results from Study 4 demonstrated that for students in laboratory experiment, monetary incentive did not induce participants to provide more accurate self-assessments.

In Ehrlinger et al. (2008, Study 4), students were tested on a subject to which they may or may not have had prior exposure. Without exposure, these students may not have been in a position to accurately evaluate their performance. The present Study 2 took place in the natural setting of students’ own classroom. Students were tested in class as part of their regular course requirement; in contrast to Ehrlinger et al. (2008), participants in this study have had exposure to the material on which they are being tested.

In Study 2, I conducted the refined analysis described in Studies 1a and 1b. The focus will be on those students who consistently performed poorly (in the bottom quartile) and those who consistently performed the highest (in the fourth quartile). Study 2 investigated whether offering an incentive reduces differences for student accuracy in estimations of both exam performance and relative standing. Based on previous research by Ehrlinger et al. (2008), I do not expect that inclusion of an incentive for judgmental accuracy will result in students decreasing the extent to which they overestimate (bottom performers) or underestimate (top performers) their exam performance.

Method

Participants

Participants were undergraduate volunteers from a moderate-sized United States Public northeastern university. Student volunteers ($N = 169$) were enrolled in a lower-division chemistry course, Chemical Principles for Engineers. Participants who took both exams and who answered both self-assessment questions numbered 165 – these students
were included in the study. For each of the two scheduled in-class exams given, the possible points totaled 100. Students had 80 minutes to complete each of the two exams.

Assessments and Measures

I examined students’ judgments of their performance on their first two regularly scheduled exams of the semester. After finishing each exam, but before handing it in, students answered two questions about their estimation regarding their own and other students’ performance on the exam. (These estimates were made before students had any direct knowledge of scores on the exam – their own or those of other students.) The wording of the questions for exam 1 was:

1. Your exam had a total of 100 possible points. How many points do you think that you will receive on this exam? ____ points.

2. How well do you think you performed on this exam compared to other students in the course? I think I performed better than ______ percent of students in the class.

After exams were scored, the teacher provided for the students detailed feedback on both their performance and performance of all students in the course (mean and distribution of scores with associated grade equivalence).

On the second exam, directly above the two questions listed above, students were informed that we would offer a $50.00 gift certificate to each of the two students who gave the most accurate estimates of their performance on the exam based on their responses to the two questions. The instructor of the course observed that there was considerable interest among the students in being one of the two winners. This response speaks to their motivation.
Results and Discussion

Consistent Poor Performers.

I examined the difference scores between judged and actual exam scores for the subset of students who performed in the bottom 25th percentile on both exams ($N = 22$). The mean difference scores and standard deviations for the two exams are provided in Table 13. The mean difference score on exam 2 was lower than that for exam 1, but the difference was not reliable, $F (1, 21) = 3.03, p < .10, \eta^2 = .13$. These results show that consistently poor performing students did not show, on average, a reliable decrease to which they overestimated their test score.

Table 13
Mean Difference Scores (Estimated Exam Score minus Actual Exam Score) and Standard Deviations for Consistent Poor Performers on Both Exams

<table>
<thead>
<tr>
<th>Exam</th>
<th>$M$</th>
<th>$SD$</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>20.43</td>
<td>12.02</td>
</tr>
<tr>
<td>2</td>
<td>14.19</td>
<td>9.97</td>
</tr>
</tbody>
</table>

Consistent High Performers.

I also examined the difference scores between judged and actual exam scores for the subset of students who performed in the top 25th percentile on all three exams ($N = 21$). The mean difference scores and standard deviations for the three exams are provided in Table 14. The mean difference score was larger for exam 2, but the means did not reliably differ, $F (1, 20) = 1.60, p < .22, \eta^2 = .07$. These results show that consistently high performing students did not show, on average, a reliable change in the extent to which they underestimated their test score.
Table 14

**Mean Difference Scores (Estimated Exam Score minus Actual Exam Score) and Standard Deviations for Consistent High Performers on All Three Exams**

<table>
<thead>
<tr>
<th>Exam</th>
<th>M</th>
<th>SD</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>-.77</td>
<td>6.79</td>
</tr>
<tr>
<td>2</td>
<td>-.264</td>
<td>6.15</td>
</tr>
</tbody>
</table>

**Consistent Poor Performers.**

I also examined the difference between students’ judged percentile rank on the exams and actual exam percentile rank for the subset of students who performed in the bottom 25th percentile on both exams (N = 22). The mean difference scores and standard deviations for the two exams are provided in Table 15 (below). There was no reliable difference among the means, $F (1, 21) = .02, p < .89, \eta_p^2 = .001$. These results show that consistently poor performing students did not show, on average, a reliable change in the degree to which they overestimated their test score.

Table 15

**Mean Difference Scores (Estimated Percentile Minus Actual Percentile) and Standard Deviations for Consistent Poor Performers on Both Exams**

<table>
<thead>
<tr>
<th>Exam</th>
<th>M</th>
<th>SD</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>35.04</td>
<td>19.24</td>
</tr>
<tr>
<td>2</td>
<td>34.45</td>
<td>13.37</td>
</tr>
</tbody>
</table>

**Consistent High Performers.** I examined the difference between students’ judged percentile rank on the exams and actual exam percentile rank for the subset of students who performed in the top 25th percentile on both exams (N = 21). The mean difference scores and standard deviations for the two exams are provided in Table 16. There was no reliable difference among the means, $F (1, 20) = .02, p < .89, \eta_p^2 = .001$. These results show that consistently high performing students did not show, on average, a
reliable change in the extent to which they underestimated their relative percentile rank.

Table 16
*Mean Difference Scores (Estimated Percentile Minus Actual Percentile) and Standard Deviations for Consistent High Performers on Both Exams*

<table>
<thead>
<tr>
<th>Exam</th>
<th>M</th>
<th>SD</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>-20.13</td>
<td>18.12</td>
</tr>
<tr>
<td>2</td>
<td>-20.04</td>
<td>25.10</td>
</tr>
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</table>
CHAPTER 5

GENERAL DISCUSSION

In this dissertation, I examined three elements related to students’ academic performance: metacognitive functioning, self-efficacy, and study behavior. Taken together, these components contribute to students’ functioning as self-regulated learners.

Metacognitive Errors

The current research builds upon and extends the findings of Kruger and Dunning (1999), Dunning et al. (2003), and Ehrlinger, et al. (2008) who observed a systematic pattern describing a tendency for middle and lower performing students to have an illusion of competence bias in their metacognitive functioning. The current study adds an important extension to these studies by examining students’ performance estimations and actual performances in college courses across three in-class exams conducted throughout the semester. In addition, the two classes in this study represent relative extremes in course difficulty – the chemistry mean exam scores for exams 1, 2, and 3 were 65.49, 61.65, and 65.63, respectively, and nursing mean exam scores for exams 1, 2, and 3 were 82.86, 83.23, and 88.33, respectively.

Consistent with laboratory-based (Kruger and Dunning’s (1999) and in-class (Ehrlinger et al., 2008; Dunning et al, 2003) research, I found a pattern of overestimation in exam scores and relative standing for bottom and average performers on each of the three course exams for students relative their actual performance. In addition, I found a corresponding pattern of underestimation in exam scores (albeit not as large as the
bottom performers’ overestimations) and relative standing for the top performers. Furthermore, students who were consistent top or bottom performers in all three exams did not learn from their prior exam performance and teacher-provided exam distribution feedback; they continued to make the same metacognitive errors in performance estimations in subsequent exams. This pattern of misestimation was consistent in both the chemistry and nursing courses. These findings speak to the solid nature of the phenomenon when considering the relative difficulty of each course (as observed by the mean exam scores). The apparent disparate rigor of these two courses might explain the finding that, although students in both courses overestimated their relative performance, only the nursing students (perhaps reflecting on the ease of the exam) demonstrated the “better than average effect” and consistently estimated their performance to be above the 50th percentile.

Contrary to Kruger and Dunning’s (1999) findings that their top performers made corrective judgments of their performance after viewing work from other, less competent peers, top performing students in my studies made no such improvement in their estimations after receiving instructor-provided feedback on score distributions and overall mean scores on exams. What might account for this apparent contradiction in findings? Kruger and Dunning provided students with information about students’ peers by giving them five tests to “grade.” This process was designed to inform students how others were performing and to allow a point of comparison with their own performance. The authors offered no detailed information regarding the actual performances on these five tests relative to the “graders.” In addition, students were expected to reassess and revise their own estimations of their performances based on only these other five tests. In
the current research, by contrast, course instructors provided students with detailed information regarding the performance of the entire class of students from which students might base a revision of performance estimates. Although students in the current research were not asked to reevaluate their current estimations (this would make no sense as they had been provided information on their score and grade on the exam), the feedback afforded them an opportunity to reflect on their performance with regard to their scores and relative standing. One might expect that having this information would have enabled more accurate estimates on the second and third exams. Top performing students in my research did not do this. Further investigation of this finding, which occurred for both the chemistry and the nursing classes, might be worthy of a later study.

Study 2 supported prior findings that motivating students with monetary incentives to provide more accurate estimations of performance was not effective in reducing predictive errors (Ehrlinger et al., 2008). In Ehrlinger et al. (2008, Study 4), students were tested on a subject to which they may or may not have had prior exposure. Without exposure, these students may not be in a position to accurately evaluate their performance. I extended Ehrlinger et al.'s (2008) research in that participants in my study were examined in the natural setting of their own classroom. Students were tested in class as part of their regular course requirement; in contrast to the Ehrlinger et al. (2008) laboratory study where participants were tested on logic, a subject to which they may or may not have had prior exposure, participants in my study were students in their regular classroom, and had been exposed to the material in which they are being tested. In addition, I examined only those students who consistently performed poorly on each of the three exams and only those students who consistently performed well on each of the
three exams. Despite the offer of a $50 gift certificate for providing the most accurate performance estimations, in neither of these cases did the students show a reliable decrease to which they overestimated or underestimated their test score. These findings were the same when evaluating for relative standing. Monetary incentive for accuracy in estimation was not sufficient motivation to resolve metacognitive errors.

**Academic Self-Efficacy**

Consistent with Bandura’s (1993, 2001) and Pajares’ (1996) theories of academic self-efficacy, students who reported higher levels of academic self-efficacy in both the chemistry and the nursing courses performed better on their first exams than their low self-efficacy counterparts. This finding has a particular import, as I found it in ongoing courses with diverse levels of rigor (nursing versus chemistry), and with an important academic measure (i.e., major course exams). In addition, higher efficacious students outperformed their low efficacious counterparts across levels of academic ability. Most important, in the chemistry course, the observed relation between self-efficacy and exam performance was not attributed to the correlation between self-efficacy and chemistry background knowledge. Considering the advantage that efficacious students have over their less efficacious peers, future studies should investigate potential methods to increase students’ academic self-efficacy.

In addition, findings in this study are consistent with those of Liem and colleagues (2008) who found that students with higher self-efficacy tended to use deep cognitive learning strategies. In the current study, chemistry students with higher self-efficacy were more likely to use active study strategies. One avenue of future study might be aimed at improving students’ measures of self-efficacy by providing them with adequate study
tools (cognitive based strategies) to help them succeed. Improved performance, in turn, should help students to achieve greater confidence in their abilities for future success.

Relations between self-efficacy and study behaviors for the nursing course, however, did not reach significance. As a possible explanation for the lack of significance, one might look to the rigor of the two courses. The chemistry class, with the lower exam score means, was the more challenging course. It is likely that students engaged in more studying in general for the chemistry exams than for the nursing exams. If this was the case, the nursing students might have had relatively little to report in terms of their study behaviors. Examination of additional courses with diverse rigor might shed light on this curious finding.

Students with higher academic self-efficacy tended to overestimate both their exam scores and their relative standing. However, for top performers, although the correlations between self-efficacy and exam performance were positive, they failed to reach significance. Most interesting was the significant positive relation between self-efficacy and percentile estimation; top performing students tended to report estimations of higher percentile ranking compared to those students with lower self-efficacy. This finding might be explained, in part, by Bandura’s (2001) notion that goal achievement can be a motivating factor driving students’ desire for successful academic outcomes. According to achievement goal theory, as described by Liem, Lau, and Nie (2008), efficacious students are oriented toward demonstrating a successful performance and elevated competence relative to their peers, and by demonstrating their achievement in a task insofar as it “announces” their competency. In my research, it is conceivable that
having students report their estimations in relative performance on an exam provided those students with higher self-efficacy an opportunity to “announce” their competency.

**Self-Reported Study Behaviors**

The present results clearly show that in both the chemistry and nursing classes, there was a *positive* correlation between reported use of active study behaviors and exam score and a *negative* correlation between reported use of passive study behaviors and exam score. Most noteworthy is that students who were both high on the active study behavior measure and low on the passive study behavior measure scored highest on the exam. This result is consistent with prior research documenting the superior effect of cognitive-supported behaviors for study (e.g., Fonseca & Chi, 2011; Metcalfe & Kornell, 2007; Metcalfe, Kornell, and Son, 2007; Thomas & McDaniel, 2007).

**Plan For Future Studies**

Potential adverse consequences of faulty self-assessments are substantial in the academic arena. Learners are influenced by their metacomprension in making decisions about what study behaviors to adopt and how to employ them (Kornell, 2009; Kornell, & Bjork, 2008; Koriat & Bjork, 2005). Because overconfidence in this setting can lead to inadequate – or premature cessation of – effortful study, uncovering possible mechanisms underlying metacognitive misjudgments could have a profound impact on academic performance. One possible corrective intervention may be through the implementation of training programs designed to promote effortful study behavior. **Making the incompetent competent.** Suppose that application of appropriate strategies and skills can facilitate competency. An empirical question follows that if the incompetent are made competent, is there an effect on these students’ metacognitive
functioning? Kruger and Dunning (1999) would argue “yes.” In a laboratory setting, the authors found that when low-performing students were provided with requisite skills for logical reasoning after finishing a logic task (followed directly, as usual, by their judgments of performance), the newly rendered competent students, after reviewing their work prior to the skills session, were more accurate in their judgments of performance relative to their peers. Conversely, students without logic skills training continued to show metacognitive miscalculation when reassessing their performances. Thus, achieving competence, the authors argued, improved their metacognitive skills. These results suggest that identifying the sources of lower performers’ faulty self-assessments may provide a crucial step toward improving academic performance.

One possible corrective intervention may be through the implementation of training programs designed to promote effortful study behavior. Although experimental manipulations used in such training programs would be expected to reduce cognitive illusions and resultant poor academic performance, there is reason to believe that the effects of such interventions will continue to reflect individual differences among training program participants.

**Concluding Remarks**

In this dissertation, I examined some of the challenges facing college students’ efforts in achieving successful academic performance. Results support past findings that poor performing students tend to make the largest errors in judgments of what they know, and how they have performed. If students have this illusion of competence, they might not avail themselves of learning opportunities to help them improve their performances. Other students are not so confident about their abilities to succeed. Lack of confidence
can be a barrier to successful academic performance. In my research, students with low academic self-efficacy tended to perform more poorly than their higher efficacious counterparts. Finding ways to help students achieve higher self-efficacy, perhaps by providing them with the tools to succeed (e.g. with cognitive-baste study skills), might inspire them to greater confidence. Many students are largely unaware of study methods that are known to produce successful performance. Teaching students appropriate methods for studying is one way to help students succeed. Working to unravel the phenomena interlacing these elements may help researchers and educators to better understand the circumstances that give rise to particular study behaviors students make in their efforts toward self-regulated learning.
REFERENCES


Prat-Sala, M., & Redford, P. (2010). The interplay between motivation, self-efficacy, and approaches to studying. British Journal of Educational Psychology, 80(2), 283-305.


APPENDIX A

RELATIVE SELF-EFFICACY

The following five questions are about the confidence you have that you are capable of performing better than other students in this course. Performing “better” refers to learning more than other students enrolled in this course.

1. How confident are you that you are capable of performing better than 15% of the other students in this course?

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<td>No</td>
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2. How confident are you that you will be capable of performing better than 30% of the other students in this course?

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<tr>
<td>No</td>
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<td>Total</td>
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3. How confident are you that you are capable of performing better than 50% of the other students in this course?

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4. How confident are you that you will be capable of performing better than 75% of the other students in this course?

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5. How confident are you that you will be capable of performing better than 85% of the other students in this course?

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INSTITUTIONAL REVIEW BOARD APPROVAL LETTER

University of New Hampshire
Research Integrity Services, Office of Sponsored Research
Service Building, 51 College Road, Durham, NH 03824-3585
Fax: 603-862-3564

06-Jul-2009

Benassi, Victor A
Center for Excellence in Teaching and Learning
11 Brook Way
Durham, NH 03824

IRB #: 4638
Study: Cognition Toolbox
Approval Date: 30-Jun-2009

The Institutional Review Board for the Protection of Human Subjects in Research (IRB) has reviewed and approved the protocol for your study as Exempt as described in Title 45, Code of Federal Regulations (CFR), Part 46, Subsection 101(h). Approval is granted to conduct your study as described in your protocol.

Researchers who conduct studies involving human subjects have responsibilities as outlined in the attached document, Responsibilities of Directors of Research Studies Involving Human Subjects. (This document is also available at http://www.unh.edu/osr/compliance/irb.html.) Please read this document carefully before commencing your work involving human subjects.

Upon completion of your study, please complete the enclosed Exempt Study Final Report form and return it to this office along with a report of your findings.

If you have questions or concerns about your study or this approval, please feel free to contact me at 603-862-2003 or julie.simpson@unh.edu. Please refer to the IRB # above in all correspondence related to this study. The IRB wishes you success with your research.

For the IRB,

Julie F. Simpson
Manager

cc: File