AN EMPIRICAL INVESTIGATION INTO THE MODERATING RELATIONSHIP OF COMPUTER SELF-EFFICACY ON PERFORMANCE IN A COMPUTER-SUPPORTED TASK

BY

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DEDICATION

I would like to dedicate my dissertation to the following people; without their encouragement and continuous support this (my graduate education, dissertation, and academic career) would not have been possible. I am grateful for their help and support.

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1. INTRODUCTION

Every year, both organizations and their employees invest a significant amount of resources in training and development programs, in the hope that these will have an important impact on employee growth and ultimately on organizational performance. Among the many different subjects, computer skills are the most frequent type of training provided by organizations (Yi & Davis, 2003). Rooted in Social Cognitive Theory (Bandura, 1997), computer self-efficacy, generally defined as a "judgment of one's capability to use a computer" (Compeau & Higgins, 1995b), has been repeatedly identified as a key outcome of training, mediating the effects of a number of influences on performance, such as training treatments, past experience and demographic variables (Marakas, Yi, & Johnson, 1998), or personality characteristics and other individual differences (Johnson, 2005), and affecting performance both directly and through its impacts on different motivational and affective mechanisms. For instance, individuals displaying high levels of computer self-efficacy are expected to be more focused and persistent, put more effort into their endeavors and be more committed to achieving their goals, be more able to cope with negative feedback, and be generally less anxious about completing the task (Marakas et al., 1998).

In addition, there is an important literature base, both in information systems and other reference and related disciplines, bearing on the issue of self-efficacy modification and development. Bandura (1997) suggested the existence of four main categories of experience affecting the development of self-efficacy judgments, e.g.

enactive mastery, vicarious experience, verbal persuasion, and physiological arousal. Researchers have sought to develop approaches focused on one or more of these conduits in order to improve the effectiveness of training programs. Among those examined, programs based on behavior modeling, e.g. observing someone perform a target behavior and then attempting to reenact it, have been shown to be particularly effective (Johnson & Marakas, 2000) and have become the focus of more detailed examinations into the processes by which learning is affected (Yi & Davis, 2003). Research has also focused on collaborative learning, either by itself or in combination with other approaches, such as behavior modeling (Davis & Yi, 2004; Keeler & Anson, 1995). Overall, this rich and growing stream of research has made computer self-efficacy an attractive target for the implementation of treatments and interventions.

There is also extensive support for the relationship between computer self-efficacy and computer-performance, in different contexts and for a variety of software applications (Compeau & Higgins, 1995a; Johnson, 2005; Johnson & Marakas, 2000; Marakas, Johnson, & Clay, 2007; Yi & Davis, 2003; Yi & Im, 2004). Given the objective of these efforts on isolating the performance effects of this central construct, dependent measures focused exclusively on syntactic- and feature-based uses of the different software packages involved, most notably productivity suites. As such, these outcomes represent knowledge situated in the first three levels of the hierarchy developed by Sein, Bostrom and Olfman (1998): syntax (actual language through

which a user interacts with the application), semantic (meaning of those commands) and functional (e.g. grouping commands into a task such as creating a document).

However, most organizational tasks require the presence of both domain and computer skills for their successful completion (Looney, Valacich, Todd, & Morris, 2006), and thus effective use of these technologies is a critical factor in reaping productivity gains, improving return on IT investments, and overall organizational performance (Yi & Im, 2004). Although computers and related technologies have become pervasive in the current organizational environment, organizational members are not primarily users of technology, but rather social actors that employ these as they attempt to carry out different activities in their various roles (Lamb & Kling, 2003).

In general, it is then possible to build a theoretical chain of reasoning connecting computer training interventions with ultimate task performance, and indeed researchers in this area often use this presumed state of affairs as justification for the importance of furthering our understanding in this realm. For instance, Compeau and Higgins (1995a) argued that user training was a widely recognized factor contributing to productive use of information systems in organizations. Yi and Im (2004) highlighted computer task performance as a major contributor to end-user productivity, while Yi and Davis (2003) remarked that effective computer training is a major contributor to organizational performance. Figure 1.1. below depicts these relationships, in each case noting past research that investigated related constructs and their relationships:

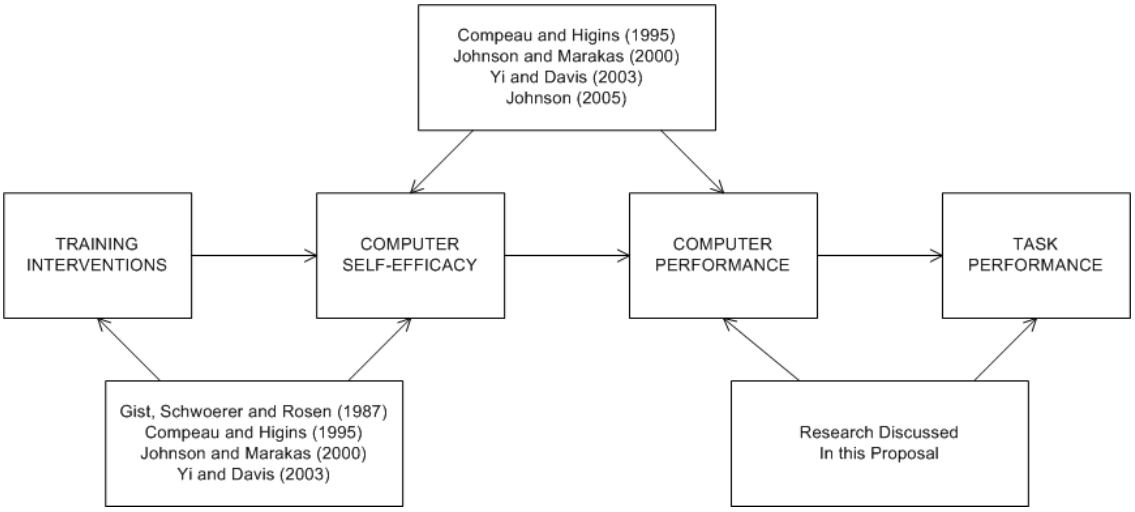


Figure 1.1 – Training – Performance Relationship

While the impacts of computer self-efficacy on computer task-performance are, as noted above, well established, it has not yet been incorporated into the nomological net attempting to explain performance in tasks requiring the use of computer technologies. Doing so would provide a clear link between training interventions and performance in organizational tasks. Researchers in this area have repeatedly argued for the need to incorporate computer self-efficacy into more complex and comprehensive models of performance that take into account perceived capabilities in other domains of organizational action (Marakas et al., 2007; Marakas et al., 1998). It is thus important to look beyond performance in computer-only tasks and accordingly position computer self-efficacy as a determinant of performance in a richer task environment.

In addition, given that organizational tasks can largely vary on the level of required computer support, it becomes relevant to understand how the effects of computer self-efficacy on task performance fluctuate as the role of the computer becomes more or less prominent. Thus, this dissertation intends to answer the following two research questions: (1) What is the relationship between computer self-efficacy and performance in a computer-supported task?, and (2) How does that relationship change for different levels of computer-support?.

This dissertation represents an improvement on extant research, most notably that conducted by Looney and colleagues (Looney et al., 2006) in at least three important aspects. First, the theoretical development of the proposed research model is more closely based on extant theory and logic, and positions computer self-efficacy in a different light than Looney et al (2006) did. In particular, rather than having a direct , even if mediated, effect on performance, computer self-efficacy is argued to moderate the relationship between beliefs of efficacy in performing the task and a joint self-efficacy mediator, referring to beliefs of efficacy in performing the task with the support of computer technology.

Second, this research includes a performance measure, while Looney et al (2006) only employed outcome expectations as the dependent variables of interest in their research model. It is argued here that the use of a performance measure represents a more foundational test of the posited influence of computer self-efficacy on task performance. Finally, the research proposed here takes into account differences in the impact information technology has had on the different tasks to

which it has been applied. Accordingly, certain effects are proposed to vary with regards to the degree of change in outcome effectiveness caused by the incorporation of technology into task performance.

In order to bound the scope of this work, the focus of this dissertation is on the performance effects of computer self-efficacy. Although certainly interesting and important, other related avenues of research, such as the modeling of computer self-efficacy through training programs, or the effects of the construct on the adoption and use of technology will not be considered in the main model under investigation.

Chapter 2 reviews existing literature on the foundations of Social Cognitive Theory, its applications to the fields of management and organizational behavior and, in particular, to information systems research. This chapter also includes a comprehensive review of prior literature dealing with the performance effects of computer self-efficacy, and in more detail considers the work of Looney et al (2006). Chapter 3 summarizes this literature, develops relevant hypotheses, and presents a comprehensive research model that will be tested in this study. Chapters 4 and 5 report on the empirical analysis conducted in order to test those research hypotheses and model. Finally, Chapter 6 discusses limitations and implications of this dissertation, and proposed new directions for future research.

2. LITERATURE REVIEW

Social Cognitive Theory

This section attempts to present a review of Social Cognitive Theory (Bandura, 1997) and its major theoretical concepts and relationships. Given the very rich and complex nature of this framework, it is unlikely this brief summary will do it justice. Thus, the reader is referred to the work of Bandura (1986a, 1997) himself for a full account. Social Cognitive Theory (SCT) and its central variable, self-efficacy, have proven to be extremely popular foundations for research in a number of distinct areas, such as academic and health behaviors, management and organizational psychology, leadership, training, negotiation and career development, to name just a few. By one account, more than ten thousand investigations involving this theory have been conducted since it was first formulated more than twenty five years ago (most notably, in 2004 alone, an average of 1.67 articles *per day* were published on self-efficacy) (Judge, Jackson, Shaw, Scott, & Rich, 2007).

In contrast to unidirectional models of causality that attempt to explain human behavior as being controlled either by environmental influences or by internal dispositions, SCT explains functioning in terms of triadic reciprocal causation between behavior, cognitive and other personal factors, and the external environment. This model of reciprocal determinism is depicted in Figure 2.1.

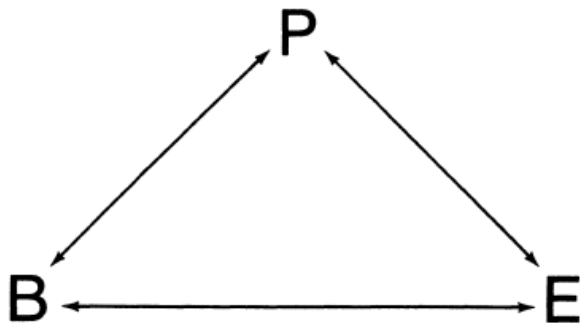


Figure 2.1 – Triadic Reciprocal Causation (Wood & Bandura, 1989b)

The model is argued to be deterministic in the sense of the production of effects by events, rather than meaning that actions are completely determined by a prior sequence of causes independent of the individual and her actions. Given that behavior is jointly determined by a number of factors operating interactively, effects produced by particular events are considered to be probabilistic, rather than inevitable, in this conceptual system. Considering the generally stated as contrasting notions of freedom of action and determinism, Bandura (1997) notes that there is no incompatibility from a sociocognitive perspective.

In this view, freedom and agentic causation are not conceived as exemption from all social influences and situational constraints, but rather as the exercise of self-influence in order to bring about desired results. The choice of actions from among available alternatives is not completely determined by environmental and situational events, but rather involves the ability to behave differently from what these forces dictate. This perspective stands in stark contrast to others such as the operant view, with its reactive stance, in which people are not considered to go beyond being

repositories of past stimuli and conducts for external simulation, without adding much of their own to their behavior and performance.

Another important aspect of Figure 2.1 is the postulated reciprocality between the environment, cognitive and personal factors, and behavior. While the underlying logic states that these tree factors influence each other in a bidirectional relationship, it does not assign equal strength to the different sources, nor does it state that influences occur simultaneously. Rather, time is involved in the activation of causal factors, their influence on others, and the emergence of reciprocal influences. Given this bidirectionality, individuals are considered to be both products and producers of their environment (Wood & Bandura, 1989b).

Self-referent thought in general, and beliefs of personal efficacy in particular, play a pivotal role in this conceptualization of human functioning. Self-regulation of motivation and action, and thus performance, is the result of several self-regulatory mechanisms that operate in concert. Noting differences from other related concepts such as the self-concept, self-esteem, effectance motivation and control beliefs, Bandura (1997) argued that:

> *"A full understanding of personal causation requires a comprehensive theory that explains, within a unified conceptual framework, the origins of efficacy beliefs, their structure and function, the processes through which they produce diverse effects, and their modifiability. Self-efficacy theory addresses all these subprocesses at both the individual level and the collective level. ... It specifies other aspects of the conglomerate self-system. These include, among other things, personal aspirations, outcome expectations, perceived opportunity*

> *structures and constraints, and conceptions of personal efficacy. Analysis of how these constituent factors work together and their relative contribution to adaptation and change provides an integrated view of the self*' (p. 10)

Self-efficacy beliefs are thus concerned with an individual perception of capability to mobilize the motivational and cognitive resources, and courses of action needed to exert control over events of personal relevance. This complements actual capabilities, in that it foments their use under difficult and stressing circumstances. Individuals with the same level of skill may then perform poorly, adequately, or extraordinarily depending on the effects their beliefs of efficacy have on their motivation and problem-solving efforts (Wood & Bandura, 1989b). Thus defined, perceived self-efficacy is a generative capability in which a number of subskills involving cognitive, social, emotional and behavioral aspects of functioning must be organized and orchestrated effectively to serve certain purposes.

Effective functioning calls for possessing the necessary skills and the efficacy beliefs to use them appropriately, requiring continuous improvisation in the face of dynamic, complex, unpredictable and often stressful situations. Three different aspects of this definition are important. First, self-efficacy is a comprehensive judgment of an individual's perceived capability to perform a particular task. Second, self-efficacy is a dynamic concept, changing over time and even during task performance as new, relevant information becomes available. And third, it reflects a

mobilization component, involving the orchestration of adaptive capacities to changing circumstances (Gist & Mitchell, 1992).

Multidimensionality

Self-efficacy beliefs vary along three important dimensions (Bandura, 1997). First, they differ in *level*; efficacy beliefs of individuals may be limited to simple task demands, extend to moderately complex ones, or encompass most taxing performance demands within a particular domain of functioning. Thus, efficacy beliefs are not decontextualized traits upon which situational demands operate, but they rather represent the performance requirements against which efficacy is judged.

Second, efficacy beliefs vary in *generality*. Individuals may judge themselves to be efficacious across a wide range of activities or only within certain and specific domains of human functioning. This assessment of generality itself can vary along different dimensions, such as the degree of similarity present in activities, the mode in which capabilities are expressed (e.g. cognitive, affective, behavioral), qualitative features of different situations, and also characteristics of individuals toward whom behaviors are directed.

Finally, self-efficacy beliefs also vary in *strength*, whereas weak beliefs are easily negated by discomforting experiences, but individuals possessing strong convictions persevere in the face of obstacles and difficulties, and will not easily overwhelmed by adversity. Strength of self-efficacy, however, is not linearly related to choice behavior, since it is postulated that a certain threshold level must be crossed

in order to even attempt a certain course of action, and higher levels of self-efficacy would also result in the same behavior being attempted. Strength of efficacy beliefs manifests itself in the greater perseverance, and thus likelihood of success, in the chosen activity.

Sources of Self-Efficacy Beliefs

Beliefs of personal efficacy are constructed from four main sources of information relevant for the formation of a judgment about capability for performing a task. Moreover, these sources are not exclusive of each other, and thus any given influence may operate through one or more of them. However, information that is available but neither processed nor integrated into cognitive thought is unlikely to have any effect on self-referent perceptions. Some of these issues are examined in more detail later when reviewing the work of Gist and Mitchell (1992). In general, the processing of self-efficacy information depends on two separable functions. The first one relates to the types of information people attend to and use, and each of the four sources of efficacy beliefs has a distinctive set of indicators and cues. The second function refers to the rules, processes and heuristics that people use to weight and integrate the different sources of information (Bandura, 1997).

The most influential source of information affecting efficacy beliefs is *enactive mastery*, e.g. repeated performance accomplishments. While positive mastery experiences serve to increase self-efficacy, negative ones are more likely to debilitate it. These experiences provide the most authentic evidence of whether an

individual is able to orchestrate the capacities required to succeed in a particular endeavor. Enactive mastery has a more stronger and generalized effect on efficacy beliefs than any of the other three sources of information. However, performance alone does not provide oneself with enough information to judge levels of capability, since many factors having little to do with the latter can have an important effect on performance. Individuals act on their self-efficacy beliefs and then assess the adequacy of those judgments based on the obtained performances.

Thus, changes in self-efficacy result from cognitive processing of diagnostic information that past performances convey about the capability to effect them, rather than the mere act of carrying out an activity. The extent to which performance experiences alter beliefs of self-efficacy depends on a host of factors such as preconceptions of capability, perceptions of task difficulty, the amount of external aid received, the circumstances of the performance, the temporal pattern of failures and successes, and the process by which these experiences are organized and reconstructed in memory (Bandura, 1997).

Second, people do not rely on past experience as the only source of information about their performance capabilities, but also are influenced by *vicarious experiences* obtained from modeled attainments. Models build beliefs of efficacy by conveying and exemplifying effective strategies to manage a variety of situations. Social comparison processes also play a role in the effects modeling obtains on self-efficacy, given that human beings partially judge their capabilities in comparison with others. Given that, for most activities, there are no objective measures of adequacy,

referential comparisons become very salient. In some cases, performance or social standards are available such that individuals may judge where they stand in comparison with some expected outcome. In others, people seek to compare themselves with similar others, such as coworkers, classmates, etc. to inform their efficacy beliefs.

Wood and Bandura (1989b) commented extensively on the different mechanisms governing modeling processes, and on their primary importance for the development of competencies through targeted training interventions. Indeed, a significant portion of research involving self-efficacy, and computer self-efficacy in particular, as reviewed later, has been conducted in the context of training programs. Four different processes govern observational learning.

First, attentional processes play an important role in determining what people selectively observe in the large variety of modeling influences available to them, and what information is extracted from those that are observed. The logic is that people cannot be influenced by observed performances if those cannot be remembered. Next, representational processes involve the transformation and restructuring of remembered information about events into the form of rules and conceptions. Retention of this information is greatly improved when individuals symbolically transform the modeled information into mental codes and then rehearse the coded information. During the third component of behavior modeling, behavioral production processes, those symbolic conceptions are now translated into appropriate courses of action, through a matching process in which guided patterns of behavior

are enacted and the adequacy of these actions are contrasted against the conceptual model, leading to an iterative process by which individuals adjust their behavior in order to achieve correspondence between actions and conceptions. Finally, motivational processes involve three major types of incentive motivators. Individuals are more likely to enact modeled strategies that produce valued outcomes, and set aside those with unrewarding or punishing effects. People are also motivated by the success of similar others, but are discouraged from pursuing behaviors that have been known to result in negative consequences. Personal, self-produced, standards provide another source of performance motivation.

Verbal persuasion represents yet another important source of information involved in the development of efficacy belies, but lags behind enactive mastery and vicarious experiences with regards to the strength by which it is able to do so. While verbal persuasion alone may have a limited effect in creating enduring efficacy beliefs, faith in one's capabilities as expressed by significant others, particularly during times of doubt or despair, can have a significant effect with respect to the mobilization and maintenance of effort. Persuasion has its greater impact on those individuals that for some reason already believe they can produce certain effects through their actions. The raising of efficacy beliefs to unrealistic levels, however, is likely to result in a failure that would not only undermine future conceptions of capability, but also discredit the source of information. The degree of appraisal disparity, that is, how different own beliefs are from what people are told, is an important contingency on the effects of social persuasion. While social appraisals that

differ markedly from judgments of current capability may be considered believable in the long run, they are unlikely to be acted upon on the short term. Persuasory appraisals are more likely to be believed when they are only moderately beyond what individuals can do at the time.

Lastly, people rely on information provided by *physiological and emotional states* in assessing their capabilities. They read their emotional arousal and tension as signs of vulnerability to poor performance. Even before computer self-efficacy had become the subject of research, computer anxiety (Heinssen, Glass, & Knight, 1987) had already attracted the interest of the information systems community. Because high arousal can debilitate performance, people are more inclined to expect success when they are not undermined by aversive arousal. Treatments that reduce emotional reactions to subjective threats through mastery experiences can help increase beliefs in coping efficacy and correspondingly improvements in performance. Thus, the fourth major way of altering efficacy beliefs is to enhance physical status, reduce stress levels and negative emotional influences, or alter dysfunctional interpretations of bodily states.

Processes by which Self-Efficacy Affects Behavior and Performance

Cognitive Processes. Efficacy beliefs affect thought patterns that can either enhance or undermine performance, and these influences take various forms. People with a high sense of efficacy tend to take a future time perspective in structuring their lives, and since most courses of action take initial shape in thought, these cognitive

constructions then serve as guides for future actions. Strong efficacy beliefs also affect perceptions of situations as presenting realizable opportunities. Those who judge themselves inefficacious, on the other hand, construe uncertain situations as risky and visualize scenarios involving failure. Perceived self-efficacy and this process of cognitive simulation also affect each other bidirectionally, positive cognitive constructions in turn strengthening efficacy beliefs. A major function of thought is to enable people to both predict the likely outcomes of different courses of action and to create the means to exert some degree of control over those (Bandura, 1997).

People draw on their existing knowledge in order to construct and weigh options, integrate predictive factors into rules, test and revise judgments against the results of actions, and also to remember which factors were tested and how well those performed. A strong sense of efficacy exerts a powerful influence on self-regulatory cognitive processes, and supports the ability to remain task oriented in the face of causal ambiguity, personal and situational demands, and judgment failures that can potentially have important repercussions for the individual. Results from a series of experiments, discussed in the next section, provide strong support for the diverse set of influences that alter efficacy beliefs, and those in turn influence performance attainments through their effects on goals and efficiency of analytic thinking.

Motivational Processes. Bandura (1997) argued that most human motivation is cognitively generated, e.g. people motivate themselves and guide their actions through exercise of anticipation and forethought. Human beings form beliefs about

what they can and cannot do, anticipate the likely positive or negative consequences of different courses of action, and then set goals and make plans to realize valued outcomes and avoid the unpleasant ones. It is possible to distinguish three different bodies of theory on motivational processes, built around causal attributions, outcome expectancies, and cognized goals. Efficacy beliefs play a central role in all of them.

Retrospective judgments of the causes of past performances are postulated to have a motivational effect according to *attribution theory*. Individuals who attribute past successes to personal capability and failure to insufficient effort will undertake more difficult tasks and persist longer in the face of negative feedback, since they perceive outcomes as being a function of how much effort is spent in pursuing them. In contrast, those who ascribe failures to situational determinants will display reduced interest and abandon courses of action in the face of difficulties. Results from extensive research indicate that causal attributions can indeed influence future performance, but that the effect is fully mediated by their influences on beliefs of self-efficacy. For instance, attributions of past success to ability heighten beliefs of personal efficacy, which in turn influence future attainments.

Social Cognitive Theory, however, presents a more comprehensive picture of the mechanisms by which past performance influences self-efficacy than does attribution theory, which is generally limited to considerations of effort, ability, task difficulty, and chance. People also consider the situation under which they performed, the amount of assistance received, and the rate and pattern of past successes as valuable information that is integrated into judgments of capability. In addition,

efficacy beliefs can also bias causal attributions. Thus, efficacious individuals are more likely to attribute failures to insufficient effort or environmental impediments, whereas those with a low sense of efficacy attribute them as arising from a lack of ability. Performance feedback that is inconsistent with perceived self-efficacy is dismissed as less accurate and more likely to be attributed to extraneous factors.

Individuals also motivate themselves by considering the *outcomes* they expect to accrue from following a given course of behavior. Expectancy-value theory essentially predicts that motivation to perform an activity is the result of expecting that doing so would secure specific outcomes, and that those outcomes are highly valued by the person considering the performance. Bandura (1997) notes, however, that people are less systematic in their consideration of potential courses of action and in their appraisal of likely outcomes than expectancy-value models would suggest, and argues that individuals act on their beliefs about what they can do as well as on their beliefs about the likely effects of their actions. A diminished sense of efficacy can then eliminate the potential allure of certain outcomes if individuals believe they cannot successfully perform the actions that would lead to them. In activities where outcomes depend on the quality of the performance, efficacy beliefs thus determine which outcomes will be foreseen, and expected outcomes contribute little to future performance when efficacy beliefs are statistically controlled for in research models.

Lastly, behavior is also motivated and directed by *goals* which result from forethought and self-regulatory mechanisms. Cognitive motivation based on the pursuit of goals or standards is further mediated by three different types of self-

influences, e.g. affective reactions to performance such as anticipated satisfaction from fulfilling valued standards or self-dissatisfaction with poor performance, perceived self-efficacy for goal attainment, which influences which challenges to undertake, how much effort to spend in the endeavor, and how long to persevere in the face of difficulties, and adjustment of standards in light of past attainments, which depend on the construal of the pattern and level of progress being made.

The way these three self-influences are postulated to operate in regulating motivation, however, varies on the degree to which performance falls short of standards. While perceived efficacy contributes to motivation at all discrepancy levels, discontent is proposed to become more influential when performance falls substantively or moderately short of the expected standard. When matching or approximating that standard occurs, however, people do not invest as much effort in closing the rather small gap. The self-setting of increasingly challenging goals, which has an important effect on motivation to purse and accomplish them, occurs mostly as individuals start to surpass their initial standards.

There is significant evidence on the effects of efficacy beliefs on the operation of personal goals, by influencing the level at which goals are set, the strength of commitment to them, strategies used to reach those, amount of mobilized effort and further intensification of effort when performance falls short. In the regulation of action, personal goals based on perceived competency have significant functional value, in that they prevent people from taking on challenges they could not hope to fulfill. Goals can have a reciprocal effect on self-efficacy, on the other hand, when

they are socially assigned, since setting challenges for others is an indication of belief in their ability to accomplish them. Thus, it is not goals by themselves that affect efficacy but they represent an expression of confidence in that the individual has what it takes to reach them.

Goal intentions, however, do not automatically activate the different processes that govern the level of motivation to pursue them, but rather certain properties of goal structures have an effect on how strongly the self-system will react to any given endeavor. More explicit standards regulate performance by clearly delineating the type and amount of effort required to reach them, and generate satisfaction by allowing unambiguous signs of personal accomplishment (goal specificity). The amount of effort and satisfaction involved in the pursuit of goals is also a function of the level of challenge they represent. When satisfaction is contingent on achieving difficult goals, more effort will be devoted to the activity than when objectives are within easy reach (goal challenge). The relationship only holds, however, when participants personally accept the goals and remain committed to them as the endeavor develops. The effectiveness of goal intentions on regulating motivation and action is also partly dependent on how far into the future the goals are projected (goal proximity). Distal goals alone are too far removed in time to provide effective incentives to motivate current action, and thus need to be supplemented by more proximal ones that motivate behavior in the here and now.

Affective Processes. Efficacy beliefs also play a pivotal role on the regulation of affective states, affecting the nature and intensity of emotional experiences through

the exercise of personal control on thought, action, and affect. In the first case, efficacy beliefs create attentional biases and influence whether and how events are construed, represented, and retrieved in ways that are emotionally benign or perturbing. Also, perceived cognitive abilities influence the control of negative trains of thought that intrude in the flow of consciousness and distract attention from the task and situation at hand. In the action-oriented mode of influence, efficacy beliefs support courses of action that transform the environment in ways that improve its emotional potential. The affective mode influences self-efficacy to negatively affect aversive emotional states once they have been aroused.

Social Cognitive Theory in Organizational Behavior and Work Settings

Many of the tenets and relationships involved in Social Cognitive Theory, particularly as they relate to its dynamics aspects, were investigated in a series of studies using simulated organizations by Bandura and his colleagues (Bandura & Jourden, 1991; Bandura & Wood, 1989; Cervone, Jiwani, & Wood, 1991). In this research program, participants took on the role of managers in a manufacturing simulation, who received weekly orders for items and had a roster of available employees that could be dynamically assigned to different production subfunctions. The correct matching of employees to production requirements allowed subjects to attain a higher level of organizational performance. After employees had been assigned to a specific function for any given trial, subjects could assign employees different production goals, which had varying motivational effects. After completion

of each trial the simulated managers could provide feedback and social incentives to their employees, again having varying, but unknown, effects on motivation on subsequent time periods. To summarize, participants needed to learn and master a number of decision rules, some of which were nonlinear, and discover the best way to motivate each specific employee.

Bandura and Wood (1989) examined the effects of perceived controllability and performance standards on decision making in this environment. The authors argued that, when individuals believe that the environment is controllable, at least in matters that are important to them, they are more motivated to exercise their personal efficacy, thus resulting in an increased likelihood of success. Experiencing success, in turn, validates the increased effort and the controllability of the environment. The opposite is expected when situations are approached as essentially uncontrollable. In addition, participants in this simulation received weekly performance standards for achieving gains in performance, which were either relatively difficult or easy to fulfill. The authors measured perceived self-efficacy, personal goals, analytic strategies and organizational performance at three different points in the simulation.

Results from this study show that viewing organizations as controllable heightens managerial self-efficacy. In the high-controllability condition, subjects who had been assigned an easily attainable standard displayed increasing levels of efficacy across subsequent trials, while those assigned a difficult standard showed a progressive weakening. Those participants who believed organizations were hard to control displayed low self-efficacy regardless of performance standard condition.

Self-set goals were also affected by the perceived degree of controllability, whereas more challenging goals were adopted when organizations were perceived as being under the control of the participant. Mean obtained performance was strongly affected by the induced perception of controllability. A causal model of these effects showed prior performance influencing self-efficacy, personal goal setting and subsequent performance. Perceived self-efficacy independently contributed to performance through its effects on the analytic strategies employed by participants in the simulation. In subsequent trials, however, self-efficacy affected performance directly and through its strong influence in personal goals. These findings support the major predictions that self-regulatory factors affecting performance are affected by stringency of standards and perceived controllability over the task environment. Viewing organizations as controllable results in an increased perceived capacity to manage them, whereas the opposite weakens self-beliefs of efficacy. Another important finding of this research shows that perceived uncontrollability is debilitating even in the face of easily attainable standards.

To further investigate the issue, Cervone, Jiwani and Wood (1991) studied the effects of three different task goals on self-efficacy and self-evaluative reactions to the task. In particular, participants in this study received either a moderately difficult goal, an extremely difficult task goal, or no specific goal. The authors expected varying goal conditions to moderate the relationship between self-efficacy and performance, on the assumption that when measuring their progress to the defined goal, individuals would use this information to assess their capability of reaching it

and thus use these self-efficacy judgments in the regulation of subsequent effort. This study found that assigned performance goals significantly affected use of analytic strategies, and the more challenging goals led to higher levels of performance; however, this effect was weak, and the assignment of performance goals had no effect on the mean strength of self-efficacy. In the presence of any goal, higher levels of self-efficacy, self-satisfaction with past performance, and personal goals predicted higher levels of future performance; no evidence for these relationships was found in the no-goal group. As expected, assigned goals moderated the relations between self-efficacy and performance. These results underscore the dynamic nature of self-referent thought. When working toward well-defined goals, individuals evaluate their achievements and use this feedback to assess their capabilities for future performance. These self-regulatory processes are significantly less influential in the absence of challenging performance standards.

Wood, Bandura and Bailey (1990) also examined the effects of both assigned and self-set goals on organizational performance in this simulation, but under differing conditions of task complexity. This characteristic of the environment was varied by the number of employees that subjects had to supervise, and the degree of match between skills and job requirements necessary for improved organizational performance. Thus, the complexity of the decision-making task was a direct function of the organizational complexity of the work groups supervised by participants in the simulation exercise. In addition, subjects were assigned to one of two different goal conditions: do your best, or a specific and very challenging goal. At two different

points in the simulation did subjects rate their perceived self-efficacy, acceptance of the assigned goal, and their self-set objectives. Results showed that assigned challenging goals had positive effects on organizational performance in the low but not in the high complexity condition. Self-set goals did not vary as a function of assigned goals; participants set equally challenging goals for themselves in either goal condition. The authors attributed this to basing their self-standards on other factors such as self-appraisals of managerial capability.

Bandura and Jourden (1991) studied the proposition that differential patterns of social comparison would affect future performance achievements through their effects on self-regulatory processes. The authors of this research argued that conceptions of ability as an acquirable skill foster increased self-efficacy resiliency, profit from failed experiences, the setting of higher personal challenges, and engagement in more complex analytic thinking, and that social comparison operated as an important mechanism in the self-appraisal of capabilities, given that individuals examine the latter in light of their relative standing versus the attainments of relevant others. In this simulation, participants were assigned to one of four different conditions, varying on the pattern of comparative information presented to them, namely the mean performance scores supposedly attained by others in their class.

In the first condition, subjects were provided information such that their comparison group showed similar capabilities to the participants. In the second category, the comparison group always outperformed the subjects in this condition. Third, the comparison group outperformed subjects at the outset, but this difference

was reduced and eventually reversed along subsequent trials. Finally, the fourth condition showed subjects outperforming their peers, but eventually declining in performance and ultimately being outscored. Results indicate that divergent patterns of self-regulatory influence were accompanied by corresponding changes in performance. Subjects in the similar and superior conditions maintained their self-efficacy even in the face of shortfalls in performance, those in the progressive mastery displayed a sharp rise in their efficacy across trials, whereas those in the progressive decline condition grew worse as the simulation progressed. Interestingly, early attainment of mastery resulted in a demotivating effect, as evidenced by lower self-set goals, when compared to those who had to struggle in order to attain mastery. The results of path analyses corroborate this evidence and are very similar to those obtained by Bandura and Wood (1989) and described above.

Results from these experiments were summarized by Wood and Bandura (1989b) and used to support their formulation of a Social Cognitive Theory of Organizational Management. The causal ordering of the self-regulatory influences studied in this set of experiments is shown in Figure 2.2, employing the combined data sets from all studies. Shown paths depict statistically significant relationships. The direction of causality represented in the model was based on the theoretical principles of Social Cognitive Theory and the temporal manipulations present in the experimental design employed by the authors.

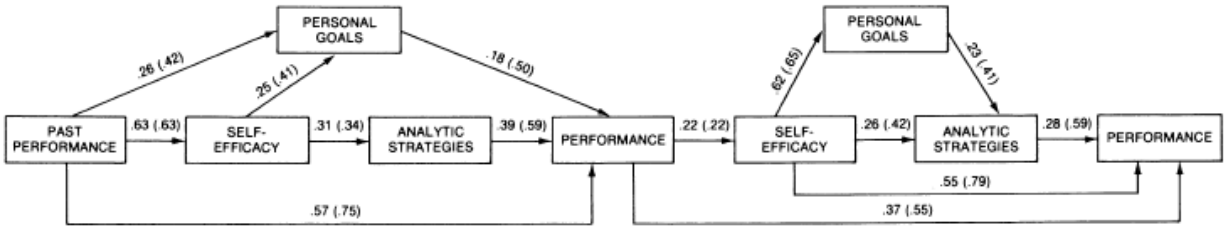


Figure 2.2 – Path Analysis of Causal Structures (Wood & Bandura, 1989b)

Prior performance is included as the first factor in order to capture by proxy possible determinants other than the self-regulatory influences that were the object of the study. Perceived self-efficacy, then, is postulated to be a result of past experiences and a significant determinant of performance. Depending on the trial block under observation, this is accomplished in a number of different ways. First, perceptions of efficacy exert an important influence on performance through their effect on the setting of more challenging personal goals. Goal systems are one of the primary mechanisms by which self-regulation of motivation and action occurs (Wood & Bandura, 1989b).

Second, self-efficacy has an effect on the quality of the analytic strategies employed by participants in the simulation, which in turn influence performance attainments through allocation of resources and adjustment of motivational factors. Finally, self-efficacy directly affects performance through its effects on a number of cognitive and motivational influences, such as exertion of effort, stress reduction, or increased persistence, among others; although the direct effect of self-efficacy on performance only become evident as the simulation progressed. These results show

that the interaction of cognitive and motivational processes is important to an understanding of how individuals approach decisions that must be made in complex and dynamic environments. They also underscore the central role that perceptions of efficacy play in the complex self-regulatory system of human beings.

Other seminal work exploring the value of self-efficacy in organizational studies includes the conceptual reviews of Gist (1987) and Gist and Mitchell (1992). In the earlier work, Gist (1987) reviewed the basic tenets of the theory, sources of self-efficacy and the mechanisms by which it influenced behavior and performance. In addition, the relationship between perceptions of efficacy and other motivational concepts, such as goals, feedback, reinforcement, and internal control were clarified. In particular, the author distinguished between the concept of self-efficacy and that of effort-performance expectancy used in expectancy theory. First, while the former focused on a belief that an effort will lead to a desired performance, efficacy beliefs focuses on the conviction that one can execute the behavior in question. And second, measures of self-efficacy typically assess expectations for a range of goals or performances, while expectancy measure generally focus on a single assigned goal. Finally, Gist (1987) laid out the value and implications of Social Cognitive Theory in general, and self-efficacy in particular, for the fields of organizational behavior and human resource management, in areas such as employee selection, training and counseling, leadership, appraisals of performance, setting of incentives and motivation in general.

Gist and Mitchell (1992), on the other hand, focused more on the determinants and sources of self-efficacy, and the development of appropriate and effective change strategies. The authors expanded on the four categories of experience used in the development of self-efficacy originally proposed by Bandura (1986a) and theorized that the processes of cognitive appraisal and integration of experience were the ones that ultimately determined self-efficacy. As such, the latter could be conceptualized as a superordinate judgment of performance capability induced by the integration and assimilation of multiple performance determinants. The process proposed by the authors is depicted in Figure 2.3 below.

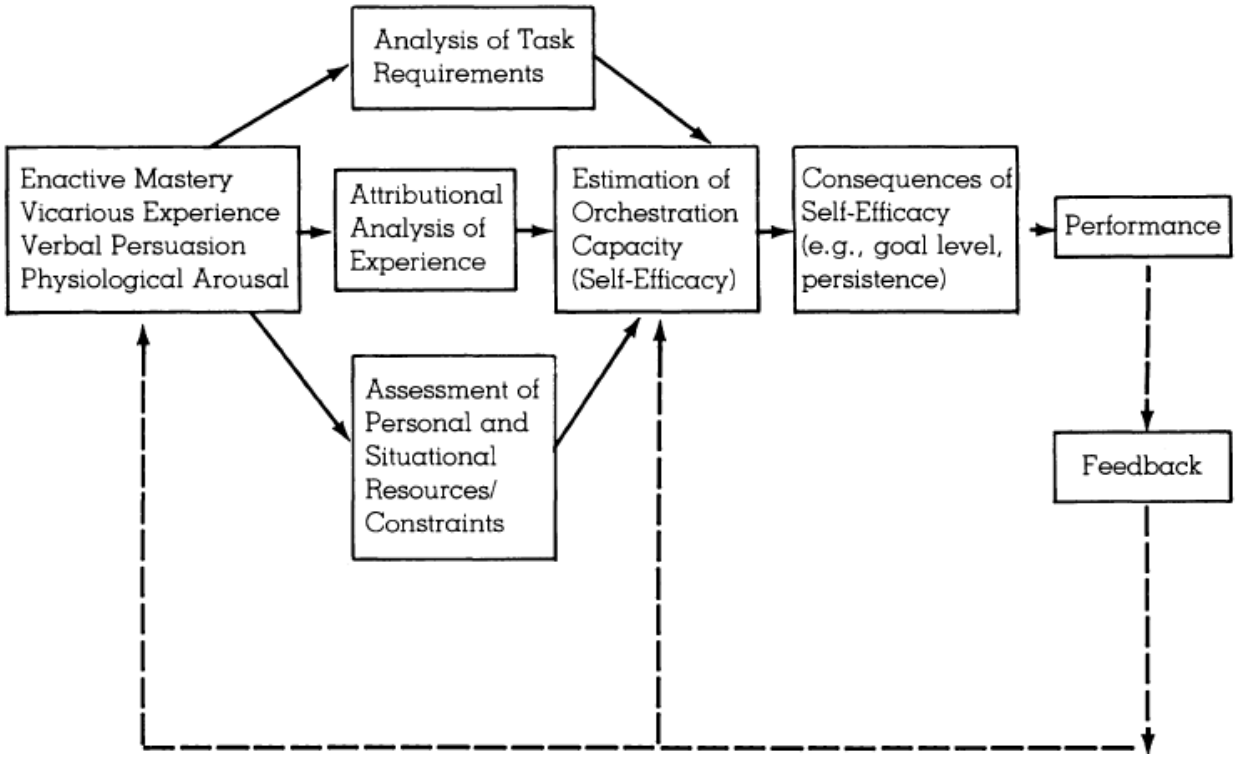


Figure 2.3 – Model of the Self-Efficacy – Performance Relationship (Gist & Mitchell, 1992)

The model depicts three different processes mediating between primary determinants and estimations of capacity (e.g. self-efficacy). The first is an analysis of task requirements, where the individual takes stock of what it takes to perform at various levels. This process is argued to be more explicit when the task is novel or has only been observed but never performed before. As performance of the task becomes more frequent, the individual is expected to rely on interpretations of the causes of past performance levels. Second, attributional analyses of past experience involve a judgment of the reasons why a particular performance was or was not achieved. Lastly, individuals engage in an assessment of the self and the setting by which the access to and availability of specific resources and constrains limiting performance are considered. These three assessment processes are thought to yield information used in a summary judgment process which estimates self-efficacy for the performance of a particular task at a certain level.

Based on these mechanisms, and more generally on attribution theory, Gist and Mitchell (1992) categorized information cues used to arrive at efficacy judgments into external and internal. The former included cues about the task itself, such as task attributes and complexity, the task environment, and modeling influences through both verbal persuasion and social comparison processes. Internal cues, on the other hand, involved familiarity with the task through personal or vicarious experience, and emotional arousal (both positive and negative). Based on this and the work reviewed above, the authors proposed a three-dimensional model of efficacy determinants, varying the nature of information cues (internal vs. external), variability of the

determinant (low vs. high) and the controllability of the causal influence (also classified as internal vs. external). The degree of change in self-efficacy due to interventions and treatments should then be influenced by these three factors, in addition to the initial level of self-efficacy present; in particular, within-participant analyses of self-efficacy should carefully consider the existence of ceiling effects when pre-test levels of self-efficacy are already high.

Another novel issue raised by Gist and Mitchell (1992) refers to the existence of individual differences in the composition of self-efficacy beliefs, which in turn affect the degree of change in self-efficacy that could be expected from interventions. Even when displaying similar levels of perceived efficacy, individuals may still vary in their perceptions of what proportion of the necessary resources for successfully completing the task depend on ability and on effort. As such, interventions designed to enhance efficacy through training and the provision of task knowledge may have more of an impact on those individuals that believe ability is the primary determinant of perceived capability, while for those individuals that feel effort is the most important issue, interventions designed to increase intentions to apply and expend energy on the task might be more effective.

Gist and Mitchell (1992) thus developed a set of propositions dealing with the processes involved in the formation of efficacy judgments and the appropriateness of different interventions designed to enhance them. First, they argued that in novel situations efficacy is formed through the assessment of task requirements and personal and situational resources and constraints. The same limitations and processes

involved in complex judgments involving extensive and sometimes conflicting information cues are involved. Second, as experience with the task increases, individuals will start to more heavily rely on attributional analyses of past experience and performance as determinants of efficacy, rather than conducting the more comprehensive assessments described above. Finally, the effectiveness of efficacy-enhancing interventions will depend on the determinants of this judgment that are affected by the treatment, and the weight that those affected have on this determinant of performance.

Decades of research involving self-efficacy and work-related behaviors have generated a rich and extensive literature that would be impossible to review in any comprehensive manner. Empirical findings have demonstrated the relationship with work performance in a wide variety of settings, such as idea generation (Gist, 1989), newcomer adjustment (Saks, 1995), coping with career events (Stumpf, Brief, & Hartmann, 1987), creativity in the workplace (Tierney & Farmer, 2002), skill acquisition (Mitchell, Hopper, Daniels, George-Falvy, & James, 1994), and even seasickness (Eden & Zuk, 1995), including computer-related behaviors (Gist, Schwoerer, & Rosen, 1989; Martocchio, 1994; Martocchio & Judge, 1997).

The overall relationship between self-efficacy and work-related performance was analyzed by a large scale meta-analysis conducted by Stajkovic and Luthans (1998). Reviewing in excess of one hundred different studies, the authors examined both the general performance effects of self-efficacy, as well as the significant within-group heterogeneity of individual correlations. The latter was accomplished by

employing a two-group moderator analysis that partitioned the sample according to the level of task complexity and the setting in which the studies had been conducted (laboratory versus field experiments). Task complexity was conceptualized as a function of objective attributes of the task, such as the product of the task, the set of acts that are necessary to execute the task in question, and the information cues upon which the individual can base judgments or execute performance of the task (Wood, 1986).

Task complexity thus defined was expected to moderate the relationship between self-efficacy and performance for both theoretical and operational reasons. Among the former, more complex tasks may lead to greater demands on skills and processing capacity, and thus complex behaviors would not lend themselves to complete appraisal. In addition, this increased complexity may lead to lowered perceptions of capability to execute the task, as well as distortion of self-knowledge due to selective recall of failure and inefficacious behaviors. Operational issues associated with more complex tasks included a mismatch between efficacy and performance domains, and the limited scope of self-efficacy, under the assumption that more complex performances do require multi-dimensional measures of efficacy, which are rare in extant research.

Regarding the research setting, Stajkovic and Luthans (1998) noted several reasons why contextual factors may contribute to observed disparities in the relationship of interest. First, estimation of self-efficacy may be different in realistic settings because individuals have to take into account a number of constraints on

performance that are not generally present in simulated environments, such as available resources, task interdependence, distractions and working environment, and physiological or psychological features of the working environment, such as anxiety, pressure, stress, etc. Second, task demands in actual settings are more ambiguous than in laboratory conditions, where performance is controlled and participants understand or can deduce what means are appropriate for conducting the task. Third, the amount of effort and dedication placed in performance of the task is less directly related to outcomes in organizational environments, where in most cases there is some degree of dependence on the efforts of others or coordinated activities by groups. Fourth, situations where negative consequences from misjudgments of capabilities are unlikely to arise do not invite accurate assessments of self-efficacy. Finally, temporal proximity and specificity of assessment between self-efficacy and performance measures are more likely to exist in simulated rather than natural settings.

Overall results from the meta-analysis, exclusive of moderator considerations, indicated a positive and significant correlation of self-efficacy and performance of 0.38 ($p < 0.01$). Further analyses indicated the presence of an interaction between moderators, such that average correlations between self-efficacy and performance were strongest for low complexity tasks performed in laboratory settings (0.50, $p < 0.01$), and weakest, but always significant, for highly complex tasks assessed in field settings (0.20, $p < 0.01$).

In follow-up research, Judge et al (2007) noted that past research such as that reviewed above had failed to control for the effects of individual differences like

general mental ability, personality, and experience, when considering the self-efficacy – performance relationship. Given that these differences have been shown in the past to have performance effects, and that they could also arguably be conceptualized as antecedents to efficacy beliefs, the contribution of self-efficacy to work-related performance was not as clearly established as previously thought. Through a meta-analysis, the authors controlled for those characteristics before assessing the contribution of the construct of interest to work-related performance, finding that overall relationship was not significant, with a correlation of 0.13 between the two variables.

In addition, the authors partitioned the data set according to a number of potential moderator variables, such as task complexity, interval between measurement, whether goals were assigned or there were no goals for the task, prior exposure, mode of measurement of self-efficacy (grid or Likert), and student status of participants in the studies (graduate vs. undergraduate). Results from these analyses show that self-efficacy significantly predicted work performance after controlling for individual differences only under the following conditions: low task complexity, short or intermediate interval between measures, feedback provided in close temporal proximity, goals were either self-set or assigned, but existent, individuals had been exposed to the task before, grid measures of self-efficacy were employed, performance was measured objectively, the setting was a laboratory study, or the sample was undergraduate students.

Moreover, even in those cases where self-efficacy did predict performance, its effect was not much greater than that of the more distal variables. However, it should be noted that perceptions of self-efficacy are amenable to interventions, with a rich and developing literature on the best approaches to do so. Thus, even if this study provides a more accurate picture of the effect of self-efficacy on work performance, it does not detract from its value in effecting improvements in the workplace, particularly given the rather stable nature of individual differences such as general mental ability and personality.

Turning to the focal area of interest, some of the early work on Computer Self-Efficacy was conducted by Hill, Smith and Mann (1987) and by Gist, Schwoerer and Rosen (1989). In the first case, the authors postulated that efficacy beliefs with respect to computers would be important determinants of the decision to use computers in the future, and thus a possible avenue through which adoption could be fostered. In particular, they investigated the importance of efficacy beliefs over and above beliefs about the instrumental value of using computers. The underlying rationale for their Study 1 was that perceptions of controllability would have an important impact on whether individuals decided to use computers, separately from whether they believed their use implied any particular positive or negative consequences (it has been noted that, in this regard, self-efficacy beliefs may not be altogether different from perceived behavioral control, as incorporated into Ajzen's Theory of Planned Behavior, see Ajzen, 2002; Terry and O'Leary, 1995). Their results showed that, for both men and women, behavioral intentions to use computers

were significantly predicted by both instrumentality and efficacy beliefs, and that behavior, measured as enrollment in classes requiring the use of computers, was significantly predicted by behavioral intentions.

In a second study, Hill et al (1987) predicted that the same relationships would hold, but after adding previous experience with computers as a covariate with both efficacy and instrumentality beliefs. In addition, the behavior of interest was expanded to incorporate the decision to use technological innovations in general. Using a different subject sample, their results confirmed those discussed above, even when controlling for previous experience, measured in terms of the number of times a computer had been used in the past, whether the participants had written a computer program, or used a packaged computer system.

Gist et al (1989) studied the relative effectiveness of alternative training methods designed to foster self-efficacy and the relationship of these perceptions to performance on an objective measure of computer software mastery. The two chosen training approaches were modeling, where participants watched a video of a model illustrating specific steps needed to perform a task, and a tutorial setting, where participants in the study employed an individual training program that presented concepts similar to those shown in the modeling condition. The authors assessed computer self-efficacy prior to training as a general variable that attempted to capture the confidence subjects brought to the training sessions, and software self-efficacy, post-treatment, as the focal variable of interest.

Results showed support for the hypotheses that trainees in the modeling condition would develop higher software self-efficacy than those in the tutorial condition, and that participants initially low in computer self-efficacy would report higher software self-efficacy in the modeling compared to tutorial training condition. While the relationship between software self-efficacy and performance was not examined, pretest computer efficacy was significantly related to training performance, thus providing additional support for the efficacy-performance relationship in a computer-related context. In addition, this study represents an early example of the separation between more specific and more general types of computer-efficacy perceptions.

Computer Self-Efficacy

While previously discussed in organizational behavior research, computer self-efficacy was introduced to the mainstream Information Systems literature by the seminal work of Compeau and Higgins (1995a, 1995b), which encompassed both the development and initial test of a computer self-efficacy measure, and the application of Social Cognitive Theory to computer skills training. In addition to a comprehensive review of the theoretical background and past applications of computer self-efficacy, Compeau and Higgins (1995b) developed a measure of the construct that is, as of today, the most popular one used in information systems research. While in the past computer self-efficacy measures had focused on component skills of the behavior of interest (Gist et al., 1989), the authors argued for

the need to focus measures on the task being performed, rather than on assessing its component skills. Thus, they incorporated elements of task difficulty intended to capture differences in self-efficacy magnitude. Representative items include ones like "*I could complete the job using the software package … if there was someone giving me step by step instructions; … if I could call someone for help if I got stuck; … if I had just the built-in help facility for assistance*".

The chosen subject sample for their research was that of knowledge workers, e.g. individuals whose work requires the processing of large amounts of information. In addition to following standard measurement development procedures, the authors embedded computer self-efficacy in a nomological network showing both its antecedents and consequents. Figure 2.4 shows their final, revised research model as well as the magnitude and significance of the path coefficients linking the different constructs. In addition to the results obtained, another important outcome of this research was the realization that two different dimensions may underlie the outcome expectations construct. In particular, the authors distinguished between personal- and performance-based outcome expectations, reflecting either expected outcomes having an impact in an individual's job or organizational performance, or inwards-directed, such as reflecting a personal sense of accomplishment.

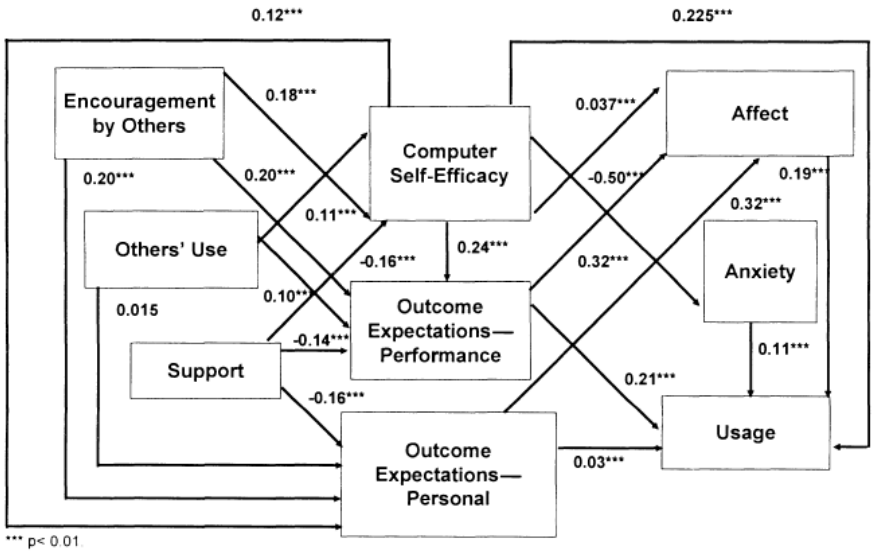


Figure 2.4 – Final Research Model from Compeau and Higgins (1995b)

This research thus helped establish and situate the construct of computer self-efficacy. In particular, encouragement by important others such as peers and superiors (representing an aspect of social persuasion in the formation of efficacy perceptions), the extent to which computers where used in the reference group of the participant, and the extent of organizational support for computer users significantly affected perceptions of efficacy. In addition, heightened beliefs of efficacy were important predictors of outcome expectations, both performance- and personal-based, affective reactions to using computers, significantly lower levels of computer anxiety, and increased usage of computers as reflected by both the duration and frequency of use at work and at home during weekends and holidays.

In follow-up research, Compeau, Higgins and Huff (1999) conducted a longitudinal investigation, with measurement one year apart, to assess the effects of

computer self-efficacy and outcome expectations on anxiety, affect and usage, using a measurement approach similar to the research just discussed above. Their results, depicted in Figure 2.5, underscore the predictive value of computer-self efficacy, even when measured over a rather long time interval. Taking into account both direct and indirect effects on usage, computer self-efficacy explains almost 20% of the variance in the ultimate construct of interest.

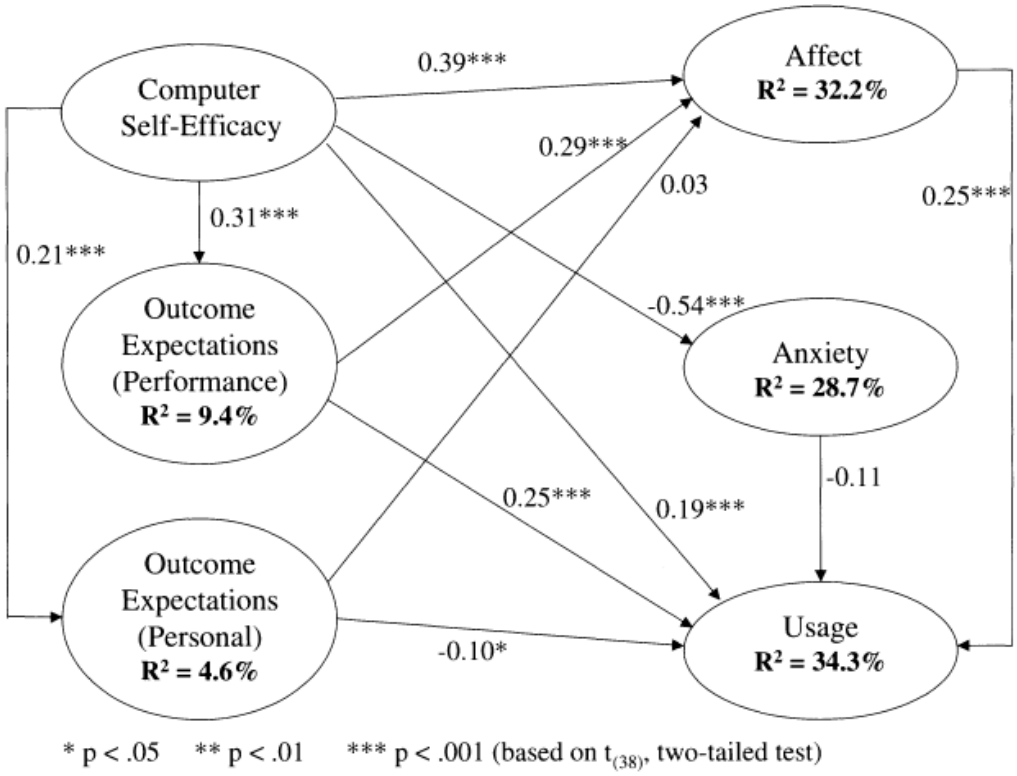


Figure 2.5 – Results from Compeau, Higgins and Huff (1999)

Building on past research such as that of Gist et al (1989), Compeau and Higgins (1995a) examined the role of behavioral modeling training in the formation of perceptions of computer self-efficacy, outcome expectations, and performance.

Participants in the modeling condition were expected to develop higher levels of each variable than those in the non-modeling condition, essentially lecture-based training. In addition, the authors controlled for the effects of past performance, as an indicator of enactive mastery, on all three outcomes of interest. The research design consisted of a two-day training course covering both spreadsheet and word processing applications, with eight groups that differed in terms of the order in which packages were taught and in the use of the two different instructional approaches. One strength of this design lied in that both groups received significant instruction in the use of the two software packages, as opposed to prior research where the control group had been untreated. This allowed for a more strict test of the benefits of modeling-based techniques.

The manipulation was conducted through a videotape where a model performed introductory exercises on a computer, initially expressing frustration but eventually being able to achieve success in the various tasks. Prior performance was operationalized as that arising from the testing received after the first day of training, and thus served as a proxy for past success with the applications, since it was measured on a different package than the one examined in the research model into which it was incorporated. While results strongly supported some aspects of their research model, others were supported only for one or the other software package, and some were unsupported across the board. The effects of the modeling treatment on self-efficacy were only significant in the case of the spreadsheet package, not significant for the word processing application in day one of the training program,

and significant but in the opposite direction in day two (e.g. when the spreadsheet training had occurred on the first day). Table 2.1 shown next highlights the equivocal results obtained by the authors.

Table 2.1 – Summary of Hypotheses from Compeau and Higgins (1995a)

Hypothesis	Model 1 (Lotus 1)	Model 2 (WP 1)	Model 3 (Lotus 2)	Model 4 (WP 2)
H1: Modeling → Self-efficacy	0.398*(✓)	−0.017	0.161*(✓)	−0.173*(×)
H2a: Modeling → Performance O.E.	−0.230*(×)	0.194*(✓)	0.148*(✓)	0.166
H2b: Modeling → Personal O.E.	−0.416*(×)	0.201*(✓)	0.216*(✓)	0.224*(✓)
H3: Modeling → Performance	0.243*(✓)	−0.012	0.194*(✓)	−0.203
H4a: Self-efficacy → Performance O.E.	0.577*(✓)	0.432*(✓)	0.507*(✓)	−0.006
H4b: Self-efficacy → Personal O.E.	0.461*(✓)	0.139*(✓)	0.205*(✓)	0.157*(✓)
H5: Self-efficacy → Performance	0.086	0.637*(✓)	0.287*(✓)	0.439*(✓)
H6a: Performance O.E. → Performance	0.116*(✓)	−0.101*(×)	−0.143*(×)	−0.273*(×)
H6b: Personal O.E. → Performance	−0.142*(×)	−0.136*(×)	−0.259*(×)	0.083
H7: Prior Performance → Self-efficacy			0.482*(✓)	0.092
H8a: Prior Performance → Performance O.E.			−0.128*(×)	−0.121
H8b: Prior Performance → Personal O.E.			−0.210*(×)	−0.332*(×)
H9: Prior Performance → Performance			0.413*(✓)	0.340*(✓)

* $p < 0.05$.
Paths marked with an (×) are significant, but in the opposite direction to that predicted by the hypotheses.

The effect of the modeling treatment was only significant for the spreadsheet package (and significantly in the opposite direction for the model including training in the word processing application in the second session). Compeau and Higgins (1995a) offered two possible explanations for these findings. First, differences may be related to the modeling tapes, despite the efforts placed into achieving similar levels of training across both applications. On the other hand, differences may be an outcome of prior levels of familiarity with the subject matter. In this light, since

spreadsheets might have been less familiar to participants than word processing, their self-efficacy could be influenced by modeling. The authors also raised a similar explanation for the stronger relationship found between self-efficacy and performance for the word processing application when compared to the spreadsheet package. The inconsistent results related to the influence of outcome expectations were attributed to the long term effects of those, given that performance measures in this research considered only short-term performance. The finding that prior performance only influenced self-efficacy for spreadsheet training was consistent with the explanation that self-efficacy judgments are formed more automatically for more familiar packages.

Another pivotal research in this stream was the conceptual review of antecedents, consequents, and measurement of computer self-efficacy developed by Marakas, Yi and Johnson (1998). The complete conceptual model is depicted in Figure 2.6. The authors examined forty different studies that materially focused on computer self-efficacy and either developed a measure or evaluated the construct as an independent or dependent variable of interest. What follows is a limited summary of the portions of this work most relevant to this dissertation, the interested reader is referred back to the original for a more complete picture of research involving computer self-efficacy, its antecedents and manipulation, and its relationship to task performance.

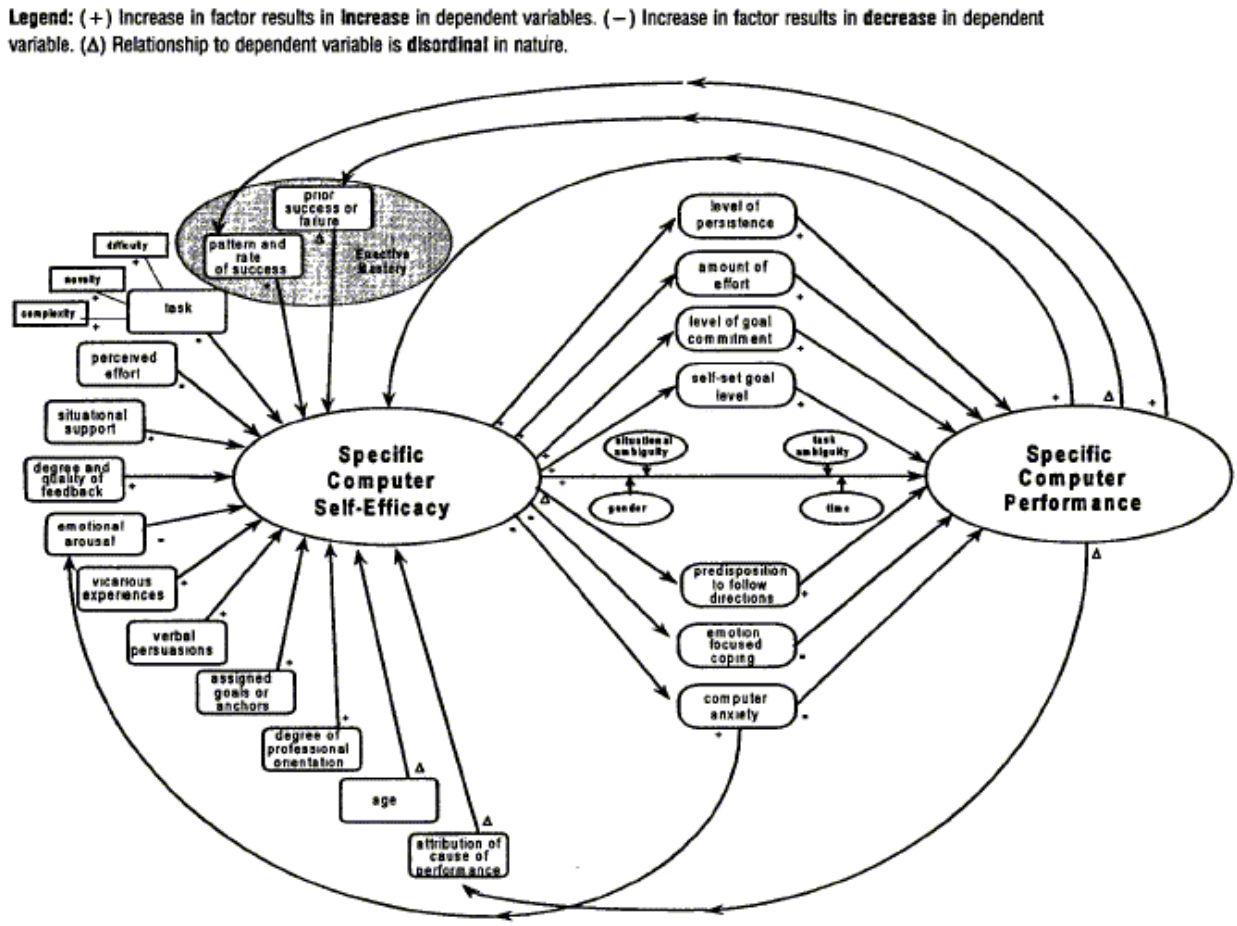


Figure 2.6 – Multifaceted Model of Computer Self-Efficacy (Marakas et al., 1998)

First, computer self-efficacy is strongly related to computer task performance, both directly and through a number of partially mediating influences. The direct effects on performance are, in turn, moderated by four different aspects of either the subjects, the task, or the research design. Among the former, gender has been found to have an effect on this relationship, in either its biological or psychological formulations. Task and situational ambiguity are two aspects of the task that moderate this relationship. In the presence of ambiguous task situations, such as those with

inaccurate or unclear feedback, ill-defined performance levels, or task interdependences, individuals are not clear about how much effort to mobilize, how long to sustain it, and when to make corrective adjustments to their current performance strategies. Finally, time elapsed between measurement of self-efficacy perceptions and performance of the task is presumed to negatively affect the relationship.

Additionally, self-efficacy is postulated to affect task performance by influencing a variety of other determinants of this outcome. In particular, higher levels of computer self-efficacy have been shown to positively affect the level of persistence and amount of effort placed in completion of the task, and the setting of more challenging goals and commitment to achieving them. All these, in turn, have a beneficial impact on performance. Higher levels of the construct are also posited to negatively influence the use of emotion based coping and lower feelings of anxiety toward the use of computers, both of which have pernicious influences on task performance. It should be noted that, along with every other path postulated by Marakas et al (1998), these relationships have received empirical support in past research.

Turning to the antecedents to computer self-efficacy, past performance has an important effect through different channels, related to the enactive mastery process described by Bandura (1997) and the causal attribution of performance made by the individual, as well as directly affecting perceptions of capability. Among the former, the prior pattern and rate of success have been found to be important determinants of

future self-efficacy – performance relationships. These are associated with the different conceptions of ability held by those experiencing success and failures. While those individuals that perceive ability as acquirable and subject to continued development and enhancement learn from their mistakes and take feedback as an opportunity for improvement, those that believe ability is stable, i.e. regarded as a fixed capacity, will reduce their estimations of efficacy following unsuccessful performance.

Other sources of efficacy perceptions such as verbal persuasion, emotional arousal and vicarious experience, already noted by Bandura (1997), are also included in the conceptual model. Next, characteristics of the focal task, such as novelty, difficulty and complexity, have an effect on how capable individuals consider themselves to be when it comes to successfully completing it. Characteristics of the task environment, such as the degree of support available for carrying out the task, or the degree and quality of feedback about progress, are also important determinants of efficacy beliefs.

In addition to their extensive review of extant research in this area, Marakas et al (1998) also noted that existing measurement of the computer self-efficacy construct was not fully in accordance with the theoretical basis established by Social Cognitive Theory. Employing examples drawn from existing research, Marakas et al (1998) developed a set of guidelines for the more accurate measurement and isolation of the computer self-efficacy construct. In particular, they argued measures should focus only on conceptions of ability and not be confounded by any benefit or outcomes

arising from performance, match the level of specificity of the task of interest and avoid cross-domain skills, and avoid inappropriate or unnecessary anchoring.

Based on this conceptualization by Marakas et al (1998) and proposed measurement guidelines, Johnson and Marakas (2000) set out to replicate the findings of Compeau and Higgins (1995a), extend their work by explaining the different issues contributing to their results, and propose a modified model of the phenomenon which more accurately reflected then current research on Social Cognitive Theory. In particular, the authors noted the presence of issues related to the theoretical specification of the model, the isolation of the constructs of interest, and the experimental methodology employed that may have contributed to the equivocal findings previously obtained. In the first category, and following Bandura (1997) by noting that performance is causally prior to outcomes, the authors argued that the relationship between performance and outcome expectations would not be found until after performance occurred, given that this provided participants with awareness as to their capacities to perform the tasks of interest. Additionally, the research model developed by Johnson and Marakas (2000) included a measure of emotional arousal, e.g. anxiety, as an intervening variable between self-efficacy and performance.

Regarding measurement of the constructs of interest, the authors compared the more general measure developed by Compeau and Higgins (1995b) with one developed according to the tenets provided by Marakas et al (1998), which focused on particular tasks related only to the spreadsheet domain. The experiment was conducted with groups receiving either measure in order to assess the benefits in

prediction that can be gained by more carefully delineating the domain of interest. Finally, Johnson and Marakas (2000) investigated the possibility that timing of measurement previously employed may have confounded increases in perceptions of efficacy that were due to the modeling condition with those that reflected enactive mastery of the material presented. The authors thus measured computer self-efficacy at both pre-manipulation and post-practice periods.

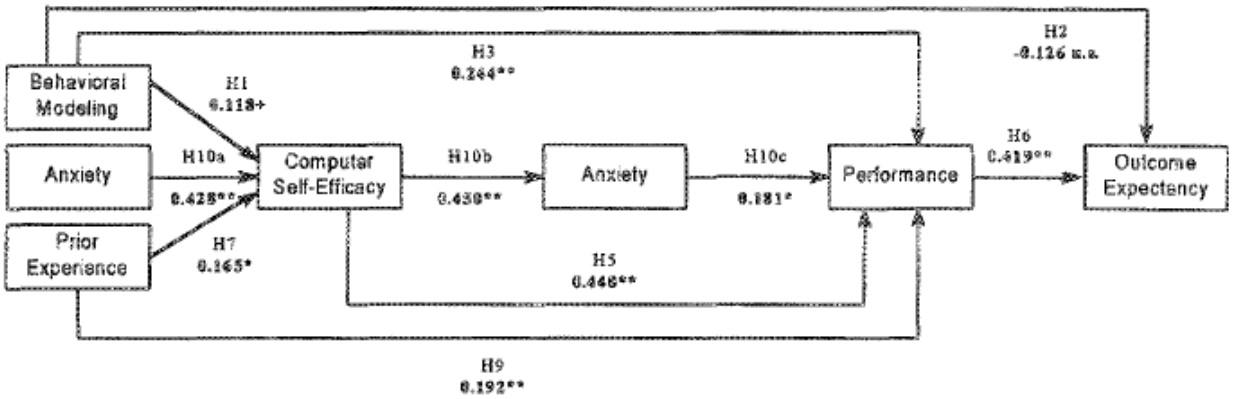


Figure 2.7 – Research Model from Johnson and Marakas (2000)

In addition to closely replicating the extant results of Compeau and Higgins (1995a), Johnson and Marakas (2000) found strong support for their revised research model, which was formulated more in accordance with the underlying theoretical background of Social Cognitive Theory (shown in Figure 2.7). Computer self-efficacy was found to be, across both specifications, a critical variable in the acquisition of computer skills and subsequent performance. The more finely timed measurement of efficacy perceptions contributed to the disentangling of mastery and modeling effects, and highlighted the need to measure this construct at all points

where change would be expected. The limited role of outcome expectations in predicting performance was also supported, and is consistent with recent conceptualizations by Bandura (1997). Finally, the comparison of alternative measures of the construct showed that they had differential levels of effectiveness, with the more general instrument of Compeau and Higgins (1995b) being better able to predict performance and more influence by the training manipulation, whereas the more specific measure was able to capture the relationship with prior experience to a greater extent.

Other Antecedents of Computer Self-Efficacy

Other researchers have expanded on the conceptual model summarized by Marakas et al (1998) and examined other antecedents to perceptions of computer efficacy. Agarwal, Sambamurthy and Stair (2000) included relevant prior experience and Personal Innovativeness in IT (PIIT) as determinants of both general and specific computer self-efficacy in their research models. PIIT, originally developed by Agarwal and Prasad (1998), is defined as the "willingness of an individual to try out any new information technology". Results, however, only supported the effects of prior experience on the general construct, and PIIT on both the general and the Windows measures.

Thatcher and Perrewé (2002) also included personal innovativeness in IT, along with other constructs such as computer anxiety, negative affect, and trait anxiety, in their expanded nomological net of the self-efficacy construct. Their study

attempted to examine the pattern of relationships among dynamic, IT-specific individual differences such as computer self-efficacy or anxiety, and stable individual differences, such as PIIT, negative affectivity and trait anxiety. The authors argued that when compared to situation-specific traits, broadly conceptualized traits may exert less influence on dynamic individual differences, and since traits lack specific behavioral targets, those may not shed light in the development of efficacy in particular domains. On the other hand, enough research was available to suggest that broad affective dispositions such as negative affectivity and trait anxiety could be conceptualized as determinants of computer anxiety. Thus, this study examined the relationship between IT-specific dynamic individual differences (e.g. computer self-efficacy and computer anxiety), IT-specific traits such as PIIT, and broad dispositions, such as trait anxiety and negative affectivity. Results show significant effects of PIIT on both computer self-efficacy and computer anxiety, a significant effect in the expected direction for computer anxiety on computer self-efficacy, and trait anxiety as a significant determinant of computer anxiety. Negative affect was not related to computer anxiety, and the latter only partially mediated the relationship between trait anxiety and computer self-efficacy.

Johnson (2005) investigated the roles of previous experience, trainee personality, learning goal orientation, and computer anxiety as antecedents of computer self-efficacy in a training context (the role of the latter as a determinant of performance in this research is reviewed elsewhere). In this research, application-specific beliefs of efficacy, rather than conceptualized at the more general level, were

the focal variable of interest. Personality differences were deemed important because, as lenses through which individuals interpret their environment, have been shown to impact performance outcomes. However, the mediating role of more proximal determinants such as computer self-efficacy has not been extensively examined. Learning goal orientation was employed as representing a trait-like perspective on the pursuit of goals.

Thus, individuals with a higher learning goal orientation are presumed to conceive ability as something that is developed over time through practice and experience, and are focused on diagnosing and improving their skills, taking advantage of feedback and errors as a natural part of the learning process. Prior experience and computer anxiety were other sources of influence identified in prior research (e.g. Marakas et al, 1998). Results from statistical analyses show previous experience displaying a significant and positive relationship with self-efficacy, and computer anxiety having a significant but negative effect, both of which confirm prior research in this area. More positive self-evaluations and higher learning goal orientation were significantly and positively related to application-specific computer self-efficacy.

Computer Self-Efficacy and Adoption Behavior

In addition to performance, researchers also investigated the role of computer self-efficacy as a distal predictor of technology adoption behavior, as an antecedent to perceived ease of use. Although Davis (1989) originally considered self-efficacy as

part of the root formulation of perceived ease of use (EOU), later research positioned computer self-efficacy in its current role. Venkatesh and Davis (1996) conducted a three-experiment study to test, among other relationships, the hypotheses that general computer self-efficacy would be a strong predictor of perceived ease of use, both before and after hands-on experience with the focal systems. Results from this research revealed significant and large effects of computer self-efficacy on perceived ease of use, both for two different systems and before and after hands-on use. The authors theorized, and empirically supported, that objective usability of the application would only be a factor after participants in their studies had the opportunity to experience the systems by themselves, but that in either case subjects would still anchor their general perception of ease of use on their individual level of self-efficacy.

Building on these results, Venkatesh (2000) used an anchoring and adjustment framework to propose that in forming system-specific EOU individuals anchor on key individual and situational variables that relate to control, intrinsic motivation, and emotion. With increasing experience, individuals adjust their system-specific perceived ease of use to reflect their interaction with the system. Understanding determinants of ease of use, such as computer self-efficacy and computer anxiety, become important from two standpoints: (a) the construct has a direct effect on intention to adopt, and indirectly through perceived usefulness, and (b) perceived ease of use is argued to be an initial hurdle that users have to overcome for acceptance, adoption and usage of a system. In the absence of direct hands-on experience with

new systems, perceived ease of use of systems is not distinct across different new systems, suggesting the existence of "common" set of determinants. In this light, computer self-efficacy and computer anxiety are conceptualized as anchors of this perception. Through a multi-site longitudinal (three measurement points) study, the author showed the consistent and strong effects of both constructs on perceived ease of use, which did not significantly change as additional experience with the application was gained.

Agarwal, Sambamurthy and Stair (2000) also examined the relationship between computer self-efficacy and perceived ease of use, but distinguished between general and specific levels of the former. In this research, both perceptions of efficacy and ease of use were conceptualized at the level of particular applications: the general Windows environment, and a spreadsheet package. In addition, a general measure of computer self-efficacy, adapted from Compeau and Higgins (1995b) was used. The authors predicted that the specific self-efficacy measure would be a more proximal predictor of perceptions of ease of use, given that it was a particularized judgment, as opposed to a the more global feeling of confidence represented by the more general measure of computer efficacy. Their results show the specific efficacy measures having significant effects on their respective ease of use judgments, and the more general measure having indirect and partially mediated direct effects on perceived ease of use for Windows (through the specific Windows self-efficacy measure).

Computer self-efficacy was also included as part of the nomological network of the construct of cognitive absorption, developed and validated by Agarwal and

Karahanna (2000). Cognitive absorption, defined by the authors as a "*state of deep involvement with the software*" (p. 673) was tested in relation to the two main technology acceptance beliefs, perceived usefulness and perceived ease of use (Davis, 1989). The inclusion of computer self-efficacy as an antecedent to these beliefs served to help establish the value of the new construct over an above already known influences. In addition to this purpose, beliefs of efficacy were found to have a significant and positive effect on perceived ease of use, once more validating the important role computer self-efficacy has on forming these perceptions and, by extension, in the overall process of technology adoption.

Recent Research on Performance Effects

Marakas et al (1998) proposed a model of the relationship between computer self-efficacy and performance, reviewed above, which included direct and indirect effects of the former on the latter, in some cases also involving moderated relationships. This section updates that model by reviewing research on the efficacy-performance relationship published in the last ten years, in addition to that conducted by Johnson and Marakas (2000), which has already been discussed.

Yi and Davis (2003) examined the relationship between self-efficacy and performance as part of their efforts to develop an improved training approach based on behavior modeling and observational learning processes such as attention, retention, production and motivation. This new model was proposed in order to provide a more detailed account of the mechanisms by which modeling-based

interventions enhanced training, and thus provide a base for both the evaluation and improvement of training techniques in the future. Software self-efficacy was measured prior to training, as part of the effort to control for pretraining individual differences, and after the training intervention as one of the main outcomes of the proposed approach, declarative knowledge being the other. Task performance was measured immediately after training and a second time with a ten day delay in between. Results from PLS analysis show that pretraining self-efficacy is significantly related to the post-training construct. The latter had significant effects on both immediate and delayed task performance, even when declarative knowledge was also included in the analysis. This confirms the role of computer self-efficacy as both one of the primary determinants of performance and one of the primary outcomes of training interventions.

Yi and Im (2004) studied the relationship between computer self-efficacy, personal goals, and performance, using data from a software training program. Considering beliefs of efficacy and personal goals is important because they provide two different, even if complementary, answers to the question of why some individuals perform better on tasks when they are similar in ability and knowledge to others that do not perform as well on the same tasks. Individuals that display higher levels of self-efficacy believe they can do more with their capacities than others that posses less confidence in their capability to perform a task. On the other hand, participants that set more challenging and meaningful goals for themselves are more likely to exert additional effort in order to achieve increased performance than those

that set less challenging objectives for themselves. In order to account for other pretraining differences, the authors also included prior experience and age as determinants of computer task performance. Results from their structural model showed no significant direct effect of computer self-efficacy on performance, but significant if rather small indirect effect through personal goals. Prior experience had a strong positive effect and age a negative one on performance. Overall, the model proposed by Yi and Im (Yi & Im, 2004) accounted for almost forty percent of the variance in the dependent variable.

Also within a training context, Johnson (2005) proposed two mediators, in addition to a direct effect, of the relationship between application-specific self-efficacy and performance: goal level, and goal commitment. These two mechanisms have been shown to be primary determinants of the motivation with which individuals approach tasks and improve performance. Individuals who set challenging goals for themselves exert greater effort and maintain it for longer, and perform better than those who set lower goals. Commitment to these goals, however, is required for them to have any motivational impact on performance; personally meaningless objectives are unlikely to motivate greater effort expenditure.

Indeed, these motivational processes have been shown to be two of the primary channels by which cognitive appraisals of capability (e.g. efficacy beliefs) operate on behavior and ultimately performance in the series of studies by Bandura and colleagues (Bandura & Jourden, 1991; Bandura & Wood, 1989; Cervone et al., 1991; Wood & Bandura, 1989a). Results from Johnson (2005) confirm these previous

findings. Application-specific computer self-efficacy has significant impacts on performance both directly and through its positive effects on self-set goals and goal commitment, for a combined standardized path coefficient of 0.2933. In addition, it explains 13% and 14% of the variance, respectively, in the two mediating constructs.

Marakas, Johnson and Clay (2007), although specifying computer self-efficacy as a formative composite, also examined its relationship to performance in the context of analyzing the differential predictive validity of measures developed at different points in the evolution of the computing domain. In order to accomplish this, the authors compared the spreadsheet measure used by Gist et al (1989) and the one developed by Johnson and Marakas (2000). While both measures significantly predicted spreadsheet performance, the more recent essentially tripled the proportion of variance explained in the dependent variable (it is not clear whether the scale developed by Gist et al, 1989 was also specified as a formative composite).

One common aspect of extant research focusing on the computer self-efficacy – performance relationship has been its limitation of the latter to aspects of specific computer skills and technical manipulation of the application package under investigation. This is appropriate in following the standards set by Marakas et al (1998) as to the need to appropriately isolate the computer self-efficacy construct and its consequences, and thus performance measures have mirrored the strict definition of the former. This characteristic of performance measures is evident by a simple review of a sample of the items employed: "*Enter a formula to compute profits (= sales – expenses) for each season in cells B8:E8*", "*Using an appropriate function,*

compute the total amounts of sales, expenses, and profits of year 2000. The computed amounts should be located in cells F6:F8", or "*Calculate % change of sales from the previous seasons. The computed amounts should be located in cells C11:E11*" (Johnson & Marakas, 2000; Marakas et al., 2007; Yi & Davis, 2003).

The ability required to correctly perform these tasks does not exceed basic arithmetic skills and knowledge about the manipulation of operations, functions, and cells using a spreadsheet package, and thus these items do represent appropriate measures of performance when the predictor is only application-specific (spreadsheet in this case) computer self-efficacy. However, most organizational tasks are not limited to the proper operation of a particular piece of software, although this is certainly an important prerequisite for successful completion. In addition, functional knowledge about the content of the task is essential, and thus predicting performance in cases where both technical and functional abilities are needed does require the use of measures of self-efficacy that combine those two aspects of the task. However, research in this area is extremely limited, essentially comprised of a single study, which is reviewed next in greater detail.

Combined Functional and Technical Self-Efficacy

The only extant research considering computer self-efficacy and its role in relationship to perceptions of self-efficacy for tasks supported by the use of information technologies is a recent study by Looney, Valacich, Todd and Morris (2006), who drew on Social Cognitive Theory (Bandura, 1997) to depict the

interrelationship of three different perceptions of personal efficacy as the determinant of performance- and personal-based outcome expectations. The setting chosen was that of online investment activities. The authors argued that online investment self-efficacy, defined as an "*individual's perceived capability to utilize online investing technologies to make effective investment decisions*" (p. 217) would be the direct determinant of the personal and performance outcomes that could be expected as a result of investing online. In addition, online investment self-efficacy was depicted as a mediator of the effects of two other self-efficacy perceptions, investment self-efficacy ("*an individual's perceived capability to make effective investment decisions*", p. 218) and computer self-efficacy (defined as an "*individual judgment of one's capability to use a computer*", p. 218) (Compeau & Higgins, 1995b). Figure 2.8 shows their original research model as well as results from statistical analyses, conducted using Partial Least Squares (Barclay, Higgins, & Thompson, 1995).

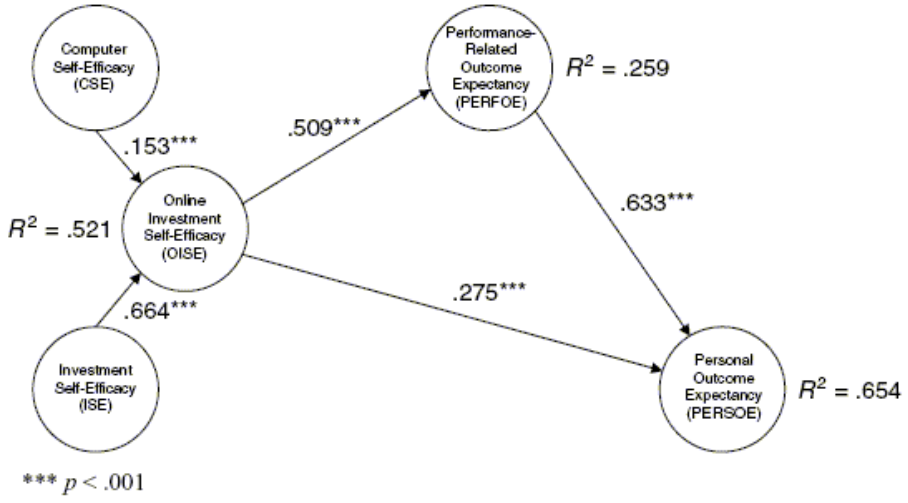


Figure 2.8 – Structural Model Results (Looney et al, 2006)

As noted above, this research represents the first effort to further our understanding of the role and position of computer self-efficacy in the nomological network of tasks whose performance is supported by the use of information technologies, and is likely to become a seminal research effort as this area of investigation continues to expand. However, both conceptual and operational limitations of that study somewhat limit the interpretation of the obtained results.

Amongst the former, and discussed in more detail in the remainder of this chapter, are the theoretical grounding for the relationship between online- and investment self-efficacy, and the positioning of computer self-efficacy vis-à-vis those other two constructs. Next, turning to operational aspects, the central construct of online investment self-efficacy did not appear to be fully isolated from the domain-measure of investment self-efficacy, as evidenced by the high cross-loadings and lack of predictive power over and above the latter.

Self-Efficacy Generality and Specificity

While Looney et al (2006) correctly point out that the level of specificity at which perceptions of self-efficacy should be measured must be in correspondence with that the researcher is interested in or seeks to predict (Bandura, 1997; Pajares, 1996), the authors based their arguments for the existence of cross-domain judgments of self-efficacy on opposing the notions of domain- and task-specificity (following from arguments made by Marakas, Yi and Johnson, 1998), and developed the concept of domain overlap to justify the existence of what they labeled *combination* self-

efficacies, those that draw from more than one domain of functioning, as opposed to *encapsulated* judgments, those that involve skills pertaining to a single domain, such as computing or investing. As such, the overlap between domains represents perceptions of capability for investing online, whereas the remainders account for either other computing technologies or offline functional investment abilities. These two issues, e.g. domain- and task-specificity of self-efficacy judgments, and domain overlap will be separately discussed next.

In their seminal review of the antecedents, consequents, and nature of the computer self-efficacy construct, Marakas et al (1998) discussed the need to adequately develop both self-efficacy and performance measures such that the effects of computer self-efficacy on computer-related tasks could be properly identified and isolated. Following from their (accurate and relevant) assertion that a number of scenarios do not rely exclusively on computer skills, but rather require a blend of both functional and technical abilities for successful completion of the task, Looney et al (2006) argued that the avoidance of cross-domain assessments of self-efficacy imposed by Marakas et al (1998) proved problematic when the intention of the researcher was to assess the relationship between self-efficacy and performance in a task requiring the use of skills drawn from various domains of functioning, resulting in inappropriate representation of capabilities, and sacrificing accuracy and explanatory power.

However, it appears that Looney et al (2006) misinterpreted Marakas and his colleagues (Marakas et al., 2007; Marakas et al., 1998). The following is the relevant quote from Marakas et al (1998, p. 154):

> "*Further, if a subject is asked to estimate his or her ability regarding a computer-related task that requires significant skills from outside the computing domain then the isolation of the CSE construct will be impaired. The outcome of this lack of parallelism will be a weakening in the observed relationship between CSE and performance as well as a reduction in the predictability of future task-specific performance based on prior measures of CSE".*

Moreover, the authors noted in their recommendations for the construction of CSE measurement instruments that "*Specific questions must avoid ability assessments that include cross-domain or general-domain skills"* (Marakas et al, 1998, Table 3, p. 154). These and other statements in that conceptual review, then, must be considered in the context of what the authors were attempting to accomplish. One of the objectives of that research was to proffer recommendations for the accurate measurement of computer self-efficacy and, by necessity, performance in a computer-task. Thus, tasks appropriate for this endeavor include those that focus exclusively on computer-skills, such as entering formulas or performing computations using a spreadsheet (for the relationship between spreadsheet self-efficacy and performance) (Marakas et al., 2007; Yi & Davis, 2003).

To summarize this issue, to the extent that the interest of the researcher lies in the accurate measurement and isolation of the effects of computer self-efficacy, the

construction of both the measure of this judgment, as well as that of performance, at a very specific level of detail and limited breadth, is well within the canons of Social Cognitive Theory (Bandura, 1997). Marakas et al (1998), however, never stated that this was intended to apply to other situations in which perceptions of capability requiring judgments about skills from multiple domains of achievement would be required, but rather viewed their research as a precursor to the investigation of more comprehensive relationships:

> "*If IS research is to pursue exploration of the complex relationships between CSE and other use and performance-related variables, we must first focus our attention on the development of reliable measures of the construct. Such measures must demonstrate not only the necessary levels of convergent and content validity but, more important, must also demonstrate evidence of strong divergent validity from other related constructs"* (Marakas et al, 1998, p. 158)

Looney et al (2006) also noted that the task-specificity of self-efficacy judgments does not necessarily imply domain-specificity, and that self-efficacy perceptions can generalize across domains depending on qualitative features of the task and skills that are shared in common. However, the fact that task-specific self-efficacy judgments draw from multiple domains of human functioning does not lead to the conclusion that the domains themselves overlap. In addition, it is not clear which common features and skills shared between the domains of investing and computing the authors relied on to assume the generalization of task-specific self-efficacy across those two areas. Social Cognitive Theory does acknowledge the

existence of an underlying structure of efficacy beliefs, such that those may generalize across domains.

Bandura (1997) notes that to expect individuals to establish a sense of efficacy every time a new activity had some degree of dissimilarity with more familiar ones would not be reflective of adaptive functioning. This network of efficacy beliefs, then, is the outcome of structured past experience and reflective thought, rather than a disjointed collection of very specific perceptions. Extant theory (Bandura, 1997, 2006) identifies five processes through which mastery experiences can produce generalities in efficacy beliefs across domains of functioning.

The first of these processes relies on similar subskills governing different kinds of activities; however, similarity perceptions are largely a personal assessment, and are not necessarily reflected in the number and quality of objectively-determined features of the tasks under consideration. Using a multi-session experiment weeks apart, Cervone (1997) contrasted top-down and bottom-up approaches to situational coherence. Using the first analytical strategy, trait theorists seek to uncover high-level personality constructs that categorize, organize, and systematize differences among individuals, but do not provide for the causal mechanisms that underlie the effects of these structures on actual behavior (Cervone, Shadel, & Jencius, 2001). Five-factor theory (McCrae & Costa, 1996, 1999) is a clear example of this approach. Social-cognitive analysis, on the other hand, employs a bottom-up approach in order to specify the causal processes that give rise to observed cross-situation behavioral coherence.

The author compared self-efficacy perceptions across a number of different situations, supporting his argument that those would be consistently higher and lower for those situations experimental subjects had previous specified (three weeks prior to measurement) as very relevant to their perceived positive and negative attributes. Conversely, judgments of self-efficacy did not vary across situations that had been nomothetically, as opposed to idiographically, specified. It should be noted that the analysis took into consideration the particular pattern of personal strengths, weaknesses, and most important traits previously specified by the participants, in effect constructing an underlying structure of self-appraisal for each individual. These results strongly support the contention that generality of self-efficacy beliefs may be highly idiosyncratic.

Another important mechanism by which generality is built is co-development. Even if different activities do not share a common subset of skills, to the extent that education and development of competencies is formally structured such that skills in different domains are acquired together, some generality of perceived efficacy is expected to occur. As discussed by Bandura (1997), formal schooling is a clear example of this process, where students could be expected to develop similar levels of efficacy, whether uniformly high or low would depend on the quality of the educational institution, due to simultaneous exposure to different domains of learning. Higher-order self-regulatory skills, such as diagnosing task demands, constructing and evaluating alternative courses of action, setting of appropriate goals, and creating self-incentives in order to sustain effort (Bandura, 2006), which are valuable in a

wide range of domains and activities, may also result in co-variation in perceived efficacy. Finally, the occurrence of powerful mastery experiences, which highlights, to oneself, a capacity to effect changes, may be reflected in an extensive reorganization of efficacy beliefs that manifests itself across different realms of functioning.

In his writings, Bandura (1997, 2006) was very careful to note that these diffusion processes are intended to account for patterns of covariance across beliefs in self-efficacy in different domains of functioning, but did not argue for the existence of a causal relationship between changes in one belief and changes in other that is related by one of those mechanisms. Rather, these would more appropriately represent examples of spurious relationships, e.g. those that can be accounted for by including a third variable that serves as a common cause, as discussed by Kenny (1979). Two examples from the investment domain employed so far may help make this point more clearly.

One investor may hold different perceptions of self-efficacy when conducting investment activities online, by phone, or by walking into a branch and talking to a financial advisor. After a successful performance while investing online, that the investor attributed to her ability to discriminate between good and bad investments, her judgment of self-efficacy for the first of these three situations may increase. Likely, it may also result in an increase in the other two investment contexts considered here. However, this generalized increase across different situations would not arise because an improvement in her self-efficacy for online investment caused an

improvement on the other two, but rather because the investor perceives her capacity to successfully invest to have improved. If, on the other hand, the successful experience was deemed to occur because of mastery of the software application used to research investments and submit transactions, that may very well not result in any changes to her perceptions of self-efficacy for investing over the phone, or by interacting with an advisor. A similar argument can be made for the case of co-development. As students attend school, their self-efficacies for different subject matters commonly taught can be expected to change somewhat in consonance. While it could be possible to statistically show a causal relationship between two of those perceptions (or even them being affected reciprocally), the underlying reason for those changes is the experience of a certain common treatment, e.g. attending school. The remaining three diffusion processes identified by Bandura (1997) operate in the same way.

It is not clear, then, how what Looney et al (2006), as noted above, labeled a "combination" judgment, can represent an instance of generalization underlying the relationship between two different efficacy domains, in this case investing and computing, when the construct is defined at a level of specificity that is higher (that is, more detailed) than any other of the two judgments involved in the relationship. On the other hand, this manuscript argues that the stated causal relationship between the more general (investment self-efficacy) and the more specific (online investment self-efficacy) judgments is appropriate, but on a rather different theoretical ground.

Investment self-efficacy, having been stated at the domain level, represents more clearly what Bandura (1997) described as an intermediate level measure. In particular, the author stated, referring to generality of assessment:

> "*Domain particularity does not necessarily mean behavioral specificity. One can distinguish among three levels of generality of assessment. The most specific level measures perceived self-efficacy for a particular performance under a specific set of conditions. The intermediate level measures perceived self-efficacy for a class of performances within the same activity domain under a class of conditions sharing common properties. And finally, the most general and global level measures belief in personal efficacy without specifying the activities or the conditions under which they must be performed … The optimal level of generality at which self-efficacy is assessed varies depending on what one seeks to predict and the degree of foreknowledge of the situational demands"* (p. 49)

In this light, use of information technologies to accomplish a particular task represents an example of a particularized judgment of a specific performance under a particular set of conditions (e.g. when using a computer or other technology in the process of task performance). Several researchers in various domains of functioning have validated this multi-level conceptualization of self-efficacy. Within the academic realm, Pajares and Miller (1994) measured mathematics self-efficacy at the course, task, and actual problem level, and related those to performance in mathematics problem-solving and the selection of a math-related major, finding that

the problem level-judgment was most related to performance on problem-solving, with course self-efficacy most related to selection of a math-related major.

Although the most general course-related self-efficacy did significantly predict problem-solving performance, the effect was minimal compared to the judgment at the appropriate level of specificity. In a series of studies, Bong (2001, 2002; Bong & Hocevar, 2002) studied the relationships among various measures of self-efficacy at different levels of specificity and achievement performances at the appropriate levels of detail. The results provide strong support for the claim that self-efficacy beliefs can be assessed at varying levels of specificity, even when attempted within a single performance domain.

Similar results were obtained in the study of health-related behaviors. In an article examining safe-sex practices, Murphy, Stein, Schlenger and Maibach (2001) tested four different models of the relationships between self-efficacy, gradations of challenge, and situational constraints on the exercise of safe-sex practices: efficacy as a unitary construct across situations and levels of challenge, situation as preeminent transferring across skills and levels of difficulty, skills as predominant irrespective of the particular situation, and multidimensional model that simultaneously accounted for both. Consistent with theory, the latter provided the best fit to the data.

Gwaltney and colleagues (Gwaltney et al., 2001) investigated the existence of an abstinence from smoking self-efficacy construct, and its manifestations across different situations commonly encountered in everyday life. The judgment of interest was found to vary across different situations, and a hierarchical model with a second

order factor for the underlying self-efficacy was found to best fit the data (first order factors representing self-efficacy across different situational contexts). In addition, the situation with the lowest self-efficacy was found to consistently predict relapses when the subject encountered with that particular context. Thus, the level of specificity at which judgments of self-efficacy are conceptualized and assessed should be representative of what the researcher is interested in predicting or measuring. The better the match in specificity, the greater the predictability of behavior (e.g. the "specificity matching hypothesis") (Eden, 2001).

Operational Issues

In addition to the conceptual discussion above, operational issues also contributed to limit the interpretation and applicability of the results obtained by Looney and colleagues (2006). Most notably, the central construct of this research, online investment self-efficacy, does not appear to have been fully isolated from one of its proposed antecedents, investment self-efficacy. First, an examination of the loadings of the items on their respective constructs reveals the existence of very high cross-loadings between them. While the loadings were obtained from an application of Partial Least Squares, which is a principal components technique and thus do not represent actual factor loadings as referred to in common factors models, there is general agreement in the literature that cross-loadings should be kept to a minimum if constructs are to be distinguished from one another. However, researchers have not yet reached agreement on how much different those should be; although Gefen and

Straub (2005) argued that loadings in their intended variable should be an order of magnitude higher than any other loading, they also proposed that a difference of 0.10 (between 0.70 and 0.60 loadings) would be enough.

In this particular case, loadings of items measuring investment self-efficacy on their intended variable ranged from 0.906 to 0.955, while loadings of items measuring online investment self-efficacy on the same latent variable ranged from 0.616 to 0.685. Conversely, loadings of online investment self-efficacy items on their variable varied between 0.850 and 0.926, while loadings of investment self-efficacy items went from 0.626 to 0.653. The authors cited Wixom and Todd (2005) in support for their contention that discriminant validity was well established even in the presence of high cross-loadings, citing the 0.10 rule as discussed above. On the other hand, Wixom and Todd (2005) also tested their data for the presence of multicollinearity between predictor variables (and found none that was significant), while Looney et al (2006) did not.

To further assess the plausibility of their proposed model, the authors examined several alternative representations of the relationships between antecedent and outcome constructs. Two of those are of particular interest and are thus reproduced below. In their second alternative model, shown in Figure 2.9, investment self-efficacy directly influences both outcome expectancy measures, with significant effects. Recall from Figure 2.8 that the percentage of variance explained was 0.259 and 0.654 for performance-related and personal outcome expectancies, respectively.

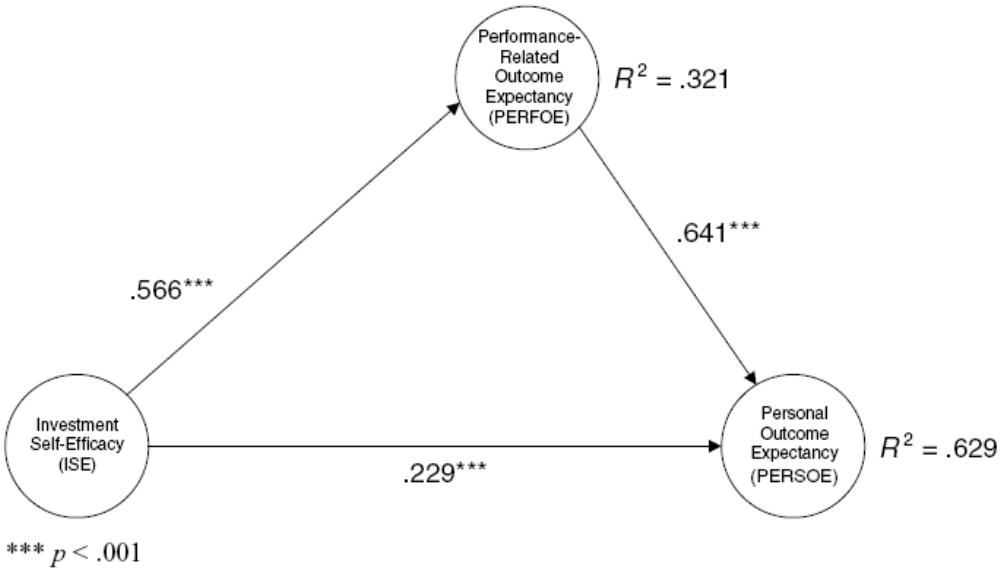


Figure 2.9 – Alternative Model 2 (Looney et al., 2006)

This alternative model shows a percentage increase in the variance explained of 24% (ΔR^2 = 0.062 from 0.259 to 0.321) in the performance-related construct, and a percentage decrease of less than 4% (ΔR^2 = -0.025 from 0.654 to 0.629) in personal outcome expectancy. In their third alternative model, computer self-efficacy is added as a direct predictor, with essentially no effects on either case (shown in Figure 2.10 next). In this model, neither path emanating from computer self-efficacy was significant.

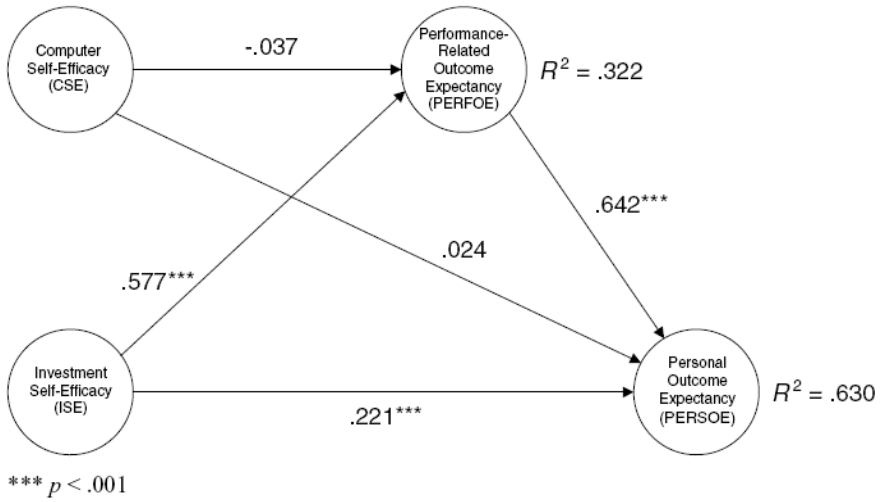


Figure 2.10 – Alternative Model 3 (Looney et al., 2006)

Although the authors followed no formal procedure to test the mediating effects of the intervening variable (online investment self-efficacy), results from a full model containing all variables and paths showed that the two paths from computer self-efficacy to the dependent variables were not significant in the presence of the mediating variable, and that this constituted evidence of full mediation of those effects. On the other hand, conventional procedures for testing mediation in regression models (Baron & Kenny, 1986) require that the independent variable whose effect is argued to be mediated by other show a significant direct effect to begin with. This was clearly not the case in this research, and thus it is difficult to argue for a mediation of the effects of computer self-efficacy.

The same model showed significant effects of investment self-efficacy on performance-related outcome expectations, over and above those accounted for by the

intervening variable. The path from investment self-efficacy to personal outcome expectancy, though, was insignificant in the presence of the mediator variable.

3. RESEARCH MODEL AND THEORETICAL DEVELOPMENT

Summary or Reviewed Literature

Social Cognitive Theory, as extensively developed by Bandura (1986a, 1997), presents a view of human functioning centered around cognitive, self-referent, and self-regulatory processes. Individuals are perceived as self-organizing and adaptive, as opposed to reactive organisms whose actions are shaped by environmental forces or determined by innate dispositions. This is the foundation underlying the system of reciprocal determinism among personal factors, behavior, and environmental influences proposed by the author to explain the interdependent nature of the different factors affecting human agency and ultimately behavior.

Social Cognitive Theory is rooted in a view of human agency in which people are proactive agents that make events occur as a result of their actions and that engage their environment in order to effect changes on it, rather than merely responding to the constraints posed by the situation. The notion of self-efficacy, those beliefs that enable individuals to exercise control over their thoughts, and by extension, actions, is central to this view on human agency. As such, individuals are viewed as both products and producers of their own social systems and environments.

The theory is comprehensive, specifying many aspects of the self-system into a unified conceptual framework. SCT accounts for the causation mechanisms leading to human actions and behavior, the structure and sources of self-efficacy beliefs, as well as the processes by which they manifest in individual and collective agency. In terms of their structure, beliefs of efficacy vary along level, strength, and generality

dimensions, effectively representing unlimited configurations of the system needed for adaptive human functioning. Theorists have also provided a coherent account of the sources of information and mechanisms by which that is incorporated into modified perceptions of capability. Among the former, Bandura (1997) included, in decreasing order of importance, four different sources of relevant information: enactive mastery, vicarious experiences, verbal persuasion, and appraisals of physiological and emotional states.

As an intermediate step between these sources of information and appraisals of capability, Gist and Mitchell (1992) outlined a set of mechanisms by which information is integrated and transforms efficacy beliefs: an analysis of task requirements, an attributional analysis of past experience, and an assessment of personal and situational constraints. In addition, the influence of these processes is theorized to vary according to the level of familiarity or routinization that the individual has reached in performing the task. Beliefs of efficacy are postulated to affect behavior and task performance in a number of different ways, both directly and through their influence on other related processes. In more detailed terms, self-efficacy perceptions influence both the choices individuals make and the courses of action needed to successfully complete the task.

People tend to perform tasks and activities where they feel competent and avoid those in which they do not. In this sense, self-efficacy provides an important input to choice behavior, although the two are not linearly related. Rather, it is argued that there is a certain threshold in perceptions of efficacy below which the activity

will not be attempted, and over which will always be attempted, although with varying degrees of success. On the other hand, self-efficacy is related to task performance through a variety of channels. In particular, three different sets of processes are involved (Bandura, 1997): cognitive, motivational, and affective. In the first case, beliefs of efficacy affect performance through their effects on thought patterns, in particular the exercise of forethought, and the perception of situations as presenting valuable opportunities that can be realized through effort and dedication. A strong sense of efficacy also exerts an influence through self-regulatory processes and the ability to stay focused and task oriented in the face of distracting influences.

Considering motivational processes, efficacy beliefs play a central role in the way individuals perceive and attribute past performance, how they formulate the outcomes that could be expected from performing an activity, and the goals that they set for themselves when doing so. In the first case, efficacious individuals are more likely to attribute past failures to insufficient effort, and thus face future performances with renewed will, while inefficacious ones are more likely to attribute them to lack of ability. Self-efficacy also affects the outcomes people expect to accrue from taking a particular course of action or exerting a certain amount of effort in performance of a task. A reduced sense of efficacy diminishes expected outcomes since individuals take a more limited view of what they can achieve and adjust their expectations accordingly. Self-efficacy also operates through goal-setting processes, effectively influencing the level at which goals are set, strength of commitment to them, and strategies and amount of effort mobilized in order to reach those.

Finally, self-efficacy also influences emotional reactions to tasks and their situations; for instance by instilling a feeling of serenity when approaching difficult tasks and activities (for an individual with a high sense of efficacy). Conversely, diminished efficacy beliefs may result in the experience of anxiety, stress, and a general narrowing of possible avenues to solve problems and address setbacks. This is another avenue by which self-efficacy influences the level of performance that can be obtained.

Social Cognitive Theory was successfully exported to the management literature by Wood and Bandura (1989b), and results from a large-scale research program supported the processes and influences described above. Researchers found perceptions of controllability, performance standards, goals (both assigned and self-set), and social comparison processes influence the dynamic interplay between self-efficacy and task performance: directly, through its effects on personal goals, and through the selection of more complex analytic strategies; even when past performance is included as a statistical control. Meta-analytic cumulation of research findings show the significant relationship between beliefs of efficacy and performance (Stajkovic & Luthans, 1998), although it has also been pointed out that their strength (Stajkovic & Luthans, 1998) and even significance (Judge et al., 2007) may be dependent on characteristics of the task, the study setting, the participants, and measurement procedures.

Self-efficacy and SCT have also become central areas of research in the training literature, particularly where behavior modeling is concerned. Indeed, it was

in this context that Compeau and Higgins (1995a, 1995b) introduced computer self-efficacy to the mainstream information systems discipline. In that set of studies the authors developed a new measure of the construct and tested a training intervention using modeling techniques on two different software applications. Although their results were somewhat equivocal, and later work by Johnson and Marakas (2000) attempted to clarify them, this research launched a new stream in the literature. Another seminal article in this area was the conceptual review and theoretical development conducted by Marakas et al (1998), which provided a comprehensive model of the self-efficacy – performance relationship that constitutes the basis of this dissertation.

In addition to examining the influence of computer self-efficacy on other related behaviors, such as technology adoption (Venkatesh, 2000; Venkatesh & Davis, 1996) and usage (Compeau & Higgins, 1995b; Compeau et al., 1999), a core group of researchers continued to further our understanding of the impacts of this construct on computer performance. Along this line, and in addition to the work of Johnson and Marakas (2000), Yi and Davis (2003) found a significant effect of post-training self-efficacy on both immediate and delayed performance, even after other training outcomes, such as declarative knowledge, were also included in the research model. Johnson (2005) also demonstrated the influence of self-efficacy on performance, directly and through its effects on goal commitment and personal goals. In contrast, Yi and Im (2004), employing a model in which both self-efficacy and goals were postulated as antecedents to computer task performance, found only a

significant effect for goals, and only an indirect effect of self-efficacy on performance through the former.

While these results clearly underscore the importance of self-efficacy as a key determinant of performance, and thus its attractiveness from a training and development perspective, conceptualizations of the dependent variable in this research have been narrowed to mostly include only the manipulation of software functionality, consistent with the arguments expressed by Marakas et al (1998) aimed at the isolation of the computer self-efficacy construct and its effects. However, and while certainly important, successful completion of most organizational tasks requires more than beliefs in possessing the capacity to operate an application, but must also include individual perceptions of efficacy about performing the underlying task itself, for which the application becomes a vehicle.

Building on this notion, Looney et al (2006) developed the only extant research postulating a linkage between computer and task self-efficacies, in this case argued to operate through a more specific perception of capability, a joint self-efficacy conceptualization. While some of the conceptual arguments employed by the authors to ground their model are debatable, and have already been discussed in the previous chapter, this research represents the point of departure for the development of the theoretical model and hypotheses that will be tested in this dissertation, as discussed next.

Research Model

Figure 3.1 depicts the research model that will be tested in this dissertation, in addition to Hypothesis 10 (not shown in the picture) which discusses the change of the effect postulated by Hypotheses 8 as the role of technology on task effectiveness increases.

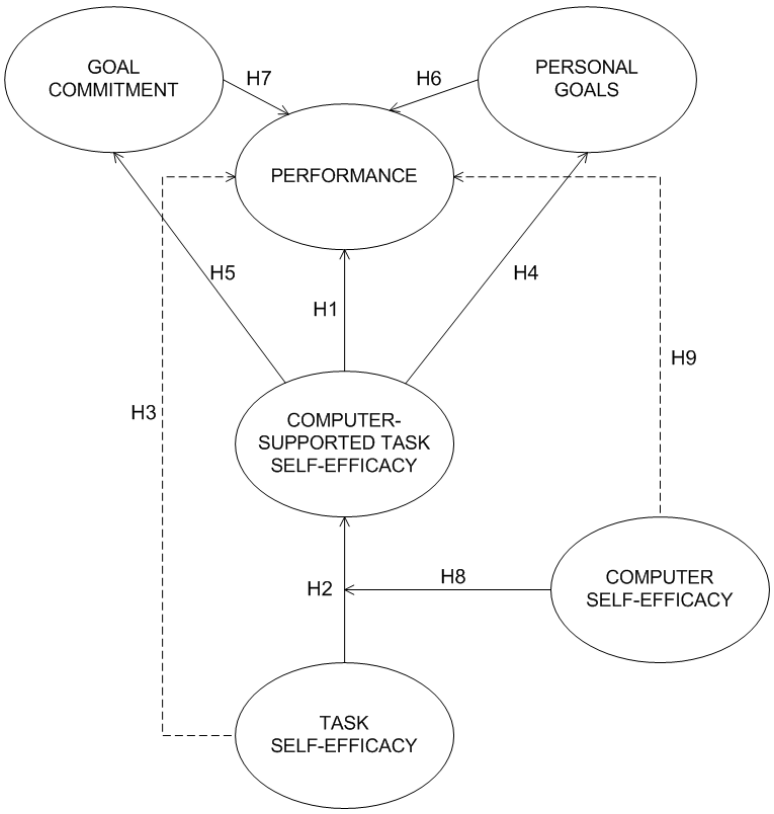


Figure 3.1 – Proposed Research Model

Hypotheses Development

As noted by Bandura (1997), when the purpose is to explain or predict particular performance in a particular situation, an efficacy measure with high specificity is warranted. Gist and Mitchell (1992) theorized that three different processes are involved in the formation of estimations of orchestration capacity (e.g. self-efficacy). The first is an analysis of task requirements, which details what it takes to perform at various levels, including which abilities would be required and how much time would be needed. Second, individuals review past experiences with the task. These two analysis yield an estimation of what it would take to do well on the task, in terms of both abilities and motivation, and their relative contribution to performance. Finally, the individual reviews the setting and availability of specific resources needed and constraints present that would have an impact on her ability to perform the task.

Bandura (1997) also noted that self-efficacy judgments are generative and integrated, and not merely a collection of subskills that may or may not represent the complete set of those required to successfully perform the task of interest. Rather than an aggregation of microcomponents, then, the inclusion of more facets of personal efficacy increases the predictive power of the assessment. Given that the focus of this work is on explaining and predicting performance in a task carried out with the support of information technologies, the assessment of the relevant self-efficacy should be conceptualized at a level of detail that matches the behavior of interest. As such, the following definition of Computer-Supported Task Self Efficacy (CSTSE) is

offered: "*an individual's perception of efficacy in performing a particular task with the support of computer technology*". As a corollary on the discussion on specificity above, the following is hypothesized:

H1: Computer-Supported Task Self-Efficacy (CSTSE) will have a positive impact on Performance in a computer-supported task.

When conceptualizing self-efficacy for a particular domain of functioning, it is more appropriate to assess the construct at an intermediate level of generality, as when attempting to predict classes of performances within generic or prototypical contextual settings (Bandura, 1997). Accordingly, the discussion on specificity of assessment by Eden (2001) and other theorists (Pajares, 1996; Pajares & Miller, 1995) notes that the prediction of specific performances by measures of self-efficacy conceptualized at more general levels of detail should be taken as a sign of the robustness of the construct even when assessment is misspecified (Murhpy et al., 2001). Several authors (Chen, Gully, & Eden, 2001; Chen, Gully, Whiteman, & Kilcullen, 2000; Salanova, Peiró, & Schaufeli, 2002) have conceptualized levels of self-efficacy as ranging from the very general to the most specific level, not unlike that developed by Bandura (1997) himself, although the latter was very skeptic about the value of any general measures devoid of a behavioral counterpart.

This line of theorizing has suggested that self-efficacy conceptualized at the more specific level represents a motivational state, and that conceptualized at the more general level a motivational trait. Other authors (Judge & Bono, 2001; Judge, Bono, & Thoresen, 2003; Judge, Locke, Durham, & Kluger, 1998) have

conceptualized highly general levels of self-efficacy as part of an individual's psychological well-being. In particular, Eden (1988) has argued that more general levels of self-efficacy positively influence more specific ones, as the tendency to feel efficacious diffuses across tasks and situations. It is possible, then, to conceptualize a series of perceptions of self-efficacy stated at different levels of specificity influencing those that are more specific, while being influenced by those that are more general. An intermediate-level judgment of capability, Task Self-Efficacy (TSE) is then defined as "*an individual's perception of efficacy in performing a particular task*". CSTSE is thus conceived as a particularized manifestation (as it relates to the performance of the task in a specific situation) of a more general construct of perceived capability to perform the task, TSE. The following is thus hypothesized:

H2: Task Self-Efficacy (TSE) will have a positive influence on Computer-Supported Task Self-Efficacy (CSTSE).

However, as CSTSE incorporates other situational determinants, in this research the use of information technologies to carry out the task, that can either enhance or hamper an individual's perception of her ability to be successful at the focal endeavor, it becomes more than a mere conduit for the expression of the effects of TSE on performance. When the interest of the researcher lies, as is the case here, in explaining performance for a task-specific behavior, it has been argued that more specific assessments of self-efficacy will mediate the effects of more general ones on the performance of interest (Chen et al., 2001). In a parallel discussion, Rosenberg

and colleagues (Rosenberg, Schooler, Schoenbach, & Rosenberg, 1995) reviewed the relationship between global and specific self-esteem, noting that the former is more closely related to psychological well-being, while the latter more strongly correlates with specific behaviors. In addition, they also theorized that specific self-esteem should mediate any effects of global self-esteem on particular behaviors.

In general, motivation theorists (Kanfer, 1991; Kanfer & Heggestad, 1997) have argued that distal theories of motivation explain mediating influences on action through proximal motivation states. More trait-like constructs such as personality characteristics, individual differences and, arguably, generalized self-efficacy are rather stable over time, and operate on behavior through their effects on more state-like individual differences, such as self-efficacy and goals (Chen et al., 2000). For instance, Martocchio and Judge (1997) showed the mediating effect of self-efficacy and self-deception in the relationship between conscientiousness and learning performance. Chen et al (2000) empirically showed the mediating effect on performance of specific self-efficacy, through which both other state measures, such as state anxiety, and more trait-like constructs, such as cognitive ability and general self-efficacy, operate. Along the same lines, Tierney and Farmer (2002) showed that a more general perception of capability, job self-efficacy, operated on creative performance through its effects on the more proximal creative self-efficacy. The authors argued that a belief in having the ability to adequately perform a task is necessary before one has the confidence that it can be performed in a certain manner, e.g. creatively. Even if mediation was only partial, there is some precedent of this

relationship within the information systems literature dealing with CSE (Agarwal et al., 2000). More direct tests of these mediation effects are needed to better understand the nomological net of self-efficacy (Chen et al., 2001):

H3: Computer-Supported Task Self-Efficacy (CSTSE) will fully mediate the effects of Task Self-Efficacy (TSE) on Performance in a computer-supported task.

In order to better assess the effects of the joint self-efficacy judgment on performance, other known determinants of the latter will also be included in the research model. Personal goals are one of the most important mechanisms by which self-efficacy influences task performance, with strong empirical evidence supporting this relationship, both in the organizational behavior (Wood & Bandura, 1989b) and information systems literatures (Johnson, 2005; Yi & Im, 2004). Individuals with a higher sense of efficacy are proposed to set more challenging goals for themselves, and these in turn are known to have important consequences for task performance (Locke & Latham, 2002). On the other hand, those that do not believe are capable of performing very well tend to set less challenging objectives for themselves, with consistent effects on performance.

In addition, Locke and Latham (1990) recommended that goal commitment, defined as "*one's determination to reach a goal*", be measured in all studies involving goal-setting given that, under certain circumstances, it will show an interactive relationship with personal goals which may account for the lack of an observed effect, and may otherwise serve as a manipulation check of the focus placed on the task by

participants in the research (H. Klein, Wesson, Hollenbeck, & Alge, 1999). Results would also help validate findings by Johnson (2005), which is the only extant research to have examined this relationship in the context of computer self-efficacy research. Following from these and the arguments exposed above, the following hypotheses are put forward:

H4: Computer Supported Task Self-Efficacy (CSTSE) will positively affect Personal Goals.

H5: Computer Supported Task Self-Efficacy (CSTSE) will positively affect Goal Commitment.

H6: Personal Goals will positively influence Performance in a computer supported task.

H7: Goal Commitment will positively influence Performance in a computer supported task.

Positioning of Computer Self-Efficacy

Although Bandura (1997) convincingly argued that multiple types of self-efficacy are relevant to performance in any given domain, few studies have examined the joint effects of more than one type on performance (Tierney & Farmer, 2002). Complex organizational tasks do usually involve the use of particular means in order to achieve the desired level of performance. However, a mismatch between self-efficacy and performance occurs when only judgments of capability for performing the prescribed means are involved as predictors of performance, since the latter

depends also on the particular influence of the selected means and how they relate to task accomplishment (Stajkovic & Luthans, 1998). In particular, Bandura (1997) stated:

> "*When personal efficacy to perform the prescribed means is used as a predictor in the hypothesized causal model, one is testing not only the predictive power of efficacy beliefs but also the validity of the posited influence of the prescribed means on attainments in the causal model … When the means that produce certain behavioral attainments are only partially understood or have not been adequately verified, efficacy beliefs should be measured at two levels of specificity: efficacy to execute the prescribed means successfully and efficacy to achieve different levels of performance attainments by whatever means people choose to do so*" (p. 63)

The current section of this work, then, deals with appropriately positioning Computer Self-Efficacy (CSE), which is argued to represent the prescribed means of attainment (e.g. performing a certain task *with the use of computer technologies*), in relationship to Task Self-Efficacy (TSE), which represents the more general level of specificity alluded to by the author. In line with these arguments, Marakas et al (2007) noted the need to develop complex models of performance that incorporate efficacy estimations of both domain and technical skills, involving the use of multiple instruments. However, there is essentially no existing research (aside from the seminal work of Looney et al, 2006) that sheds light on the form of the relationship between domain and computing skills and its effects on task performance.

In light of the discussion on the previous section, this work argues that the more specific perception of self-efficacy, that captures the use of technologies to perform the task, will be most closely related to performance. The next step, then, is to theorize how CSE is related to this intervening construct. To ground this discussion, the following definition of Computer Self-Efficacy is offered: "*an individual's perception of efficacy in performing specific computer-related tasks within the domain of general computing"* (Marakas et al., 1998, p. 128). There are essentially four different ways to position Computer Self-Efficacy in relationship to Performance, TSE and CSTSE. Each one of them is considered next.

No Effect of CSE on any construct

It would be possible to argue that CSE may not have any effect on task performance, either directly or through any intervening mediator. This appears, however, to be highly untenable. There is extensive evidence in the information systems literature of the performance effects, on computer-tasks, of CSE (Johnson, 2005; Johnson & Marakas, 2000; Yi & Davis, 2003; Yi & Im, 2004). As noted above, these tasks strictly measure the ability to manipulate features of the application under study, but are devoid of functional domain information. Nevertheless, given the fact that most, if not all, organizational activities have become heavily reliant on computer and computer-based information systems (Looney et al., 2006; Yi & Im, 2004) it does not seem reasonable to propose that perceived capability to use this technologies

bears no relationship whatsoever, direct or indirect, to the accomplishment of tasks that depend on them for successful performance.

Direct effect of CSE on Performance

Having argued that there must be a relationship between CSE and performance, one potential alternative to consider would cast CSE as having a direct effect on the ultimate measure of interest. There are, on the other hand, both conceptual arguments and empirical evidence to suggest this may not be the case. Among the former, Bandura (1997) noted that subskills necessary for successful performance do contribute to the judgment of operative efficacy but cannot substitute for it. If CSE were positioned as having a direct effect on performance, it would be then directly substituting for CSTSE, which is a more specific and encompassing judgment of orchestrating capacity. Thus, while CSE certainly contributes in some form to this judgment, it should be at least one level detached from actual performance.

In addition, when substitutable influences are modeled, as is the case with two direct effects on a third variable of interest, one should theoretically expect that changes in one variable should be able to independently account for effects on performance, regardless of particular levels of the second independent variable. Then, if CSE is positioned as having a direct effect on performance, one should accept that, by themselves, perceptions of capability to use a computer are enough to effect performance in a computer-supported task, without regard to any other domain

knowledge or skills. This does not appear to be reasonable either. Finally, there is empirical evidence to the fact that so-called "process" self-efficacies, those that assess capacity to perform subfunctions that lead to obtaining a certain performance, work through their effects on a mediating operative self-efficacy, and not directly affecting performance (Mone, 1994; Stotland & Zuroff, 1991).

Effects of CSE on performance mediated by a more specific self-efficacy

More in line with the specificity-matching hypothesis discussed by Eden (2001) and the theoretical development presented in the prior section, the effects of CSE on performance could be argued to operate through a more specific perception of capability that captures and integrates this and other domain skills that are necessary to successful performance. This is the position that was taken by Looney et al (2006) in their research model. Yet it suffers from similar issues regarding the substitution of one effect by another.

This conceptualization would propose that an individual with a high perceived mastery of computer technology, but who is devoid of any perceived capability in the functional domain of interest (e.g. accounting, investing, etc.) would perceive herself as being highly efficacious in performing a certain task, within that domain, with the use of information technologies. In a puzzling remark, Looney et al (2006) noted that this would be highly unlikely, and that perceptions of capability for both the technology and the functional domain would be necessary, at the same time, to appropriately performing the task. This suggests that an interactive relationship

between technical and functional perceived capabilities could better account for the formation of the integrated judgment of CSTSE, as discussed next.

CSE moderates the effects of TSE on CSTSE

This research positions CSE as moderating the effects of TSE on CSTSE. While certainly judgments of capability in both realms are jointly needed to influence CSTSE, TSE is positioned as the main driver of the relationship. Paralleling creativity self-efficacy research, it is argued here that, even in the presence of strong computer self-efficacy, it would be difficult for an individual to feel efficacious in performing a task when devoid of perceived functional capacity (Tierney & Farmer, 2002). On the other hand, weak computer skills are likely to erode the positive effects that Task Self-Efficacy brings to performance.

It is expected, then, that feelings of efficacy to perform a task with the support of technology would be stronger when feelings of adequacy for both functional and technology skills are present. Conversely, when both TSE and CSE are low, it is expected that CSTSE would be low too. Although bordering on speculation, the depiction of TSE as the main driver and CSE as the moderating influence would lead to expect that in situations where TSE is high and CSE is low CSTSE would be higher than in those occurrences when the opposite occurs. Finally, when multiple self-efficacies come into play in predicting performance, it is expected that the more specific and proximal type would account for the direct effects on the dependent variable (Bandura, 1997). The next two hypotheses are thus proposed:

H8: Computer Self-Efficacy (CSE) will moderate the relationship between Task Self-Efficacy (TSE) and Computer-Supported Task Self-Efficacy (CSTSE).

H9: Computer Self-Efficacy (CSE) will not have a direct effect on task Performance, over and above that accounted for by Computer-Supported Task Self-Efficacy (CSTSE).

Taxonomy of Computer-Supported Tasks and Effects on the Strength of the CSE-TSE Relationship

Finally, this dissertation proposes that the strength of the moderating effect of Computer Self-Efficacy (CSE) on the relationship between Task Self-Efficacy (TSE) and Computer-Supported Task Self-Efficacy (CSTSE) will vary according to the type of task under study. In particular, that the relationship becomes stronger as tasks vary along a continuum representing the degree of change in task effectiveness effected by the introduction of information technology into its performance. The underlying logic is that as the relative importance of the computer to successful performance of the task increases, perceptions of capability about using the technology appropriately will gain significantly more importance as determinants of the most specific judgment of self-efficacy, CSTSE. In more practical terms, as the influence of the computer on the effectiveness of the task increases, the difference in perceived capability to perform the task with the use of the technology becomes more salient for those with a higher

or lower sense of computer self-efficacy, even for individuals possessing the same belief in their capability to perform the task itself, e.g. task self-efficacy.

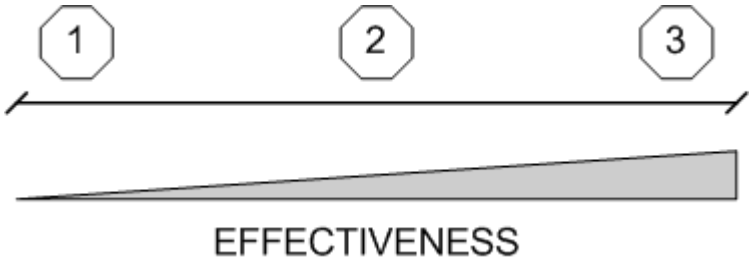


Figure 3.2 Effect of Technology on Task Effectiveness

Figure 3.2 shows three different types of tasks, which will be discussed next, positioned along the continuum in an effort to better clarify and anchor the understanding of the proposed relationship. However, they are not to be construed as the only three possible categories, but rather as reference points to help position particular tasks in this conceptualization. At the far left (labeled 1 in Figure 3.2) are those situations where the introduction of computer technologies into task performance did not significantly affect the outcome or effectiveness of the task, but rather made its execution more efficient, in terms of processing time, process automation, etc. Examples in this category include core organizational processes such as accounting, payroll and tax preparation.

In the center of the continuum (labeled 2 in the figure) are those tasks where the introduction of information systems both increased the efficiency with which the task could be implemented as well as qualitatively improved the output of the task, but in a rather incremental, even if significant, manner. One example of this category

are Decision Support Systems. While the main proposed outcome of employing this type of technology was to improve the quality of the decision being made, historically researchers have not been able to consistently show empirical validation of this argument (Barr & Sharda, 1997; Sharda, Barr, & McDonnell, 1988). More recently, Lilien, Rangaswamy, Van Bruggen and Starke (2004) made a distinction between the process and outcome impacts of using DSS. Within the former, the authors further distinguished between characteristics of the process itself, such as effort, discussion quality and alternatives considered, and the subjective evaluation of the decision process provided by the individual, along dimensions such as complexity, learning and perceived usefulness.

Turning to outcomes of employing DSS technology, these could be further classified into objective (e.g. incremental return, expert evaluation of the outcome) and subjective (satisfaction with the decision). Results from their study showed that while the use of appropriately designed DSS improve objective outcomes, subjective satisfaction with the decisions made is more equivocal, and this may be one of the underlying reasons why this technology has not seen more widespread use. However, this provides a good example of a Type 2 task. While the decision to allocate marketing resources existed before the introduction of the technology, using the latter significantly improved the quality of the decision, even if the task itself did not significantly change, e.g. the decision that needs be made is the same, use of the technology enables better outcomes.

Finally, at the far right of this conceptualization lie those tasks where the introduction of technology radically altered their outcome, or those that were not even possible before the technology was available. Examples include computer-based animation and large scale data mining, among others. Issues of efficiency in performing the task are not particularly relevant for this category, since there is no prior point of comparison.

Following from the exposition above, the last hypothesis is thus presented:

H10: The strength of Computer Self-Efficacy as a moderator in the relationship between Task Self-Efficacy and Computer-Supported Task Self-Efficacy will increase as the role of the technology in effectiveness of the task increases.

However, operational and empirical isolation of the two constructs anteceding CSTSE, namely CSE and TSE, may become difficult at the right anchor in the proposed continuum, mostly because of the co-development process described by Bandura (1997). To the extent that certain tasks only become possible with the introduction of specific technologies, training, practice, and actual performance of the task would have always been accomplished through the use of technology. Thus, it may be difficult for individuals to distinguish their perceived capability to use the technology and their perceived capability to perform the task by any means possible, when the only possibility is by using a particular technology.

4. STUDY I DESCRIPTION AND RESULTS

Research Setting Description

Consistent with the descriptions of the different task types developed in Chapter 3, this first study sought to operationalize the research model in the context of a task type I, that is, one "*the introduction of computer technologies into task performance did not significantly affect the outcome or effectiveness of the task, but rather made its execution more efficient, in terms of processing time, process automation, etc. Examples in this category include core organizational processes such as accounting, payroll and tax preparation*".

Task. The research setting chosen for this study was that of budget analysis, e.g., the preparation of projected revenues and expenses, the correct allocation of these to the appropriate time periods, comparison of projected and actual amounts, calculation and analysis of any variances between these, etc.[1] While this activity has been long performed before the advent of computer technology, the incorporation of the latter (in particular, spreadsheets) has not resulted in a marked change in the nature of the activity, although it has allowed analysts to tackle more complex scenarios as well as well as be more responsive to the changing needs of their organization environments.

[1] Please refer to the website of the U. S. Department of Labor, Bureau of Labor Statistics for a more comprehensive overview of the skills and duties of budget analysts (http://www.bls.gov/oco/ocos003.htm)

For this particular study, subjects were provided with a partially complete budget analysis spreadsheet, containing information about projected and actual income and expenses for a three-month period for a fictitious business (see Appendix B.2), in addition to instructions about what activities were still to be performed before the spreadsheet was complete (reproduced below in Appendix B.1). These included the allocation of actual income and expense information to the appropriate lines and time periods (while all the information was complete for the projected portion of the spreadsheet, the columns referring to actually incurred amounts had several missing cells in them); the creation of summarizing columns for the quarter for both budgeted and actual data, with appropriate formatting; calculation of variances between expected and actual amounts, with conditional formatting based on the direction of the variance; and the use of logical statements to answer questions about the direction and magnitude of observed variances.

The complete set of experimental materials used in this study is included in Appendix B.1 (instructions to subjects performing the task), Appendix B.2 (task materials provided to participants), Appendix B.3 (solution key), Appendix B.4 (grading criteria) and Appendix B.7 (screenshot of the data collection).

Sample and Procedures. Data for this study were collected from undergraduate students enrolled in an introductory Information Systems course which is a required prerequisite for admission to the School of Business. Performance of the task was required as part of assigned regular coursework; however, students could opt

out of their data being used as part of this research. In order to provide all participants with the same amount of time, those students who opted out were still asked to complete the data collection portion of the task. No significant differences in performance were observed between those that consented and those who did not.

The exercise took place in all sections of an off-hours lab which was mandatory in attendance and staffed by teaching assistants. All students in both sections of the course attended these sessions. In prior sessions the students received instruction in both the use of spreadsheet software as well as in the activity of completing and analyzing budgets. In addition, the participants had access to a computer-based tutorial in the use of the software, which they also used to take a mandatory test as part of the passing requirements for the course.

Subjects attending the lab on the day of the exercise had been previously informed they would be performing an in-lab assignment which had to be completed during the allotted time (50 minutes) and which would be similar to what had been covered in previous sessions. During the performance of the task participants had not access to notes or other supplemental materials. All sessions had at most thirty two students in them and were staffed by two or three teaching assistants (depending on the number of attending students) that served as proctors, but which were instructed to provide no assistance during the process. The author of this research developed the instructional materials used in the previous sessions as well as the task materials, instructions to participants, instructions to the teaching assistants, and grading criteria. All involved teaching assistants attended a training session before the

beginning of the spreadsheet portion of the lab during which they were familiarized with all materials and procedures, as well as with the grading criteria. While they were informed about the in-class exercise, the teaching assistants had no access to the task materials prior to the day in which these were delivered to the subjects participating in this research.

Measures. Measures for all six constructs present in the research model in Figure 3.1 (e.g., computer self-efficacy, task self-efficacy, computer-supported task self-efficacy, personal goals, goal commitment, and performance) were operationalized reflectively (see Appendix A for considerations and discussion on this issue), as follows. Given that the task involved the used of spreadsheet software for its performance, the application-specific spreadsheet self-efficacy measure developed by Johnson and Marakas (2000) was used. Measures for both goal commitment and personal goals that had been used in past research were also employed (Johnson, 2005; H. Klein, Wesson, Hollenbeck, Wright, & DeShon, 2001; Yi & Im, 2004). Given that the particulars of the task (e.g. budget analysis) were novel and specific to this research, a set of items were created to operationalize the definitions of task self-efficacy and computer-supported task self-efficacy in the context of budget analysis and budget analysis using spreadsheet technology, respectively (a comprehensive list of all items employed is available in Appendix B.5). Several authors have provided measure development guidelines that specifically pertain to the creation of new self-

efficacy instruments; these were followed in this research and are shown below in Table 4.1.

Table 4.1 Summary of Recommendations for Self-Efficacy Scales (Bandura, 2006; Bong, 2006; Lent & Hackett, 1987)

Area	Recommendation
Levels of specificity	Self-efficacy expectations need not be microscopically assessed, but should be tailored in specificity to the performance that one seeks to predict
Correspondence to prediction target	Efficacy expectations need to be estimated against the same skills, tasks, and situations that correspond to the key outcomes that are of interest to the researcher
Response scales	Scales with too few steps are to be avoided because they are less able to capture fine distinctions in judgments. Items using a 0-100 response scale have been shown to work best. When self-efficacy is operationalized using specific items ordered according to difficulty, the use of separate level and strength measures does convey additional information. In those situations where sequences of behavior are heterogeneous, level items lose their Guttman-scale properties and may become redundant.
Temporal proximity	Assessments of both self-efficacy and focal performance should be conducted in close temporal proximity, given that participants' self-efficacy, situational demands, or both can change during the assessment interval.
Content validity	Items should reflect the activity of interest, and be phrased in terms of *can do* (capability) instead of *will do* (intention). Should also be distinguished from other related constructs such as self-esteem, locus of control, and outcome expectancies.
Response instructions	Preliminary instructions should establish appropriate frame for participants. They are asked to judge operative capabilities as of the time of the study, and not potential or expected ones in the future.
Item analysis	Items tapping the same domain should be correlated with each other and with the total score. Factor analysis should be used to verify the homogeneity of items. Different domains require different sets of scales with within-scale homogeneity.

Performance was obtained as a result of teaching assistants grading the submissions in accordance with the a priori developed solution key (Appendix B.3) and grading criteria (Appendix B.4). Each teaching assistant graded approximately thirty submissions. In order to verify the accuracy of the grading and consistent application of the solution and grading criteria, and independent grader was trained in

the grading procedure and was provided with a random sample of eighty submissions, which were then compared using the agreement indexes developed by McGraw and Wong (1996) and where found to be in very close correspondence for each assigned grade (an a priori power analysis using the procedures outlined by the authors determined eighty was a sample size large enough to detect differences of any substantial magnitude). The independent grader had not been aware of the existence of this study prior to being recruited for this purpose.

Data Collection. The collection of data for all measures as well as the performance of the task were accomplished through the use of a spreadsheet specially designed and coded for this purpose, which is available from the author upon request (a screenshot is included in Appendix B.7). After being instructed to begin the task by opening the file, participants were presented with the consent information as approved by the HSCL (Human Subjects Committee Lawrence Campus). After agreeing to participate, the spreadsheet recorded, in a hidden worksheet, the time at which the exercise started. Participants were then sequentially presented with a set of worksheets containing instructions for responding to the various measures of interest for this research, starting by demographics and then personal goals, goal commitment, computer self-efficacy, task self-efficacy, and computer-supported task self-efficacy (results from a pilot test reveled no ordering effects for the last three measures).

The spreadsheet was designed so that only one worksheet was visible at any time and participants could not go back to revise or change their answers to previous

questions. In addition, all questions needed to be answered in order to proceed to the next worksheet; this prevented the occurrence of missing data. After answering all the questions included in the measurement instrument (available in Appendix B.5), participants were presented with the incomplete budget spreadsheet shown in Appendix B.2 and could use any remaining time to complete the assignment. Every time the spreadsheet was saved the time was recorded and thus the last saved time corresponds to closing the spreadsheet before turning in the assignment. Since participants had to stay in the lab during the exercise and had to turn it in before the end of the session, it appears safe to assume that the elapsed time from consent to last save accurately represents the time devoted to completing the task.

Statistical Analysis Approach

The data collected for this study were analyzed with the CFA-SEM framework, in particular the MPlus software package developed by Muthén and Muthén (2004). The measurement model consists of seven different factors with the items in each instrument loading on their respective factor, with no cross-loadings.

There are, however, a number of correlated residuals both across and within factors, which are a function of the design of the CSE, TSE and CSTSE measures, and were defined prior to data collection. These can be categorized into three groups (a complete list of the correlated residuals can be found in Appendix B.6). First, the residual for each item in the CSTSE measure is correlated with the residual for the corresponding item in the TSE measure. This occurs because the items in the CSTSE

measure were built by taking the items in the TSE measure and incorporating the necessary spreadsheet activities that would be needed to successfully complete parts of the exercise. For instance, TSE1 reads “I believe I have the ability to correctly distinguish between income and expenses”, while CSTSE1 reads “I believe I have the ability to distinguish between income and expenses and enter these amounts into the appropriate cells in a spreadsheet”.

The second group of correlated residuals includes those between the CSE and CSTSE measures, for reasons similar as those given above. Each item in the CSTSE measure was built by incorporating spreadsheet activities into task activities, resulting in items in both measures sharing the same spreadsheet skills. As an example, CSE3 reads “I believe I have the ability to enter numbers into a spreadsheet”, whereas CSTSE1 incorporates entering numbers into a spreadsheet with distinguishing between income and expenses, i.e. “I believe I have the ability to distinguish between income and expenses and enter these amounts into the appropriate cells in a spreadsheet”.

Finally, while there is a one-to-one correspondence between items in the TSE and CSTSE measures, some items in the CSTSE measure share content with the same item from the CSE measure (since they refer to the same spreadsheet skill). For instance, the residuals for both CSTSE1 and CSTSE2 are both correlated with that of CSE3, since both items in the CSTSE measure share the same spreadsheet content. Accordingly, the residuals for CSTSE1 and CSTSE2 are also allowed to correlate to account for this effect.

Hypothesis 8 requires testing an interaction within a latent variable framework, which has proved somewhat troublesome in the past, generally requiring the establishment of non-linear constraints such as those used by Kenny and Judd (1984) or using a two-step approach as developed by Ping (1996). More recently, other authors have developed unconstrained approaches that take advantage of mean- (H. Marsh, Z. Wen, & K.-T. Hau, 2004) or residual-centering (Little, Bovaird, & Widaman, 2006) to estimate non-linear effects such as interactions and power terms within latent variable SEM. The latter, however, require the inclusion of product-indicators and the development of a complex mean or residual structure for their estimation (in addition to the already present structure of correlated residuals, as discussed above). While conceptually tractable, given that there are nine items in the CSE factor and seven in the TSE factor, the inclusion of an additional sixty three (nine times seven) items in the model, along with correlated residuals, resulted severe convergence and estimation problems.

An alternative approach based on Latent Moderated Squares (LMS) (A. Klein & Moosbrugger, 2000) was employed to model the interaction between CSE and TSE, which takes into account that both the latent endogenous variables and its indicators deviate from traditional normality assumptions. The LMS approach represents the joint distribution of the indicator variables as a finite mixture of normal distributions, and then maximum likelihood is employed to estimate the parameters in the model, as well as providing estimates of the standard error for each one of them. Simulation results by Klein and Moosbrugger (2000) indicate that the parameters thus

estimated are unbiased, as are the their standard errors, for models with four hundred data points in them (although the type I error was higher than nominal in their simulation). Simulation results from Little et al (Little et al., 2006) provide additional evidence of the accuracy of this approach.

Hypotheses 3 and 9 posited the full mediation of the effects of TSE and CSE, respectively, on Performance by CSTSE. In addition to including the direct paths from TSE and CSE on Performance in the model, establishing mediation also requires showing the existence of a significant indirect effect from the distal variables to the dependent variable through the intervening mediator. Traditional approaches to testing mediated effects have relied on estimates from a group of models, such as those proposed by Baron and Kenny (1986), in conjunction with a test of significance for the indirect effect based on the product of the two direct effects (from the distal variable to the mediator, and from the mediator to the dependent variable) and an estimate of the standard error of this product, most commonly that given by Sobel (Sobel, 1982). This procedure assumes that the product of two normally distributed variables divided by its standard error is itself normally distributed. There is, however, extensive evidence that this is not the case (MacKinnon, Lockwoord, & Williams, 2004; Williams & MacKinnon, 2008).

Simulation studies have shown that, while the standard error thus estimated is unbiased for small sample sizes, the confidence intervals calculated using this estimate for the standard error do not perform well, where for positive values for the indirect effect, these show a negative bias, e.g., a greater proportion of true values

falling to the right of the confidence interval than to the left (Williams & MacKinnon, 2008). On the other hand, procedures based on resampling, in particular the bias-corrected bootstrap, have been shown to have greater power and more accurate type I error rates than other alternatives (Williams & MacKinnon, 2008). Consequently, the confidence intervals for both indirect effects tested in this research were calculated using bias-corrected bootstrapping (with 5,000 bootstrap samples drawn with replacement from the original sample collected).

Sample

Three hundred and twenty three undergraduate students enrolled in an introductory course in Information Systems participated in this exercise as part of regular assigned coursework. The average time taken to complete the task was forty five minutes, which is consistent with the duration of the lab section in which the students completed their assignment. Table 4.2 shows the characteristics of the sample. The average task performance across all subjects was 22.27 (standard deviation 6.41), which translates into an average of 74% of possible points.

Table 4.2 Sample Descriptive Statistics

Characteristic	*Number of Participants*	*Percentage of Participants*
Gender		
Male	215	67%
Female	108	33%
Age		
18-20 years old	269	83%
21-23 years old	49	15%
24-26 years old	4	1%
27-29 years old	0	0%
30 or more years old	1	0%
Student Status		
Freshmen	2	1%
Sophomore	229	71%
Junior	75	23%
Senior	17	5%

Results

A preliminary examination of the data collected revealed that the indicators for the Goal Commitment factor loaded poorly on the intended construct. This was a rather surprising find, given that the scale employed in this research had been extensively used and validated in previous studies. Originally developed by Hollenbeck, Williams and Klein (1989), this scale was subsequently the focus of a measurement model meta-analysis which combined data from seventeen independent samples (H. Klein et al., 2001). The latter study provided satisfactory evidence about the psychometric properties of the scale.

In order to better understand the issue, two subsequent analyses were performed. First, a one-factor CFA was fitted to all nine items in the original scale, which showed evidence of poor fit. These results are shown in Table 4.3 below.

Table 4.3 – One-Factor Goal Commitment CFA

Indicator	*Loading*	*S.E.*	*T-Value*	*Std. Loading*
GC1*	0.158	0.071	2.225	0.128
GC2*	0.209	0.062	3.370	0.193
GC3*	-0.053	0.089	-0.596	-0.034
GC4*	0.330	0.068	4.884	0.277
GC5	1.689	0.083	20.233	0.900
GC6*	0.137	0.085	1.603	0.093
GC7	1.690	0.081	20.982	0.921
GC8	1.454	0.082	17.809	0.827
GC9*	0.142	0.089	1.600	0.092
* Items that were negatively worded and reverse coded for the analysis				
Fit indexes: $\chi^2_{(27)} = 435.670$ ($p < 0.001$), CFI = 0.640, TLI = 0.520, RMSEA = 0.216.				

Only three of the nine items in the scale displayed adequate loadings (GC5, GC7 and GC8); all three are the only positively worded items in the instrument, while the remaining six were negatively worded and had to be reverse scored prior to conducting the analyses. In light of this, a second CFA model with two factors was fit to the data, with all the positively worded items loading on one factor, and all the negatively worded ones loading on another (a complete list of the items used for this measure can be found in Appendix B.5). Table 4.4 displays the results from this two-factor solution.

Table 4.4 – Two-Factor Goal Commitment CFA

Indicator	*Loading*	*S.E.*	*T-Value*	*Std. Loading*
Positively Worded Items				
GC5	1.689	0.084	20.218	0.900
GC7	1.694	0.081	21.036	0.923
GC8	1.454	0.082	17.799	0.827
Negatively Worded Items				
GC1	0.687	0.071	9.706	0.559
GC2	0.836	0.058	14.310	0.773
GC3	0.786	0.089	8.783	0.512
GC4	0.778	0.067	11.682	0.653
GC6	0.796	0.086	9.292	0.538
GC9	0.766	0.090	8.535	0.499
The two factors were correlated at 0.208 ($p < 0.001$).				
Fit indexes: $\chi^2_{(26)} = 75.689$ ($p < 0.001$), CFI = 0.956, TLI = 0.939, RMSEA = 0.077.				

These results show that the two-factor solution provides a much improved model over the one previously reported, with all indicators loading significantly on their intended factors, and in the expected direction. All fit indexes for the two-factor model are within the boundaries of acceptable fit, even though the chi-square statistic remains significant (although it is much reduced for a change that only reduced the degrees of freedom by one). Given these results, a decision was made to only include the positively worded items in tests of the overall research model for this dissertation. These items adequately capture the definition of the construct ("*one's commitment to reach a goal*") (Locke & Latham, 1990): GC5 – I am strongly committed to pursuing this goal, GC7 – I think this is a good goal to shoot for, and GC8 – I am willing to put forth a great deal of effort beyond what I would normally do to achieve this goal.

The measurement model displayed good fit with the data, as evidenced by different fit indexes (RMSEA = 0.065 with the 90% confidence interval between 0.059 and 0.071, where RMSEA < 0.08 is considered acceptable fit, and RMSEA < 0.05 close fit; CFI = 0.957 and TLI = 0.949), although the χ^2 statistic remained significant ($\chi^2_{(317)}$ = 751.829). Table 4.5 next shows the correlations amongst latent variables.

Table 4.5 Correlations amongst Latent Variables

	CSE	TSE	CSTSE	GC	PG	Performance
CSE	1.000					
TSE	0.840	1.000				
CSTSE	0.832	0.918	1.000			
GC	0.257	0.246	0.219	1.000		
PG	0.316	0.332	0.364	0.119	1.000	
Performance	0.309	0.305	0.343	0.061	0.257	1.000

The guidelines for construct validation set forth by Straub, Boudreau and Gefen (2004) for research employing CFA/SEM as the main analytical approach. These include, for convergent validity, fit indexes over 0.90, item loadings over 0.707 and item residuals smaller than 2.56; for discriminant validity, fit indexes over 0.90, insignificant χ^2 as well as significant t-values for item loadings; and composite reliability over 0.70. In addition, Edwards (2003) noted that a direct approach to testing discriminant validity involves assessing whether the correlations between latent factors are statistically different than one.

Appendix B.8 shows all the indicator loadings, standard errors, t-values, and standardized loadings. In all cases, the loadings were above the 0.707 threshold indicated by Straub et al (2004) and there were no item residuals larger or close to 2.56. In addition, as noted above, all fit indexes were over 0.90 (CFI = 0.957, TLI = 0.949). The same appendix shows that all loadings were significantly different from zero, as evidenced by their t-values (the smallest t-value was 7.087 for CSTSE4). The χ^2 statistic was, however, still significant; on the other hand, this statistic is sensitive to large sample sizes and models with large numbers of indicators (Bearden, Sharma, & Teel, 1982; Segars, 1997).

In addition, discriminant validity for all the constructs tested in this research was established by sequentially constraining the correlations between pairs of constructs to equal unity, and performing a chi-square difference test (with one degree of freedom) to establish whether perfect correlations between constructs resulted in a significant decrease in the fit of the overall model to the data. These

results are shown in Table 4.6. In all cases fit became significantly worse when the model was thus constrained.

Table 4.6 – Tests of Discriminant Validity Constraining Correlations to Unity

Model	χ^2	d.f.	$\Delta\chi^2$	d.f.	p
Base Model	751.829	318			
CSE – TSE	1396.624	317	644.795	1	< 0.0001
CSE – CSTSE	1233.024	317	481.195	1	< 0.0001
CSE – GC	1413.909	317	662.080	1	< 0.0001
CSE – PG	3527.135	317	644.795	1	< 0.0001
CSE – PERF	3535.728	317	2783.899	1	< 0.0001
TSE – CSTSE	998.971	317	247.142	1	< 0.0001
TSE – GC	1416.958	317	665.129	1	< 0.0001
TSE – PG	2882.108	317	2130.279	1	< 0.0001
TSE – PERF	2905.334	317	2153.505	1	< 0.0001
CSTSE – GC	1422.449	317	670.620	1	< 0.0001
CSTSE – PG	1921.107	317	1169.278	1	< 0.0001
CSTSE – PERF	1936.535	317	1184.706	1	< 0.0001
GC – PG	1438.779	317	686.950	1	< 0.0001
GC – PERF	1441.755	317	689.926	1	< 0.0001
PG – PERF	1849.623	317	1097.794	1	< 0.0001

The reliability of each multi-item measure was estimated using the composite reliability statistic (Werts, Linn, & Jöreskog, 1974), where λ_i, F, and θ_{ii}, are the factor loading, factor variance, and unique/error variance respectively:

$$\rho_c = \frac{\left(\sum \lambda_i\right)^2 * Var(F)}{\left(\sum \lambda_i\right)^2 * Var(F) + \sum \theta_{ii}} = \frac{\left(\sum \lambda_i\right)^2}{\left(\sum \lambda_i\right)^2 + \sum (1-\lambda_i^2)}$$

When using unit scaling procedures, the loadings for each item are shown in Appendix B.8, the factor variance is set at 1, and θ_{ii} is 1 minus the square of λ_i,. The resulting composite reliabilities were quite high for all multi-item factors: 0.963 for

Computer Self-Efficacy, 0.956 for Task Self-Efficacy, 0.963 for Computer-Supported Task Self-Efficacy, and 0.915 for Goal Commitment.

Next, correlations between variables were converted, where appropriate as shown in the research model in Figure 3.1, into regression paths in order to test the hypotheses set forth in the previous chapter. Figure 4.1 shows the results of these tests.

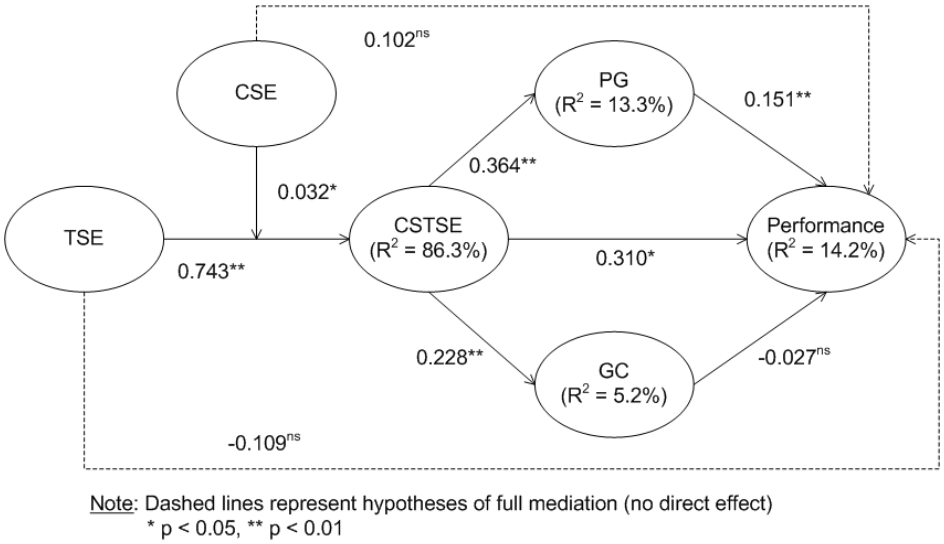


Figure 4.1 – Results from SEM Analysis

All but one of the direct effect hypotheses were supported by the results of the structural equation test of the model, shown above. Hypothesis one predicted a direct effect of CSTSE on Performance, which was supported by the data (b = 0.310, p < 0.05), as well as hypothesis two, with an expected effect of TSE on CSTSE (b = 0.743, p < 0.01). Hypotheses four and five were supported as well, with significant effects from CSTSE to Personal Goals (b = 0.364, p < 0.01) and Goal Commitment (b = 0.228, p < 0.01), respectively. Whereas hypothesis six, which posited a direct effect

from Personal Goals to Performance, was supported ($b = 0.151$, $p < 0.01$), hypothesis seven was not. The path from Goal Commitment to Performance was not found to be significantly different from zero ($b = -0.027$, $p > 0.10$).

Hypotheses three and nine proposed the full mediation of the effects of TSE and CSE, respectively, on Performance through CSTSE. In both cases the direct paths were not significant ($b = -0.109$, $p > 0.10$ for the path from TSE to Performance; and $b = 0.102$, $p > 0.10$ for the path from CSE to Performance). However, in addition to showing non-significant direct effects from the posited distal predictors to the dependent variable, the analysis of mediation requires the presence of a significant indirect effect, otherwise there would be no effect to be mediated in the first place. In both cases, the confidence intervals that resulted form the bootstrapping process described above did not contain zero, providing evidence of the presence of a significant indirect effect from both CSE to Performance ($b = 0.065$) and from TSE to Performance ($b = 0.230$).

Finally, hypothesis eight proposed the presence of a moderating relationship by CSE on the path from TSE to CSTSE. The analysis conducted with LMS (Klein and Moosbrugger, 2000) shows a significant moderating effect ($b = 0.032$, $p < 0.05$; the direct effect of CSE on CSTSE was also significant, $b = 0.209$, $p < 0.01$).

5. STUDY II DESCRIPTION AND RESULTS

Research Setting Description

Consistent with the descriptions of the different task types developed in Chapter 3, this second study sought to operationalize the research model in the context of a task type II, that is, "*those tasks where the introduction of information systems both increased the efficiency with which the task could be implemented as well as qualitatively improved the output of the task, but in a rather incremental, even if significant, manner. One example of this category are Decision Support Systems".*

Task. The task employed in this study was adopted from Lilien, Rangaswamy, van Bruggen and Starke (2004). In particular, the ABB Electric case was used. This is one of two decision scenarios, and accompanying Decision Support Systems, developed by the authors in order to investigate the differential effects of the use of DSS technology on objective and subjective outcomes: project- and performance-based. The decision scenario involves the allocation of a supplementary marketing budget to a reduced set of twenty customers to be recommended by participants in the study. While decisions such as these have been made in organizations prior to the introduction of information technology, the introduction of support capabilities embodied in DSS was intended to improve the effectiveness of decision-making and, as result, the outcome of the decision, even if results in this regard have sometimes been equivocal (Barr & Sharda, 1997; Sharda et al., 1988);

however, see Lilien et al (2004) for a more recent conceptualization of the effects of DSS use on objective and subjective process and performance outcomes. One attractive feature of the task used here, from the perspective of external validity, is that it is based on a real situation faced by ABB Electric in the past, and the outcome and context of the decision matches the one actually faced by decision makers, as reported in Gensch (1984; Gensch, Aversa, & Moore, 1990).

In this research, participants were provided with the results of a customer survey where each one of four possible suppliers (including ABB) was rated on several dimensions, such as invoice price, technical specifications of the products offered, availability of spare parts, etc., as well as information about from which of the four suppliers each customer had last purchased, and the expected purchase volume (in dollars) for the coming year. In addition, participants had access to a decision model (based on a multinomial logit analysis of purchase probabilities) that estimated the probability, for each supplier, that the customer would purchase from them in the coming year.

All subjects were informed that the company had traditionally targeted their largest customers with special marketing campaigns, but the consulting company that developed the probability model had introduced the concept of "switchability", where it would be most rewarding to especially target those customers where ABB was a narrow first choice or a close second, and pay less attention to those customers that had either very high or very low probability of purchasing from ABB. A

comprehensive description of the scenario and supplemental materials is include in Lilien et al (2004).

The complete set of materials used in this study is included in Appendix C.1 (the ABB Electric case description), Appendix C.2 (description of the decision model), Appendix C.3 (screenshot of the survey results), and Appendix C.4 (screenshot of the decision model).

Sample and Procedures. Data were collected from a sample of undergraduate students enrolled in a required introductory Information Systems course, a prerequisite for admission to the School of Business. Performance of the task was optional and outside of regular class hours, and students received extra credit towards their grade in that course. Students willing to participate were provided with the case and decision model descriptions shown in Appendixes C.1 and C.2, as well as a spreadsheet that delivered the results of the customer survey, allowed (but not mandated) the use of the decision model, and recorded the results.

While students could complete the task in a time and setting of their own choosing, they were asked to complete the assignment in a single sitting. Hidden code was included in the spreadsheet to verify this was indeed the case. No violations of these guidelines were detected. As noted above, these materials were adapted from Lilien et al (2004), whereas the algorithm used in the decision model, as well its implementation in a spreadsheet, were adapted from Gensch (1984; 1990) and Lilien and Rangaswamy (1998), respectively.

Measures. Measures for all six constructs included in the research model in Figure 3.1 (i.e., computer self-efficacy, task self-efficacy, computer-supported task self-efficacy, personal goals, goal commitment, and performance) were operationalized as follows. In contrast to Study I, where a measure of computer self-efficacy (in particular, spreadsheet self-efficacy) was readily available from earlier research by Johnson and Marakas (2000), all three self-efficacy measures used in this second study were developed specifically for this research, following the guidelines included in Table 4.1 and associated discussion. The same measures for personal goals and goal commitment used in the first study were employed here; in the particular case of personal goals, this was operationalized with a single item expressed in terms consistent with the task at hand (e.g., "what is your personal goal in terms of the percent increase in sales that you want to achieve") – items for all measures are included as Appendix C.5.

Performance was operationalized according to the following. In the original reporting of the scenario faced by ABB Electric (Gensch et al., 1990) the decision model employed in this research was used to segment the population of customers into four different groups, based on significant differences in the probabilities of future purchase by each customer from each of the four suppliers. In this light, customers were categorized as *brand loyal*, where ABB had the highest estimated purchase probability, and this probability was significantly higher (at an alpha level of 0.05) than the one for the next supplier; *competitive*, where ABB Electric had the highest future purchase probability, but not significantly higher than that for the next

supplier; *switchable*, where ABB Electric was a close (i.e., not significantly different) second; and finally *competitor's brand loyal*, where the estimated probability of future purchase from any other supplier was significantly higher than that for ABB Electric.

Concentrating on either *brand loyal* or *competitor's brand loyal* customers yielded little to none market share gains, while focusing on *competitive* or *switchable* customers resulted in important and positive changes in sales, while overall industry sales exhibited an overall downward trend. At the same time, a sales district that approached the issue using a strategy of focusing on their largest customers (by sales volume) displayed a ten percent decline in year-over-year sales. This provided a natural control and further evidence of the applicability of the approach provided by the consultants (Gensch et al., 1990). In their implementation of this scenario, Lilien et al (2004) calculated incremental sales (the performance measure) using the following approach: zero if the chosen customers was not classified as either switchable or competitive, and otherwise equal to *adjustment factor * ((1 – P(Buying from ABB)) * max sales potential*, where *P(Buying from ABB)* was the estimated purchase probability as calculated by the multinomial logit model described above, *max sales potential* was the amount of budgeted future purchases for each customer, and *adjustment factor* was a multiplier (0.40) estimated so that the overall sales increase arising from switchable and competitive customers would match the actual outcome realized by ABB Electric. The same approach was employed here.

Data Collection. Data for this study was collected in a manner similar to that of Study I, using a spreadsheet specifically developed for this purpose. Collection procedures differed from those of the prior study on only two accounts. First, after having collected data for all the measures of interest, subjects were presented with the results of the customer satisfaction survey alluded to above (see Appendix C.3 for a screenshot) as well as a worksheet where their recommendations about which customers to target could be noted. Second, as shown in Appendix C.3, the survey also included a button allowing participants to input the results of the survey into the decision model; all participants chose to do so. After pressing this button, the outcomes of the decision model were shown (see Appendix C.4); at this stage, subjects participating in this research could see three different worksheets: the customer satisfaction survey, the decision models, and the answer worksheet for noting their recommendations.

In addition, as a check on the usage of the model, the latter contained a question asking participants to note which option best described their use of the DSS that was provided, from the following: "I did not run the model", "I ran the model but did not use the results in my answer", "I ran the model and used the results to inform my answer", and "I ran the model and extensively relied on the results to inform my answer". All participants selected one of the latter two alternatives. While the spreadsheet recorded the pressing of the button (i.e., the model was run), this provides additional evidence to the fact that not only subjects run the decision model provided but used the results in the formulation of their recommendation. Finally, every time

the spreadsheet was saved the time was recorded and thus the last saved time corresponds to closing the spreadsheet before uploading their results. This was used to verify that all participants had completed the task in one setting and within a reasonable timeframe (e.g., that they had not left and return later to finish the assignment).

Statistical Analysis Approach. The analysis of the data collected was performed in a manner identical to the one used for Study I.

Sample

Undergraduate students enrolled in multiple sections of an introductory course in Information Systems participated in this exercise in exchange for extra credit towards their course grade. The average time taken to complete the task was thirty seven minutes. Only those responses that contained a complete exercise (e.g., those where participants had selected a set of customers and thus the performance measure could be calculated) and showing no evidence of having been completed on more than a reasonable amount of time were retained in the analysis; two hundred and ninety nine is the final usable sample. Table 5.1 shows the characteristics of the sample.

Table 5.1 Sample Descriptive Statistics

Characteristic	*Number of Participants*	*Percentage of Participants*
Gender		
Male	181	61%
Female	118	39%
Age		
18-20 years old	235	79%
21-23 years old	59	20%
24-26 years old	5	2%
Student Status		
Freshmen	4	1%
Sophomore	208	70%
Junior	66	22%
Senior	21	7%

Results

Preliminary examination of the data revealed a similar pattern regarding the loadings of the items for the Goal Commitment measure as had been the case in the first study, although the fit was very good nonetheless. Table 5.2 shows a standalone analysis of all the items in this measure, using a single factor model. Results show that, while the fit was excellent, the pattern of loadings indicates only three items (the positively worded ones, GC5, GC7 and GC8) loaded highly on the intended construct.

Table 5.2 – One-Factor Goal Commitment CFA

Indicator	*Loading*	*S.E.*	*T-Value*	*Std. Loading*
GC1*	0.188	0.074	2.544	0.153
GC2*	0.299	0.078	3.838	0.229
GC3*	0.076	0.079	0.953	0.058
GC4*	0.337	0.078	4.303	0.256
GC5	1.208	0.065	18.708	0.881
GC6*	0.202	0.070	2.894	0.174
GC7	1.300	0.067	19.494	0.905
GC8	1.141	0.066	17.314	0.836
GC9*	0.173	0.073	2.366	0.142
* Items that were negatively worded and reverse coded for the analysis				
Fit indexes: $\chi^2_{(27)} = 29.039$ (*p* ns), CFI = 0.997, TLI = 0.996, RMSEA = 0.016.				

Next, Table 5.3 shows the analysis of the same items loading this time on two separate but correlated factors, based on the positive or negative wording of the items. While the two factors were highly correlated, only the positively worded items loaded at acceptable levels on their factor. The negatively worded items, on the other hand, were inconsistent in the magnitude and significance of their loadings. Taken together, these results replicate findings from Study I in this respect. Given this pattern of loadings, and to ensure the comparability of both studies, only the three positively worded items in the measure were used in the overall research model as indicators of the construct of Goal Commitment.

Table 5.3 – Two-Factor Goal Commitment CFA

Indicator	*Loading*	*S.E.*	*T-Value*	*Std. Loading*
Positively Worded Items				
GC5	1.209	0.065	18.722	0.882
GC7	1.300	0.067	19.473	0.904
GC8	1.141	0.066	17.323	0.837
Negatively Worded Items				
GC1	0.217	0.092	2.367	0.177
GC2	0.362	0.104	3.481	0.278
GC3	0.083	0.094	0.884	0.064
GC4	0.403	0.108	3.733	0.306
GC6	0.275	0.090	3.068	0.237
GC9	0.190	0.090	2.112	0.156
The two factors were correlated at 0.818 ($p < 0.001$).				
Fit indexes: $\chi^2_{(26)} = 28.219$ (p ns), CFI = 0.997, TLI = 0.995, RMSEA = 0.017.				

The measurement model showed excellent fit to the data, as evidenced by fit indices (RMSEA = 0.030, CFI = 0.990, TLI = 0.988), although the chi-square ($\chi^2_{(286)} = 360.476$, $p < 0.05$) was significant. Table 5.4 next shows the correlations amongst latent variables.

Table 5.4 Correlations amongst Latent Variables (Measurement Model)

	CSE	**TSE**	**CSTSE**	**GC**	**PG**	**Performance**
CSE	1.000					
TSE	0.671	1.000				
CSTSE	0.739	0.856	1.000			
GC	0.359	0.402	0.450	1.000		
PG	0.429	0.424	0.501	0.404	1.000	
Performance	0.446	0.456	0.529	0.428	0.440	1.000

Appendix C.6 shows all the indicator loadings, standard errors, t-values, and standardized loadings. In all cases, the loadings were above the 0.707 threshold and there were no item residuals larger or close to 2.56. In addition, as noted above, all fit indexes were over 0.90 (CFI = 0.990, TLI = 0.988). The same appendix shows that all loadings were significantly different from zero, as evidenced by their t-values. In addition, discriminant validity for all the constructs tested in this research was

established by sequentially constraining the correlations between pairs of constructs to equal unity, and performing a chi-square difference test (with one degree of freedom) to establish whether perfect correlations between constructs resulted in a significant decrease in the fit of the overall model to the data. These results are shown in Table 5.5. In all cases fit became significantly worse when the model was thus constrained.

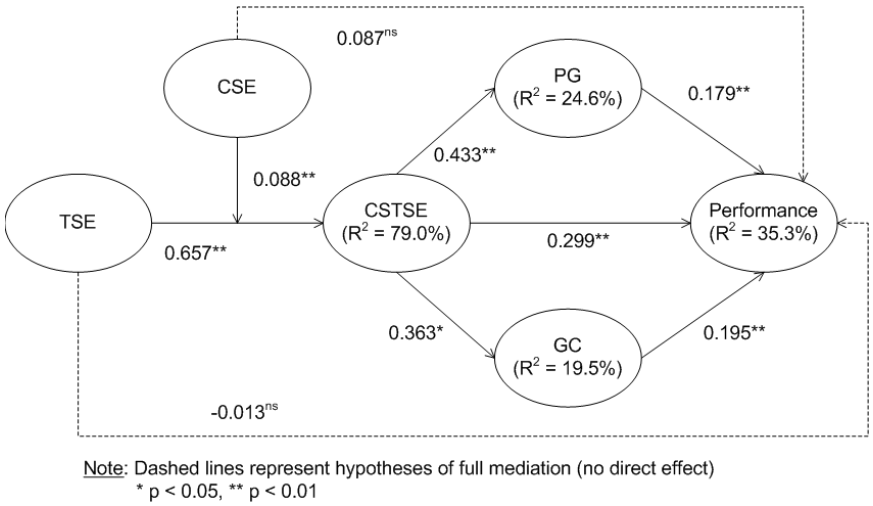
Table 5.5 – Tests of Discriminant Validity Constraining Correlations to Unity

Model	χ^2	d.f.	$\Delta\chi^2$	d.f.	*p*
Base Model	360.476	286			
CSE – TSE	1099.810	287	739.334	1	< 0.0001
CSE – CSTSE	1122.767	287	762.291	1	< 0.0001
CSE – GC	892.547	287	532.071	1	< 0.0001
CSE – PG	1829.256	287	1468.780	1	< 0.0001
CSE – PERF	1808.143	287	1447.667	1	< 0.0001
TSE – CSTSE	734.981	287	374.505	1	< 0.0001
TSE – GC	876.967	287	516.491	1	< 0.0001
TSE – PG	1660.663	287	1300.187	1	< 0.0001
TSE – PERF	1632.385	287	1271.909	1	< 0.0001
CSTSE – GC	860.539	287	500.063	1	< 0.0001
CSTSE – PG	2462.947	287	2102.471	1	< 0.0001
CSTSE – PERF	2414.228	287	2053.752	1	< 0.0001
GC – PG	883.302	287	522.826	1	< 0.0001
GC – PERF	873.591	287	513.115	1	< 0.0001
PG - PERF	1254.304	287	893.828	1	< 0.0001

The reliability of each multi-item measure was estimated using the composite reliability statistic (Werts et al., 1974), resulting in high reliabilities for all multi-item factors: 0.936 for Computer Self-Efficacy, 0.930 for Task Self-Efficacy, 0.974 for Computer-Supported Task Self-Efficacy, and 0.907 for Goal Commitment.

Next, correlations between variables were converted, where appropriate as shown in the research model in Figure 3.1, into regression paths in order to test the

hypotheses set forth in the previous chapter. Figure 5.1 shows the results of these tests.



Note: Dashed lines represent hypotheses of full mediation (no direct effect)
* p < 0.05, ** p < 0.01

Figure 5.1 – Results from SEM Analysis

All direct effect hypotheses were supported from the results of the model shown in Figure 5.1 above. Hypothesis one argued for a direct and positive effect of Computer-Supported Task Self-Efficacy (CSTSE) on Performance, and was supported by the data collected in this study (b = 0.299, p < 0.01). The same conclusion can be reached in terms of hypothesis two, which predicted a positive effect of Task Self-Efficacy (TSE) on CSTSE (b = 0.657, p < 0.01). Hypotheses four and five were also supported, with significant effects from CSTSE on Personal Goals (PG; b = 0.433, p < 0.01) and on Goal Commitment (GC; b = 0.363, p < 0.05). Next, hypotheses six and seven, which posited effects of PG and GC on Performance, respectively, were also supported by the data (b = 0.179, p > 0.01 for the path from PG to Performance; b = 0.195, p < 0.01 for the path from GC to Performance).

Hypotheses three and nine put forward arguments for the full mediation of the direct effects of Computer Self-Efficacy (CSE) and TSE on performance, respectively, by the intervening construct CSTSE. As shown in Figure 5.1, the direct paths from both CSE ($b = 0.087$, $p > 0.10$) and TSE ($b = -0.013$, $p > 0.10$) were not significant. In addition, indirect effects on Performance through CSTSE were estimated for both distal constructs, and their statistical significance assessed using confidence intervals built by bias-corrected bootstrapping. Both indirect effects were positive ($b = 0.196$ for the indirect effect of TSE, and $b = 0.089$ for the indirect effect of CSE) and significantly different from zero, as evidenced by the confidence intervals not containing the latter. These results lend support to both hypotheses.

Hypothesis eight argued for the existence of a moderating effect of CSE on the relationship between TSE and CSTSE, and was supported in Study I. As well, results from this study also provide positive evidence for this hypothesis, obtained from the LMS procedure (A. Klein & Moosbrugger, 2000) implemented in the MPlus (Muthén & Muthén, 2004) statistical software. The analysis shows a significant moderating effect ($b = 0.132$, $p < 0.01$; the direct effect of CSE on CSTSE was also significant, $b = 0.298$, $p < 0.01$). Finally, having collected data from two different tasks along the continuum described in Chapter 3 allows for a first testing of hypothesis ten, which stated that the strength of CSE as a moderator of the relationship between TSE and CSTSE would increase as the role of technology in the effectiveness of the task increased. This test can be performed using a parametric approach as in the following formulas:

$$se_p = s_p\sqrt{\frac{1}{m}+\frac{1}{n}}\ ,\ s_p = \sqrt{\frac{(m-1)s_1^2+(n-1)s_2^2}{(m+n-2)}}\ ,\ se_x = \frac{s_x}{\sqrt{n}} \text{ and } t_{m+n-2} = \frac{(b_1-b_2)}{se_p}$$

The use of unstandardized regression coefficients is required since the standard errors produced by statistical software packages refer to these and not to the standardized path coefficients, which on the other hand are the ones generally reported in research models such as those presented in Figures 4.1 and 5.1 The ratio shown in the formula is distributed as a *t* with *m+n-2* degrees of freedom. Replacing in the third formula it is possible to obtain the standard deviations for each coefficient from the sample size in each study and the standard error reported by the analysis; for Study I, the standard deviation is 0.863 (0.048 * 17.97, the first being the standard error of the regression coefficient and the second the square root of the sample size); accordingly, for Study II, the standard deviation is 1.072 (0.062 * 17.29). Replacing into the second formula, it is possible to obtain the pooled standard deviation:

$$s_p = \sqrt{\frac{(323-1)0.863^2+(299-1)1.072^2}{(323+299-2)}} = 0.969$$

Feeding the pooled standard deviation into the first formula presented above, the pooled standard error equals 0.078. Finally, the *t* ratio, with 620 (323 + 299 – 2) degrees of freedom is – 2.546, indicating that the first regression coefficient (from Study I) is significantly smaller than the second coefficient (from Study II). However, the two standard deviations obtained before are not equal or close to each other, which may indicate that the homogeneity of variance assumption underlying the parametric test just performed may not be tenable. An alternative is to employ the

approximation to the pooled standard error due to Satterthwaite, which does not assume equal variances:

$$se_s = \sqrt{\frac{s_1^2}{m} + \frac{s_2^2}{n}} = \sqrt{\frac{0.863^2}{323} + \frac{1.072^2}{299}} = 0.0784$$

The *t* ratio calculated using the difference between regression coefficients and this alternative estimation of the pooled standard error yields – 2.525, which also supports the expectations set forth in hypothesis ten.

6. DISCUSSION, LIMITATIONS AND CONCLUSION

Summary and Interpretation of Results

The research model depicted in Figure 3.1 above and associated hypotheses were tested using the data collected in Studies I and II. Given that the results obtained from both studies are largely parallel, these will be discussed together for each hypothesis, and any differences noted where appropriate.

Hypothesis one argued that computer-supported task self-efficacy would have a positive and significant impact on performance in a computer-supported task. Data from both studies provided support for this hypothesis. In each case, study participants showing higher levels of computer-supported task self-efficacy performed better in the specific task than those participants showing lower levels of the construct. The effects of computer-supported task self-efficacy on task performance were positive and significant, even in the presence of other constructs known to affect performance, such as personal goals and goal commitment (see the discussion on hypotheses six and seven below).

Hypothesis two proposed a direct and positive effect of task self-efficacy on computer-supported task self-efficacy. This relationship was predicated on the conceptualization of self-efficacy beliefs, due to Bandura (1997) and Eden (2001), as a continuum ranging from more general to more specific levels. Accordingly, whereas computer-supported task self-efficacy is defined at a detailed level, i.e., referring to a specific task and under a specific set of conditions, task self-efficacy is

conceptualized at a an intermediate level of generality, referring only to the task of interest but not to the particular context in which the task is performed, in this case with the support of technology. The analysis of the data collected in the two studies supported this hypothesis: those subjects with higher efficacy beliefs, measured at the task level, had higher expectations for performance of the same task, when measured at the more specific level that included awareness of using technology to support their work.

The third hypothesis put forth in Chapter 3 argued that any effects of task self-efficacy on performance would be fully mediated by the intervening construct of computer-supported task self-efficacy. Arguments for this proposed relationship were derived from the notion that more specific assessments of capability – that is, self-efficacy beliefs – should mediate any effects more general ones may have on actual task performance (Chen et al., 2001). This line of reasoning is also consistent with theories of motivation noting that more distal and stable traits influence action not directly but through their effect on intervening, more fluent and state-like dispositions (Kanfer, 1991; Kanfer & Heggestad, 1997), such as computer-supported task self-efficacy. The statistical analyses of both direct and indirect effects of task self-efficacy on performance provided support for this hypothesis; whereas the results indicate the existence of a significant and positive indirect effect of task self-efficacy on task performance, this relationship is fully mediated by the more specific perception of the self, computer-supported task self-efficacy.

Hypothesis four and five posited direct and positive effects of computer-supported task self-efficacy on personal goals and goal commitment, respectively. Both of these relationships were supported by the data collected for this dissertation. Higher levels of computer-supported self-efficacy were associated with higher levels of both personal goals and goal commitment beyond reasonable chance. Thus, those individuals who had higher expectations of themselves related to the performance of the focal task with the support of information technology set higher goals for the exercise and were also more committed to achieving them. These results are consistent with past research on the nomological net of self-efficacy beliefs, and as a result serve to validate the appropriateness of the newly developed measures for this construct in both studies.

Hypotheses six and seven referred to the effects of these two constructs, personal goals and goal commitment, respectively, on task performance. These were included in the research model in an effort to better understand the relative contribution of computer-supported task self-efficacy to task performance, over and above that of other influences known from the extant literature on the area. Given that hypothesis seven was not supported in the first study, these two propositions will be discussed separately.

The first of these two hypotheses, number six, stated that personal goals would have a positive direct effect on task performance; that is, individuals that set higher goals for themselves performed better than those that set lower goals for the upcoming task. Analyses from both studies supported this assertion.

Hypotheses seven, on the other hand, was only supported in the second study, involving the use of decision support technology on a marketing resource allocation scenario. Recall that this hypothesis proposed that those individuals that were more committed to achieving the goals they had set for themselves performed better in the task than those that were less committed to achieving those goals. This relationship was not supported by the data collected in conjunction with the first study – where participants prepared a budget with the help of spreadsheet software. This represents the only hypothesis that was not supported in the research reported here.

Hypothesis eight, discussed next, is one of the most important contributions this research set forth to achieve. In this hypothesis, the position of the computer self-efficacy construct versus task self-efficacy and computer-supported task self-efficacy is challenged. While previous research had posited a direct relationship between computer self-efficacy and computer-supported task self-efficacy (Looney et al., 2006), the theoretical arguments discussed on Chapter 3 lead to the proposition of an interactive relationship between computer and task self-efficacy, with respect to their joint effect on computer-supported task self-efficacy. Support for the moderating effect of computer self-efficacy was found on both studies. These results add an additional level of complexity to the tripartite relationship between the task, computer, and computer-supported task self-efficacy constructs than would arise from our current understanding of this research stream.

Hence, given the positive moderating effect of computer self-efficacy on this relationship, those individuals with high levels of both computer and task self-

efficacy jointly would achieve the highest levels of computer-supported task self-efficacy, and thus these two more distal constructs reciprocally enhance their effects on the beliefs of efficacy measured at the more specific levels. This is in contrast with the positive, but independent effects of computer and task self-efficacy on the intervening efficacy construct as shown in the current literature (Looney et al., 2006). Notably, the magnitude of the interactive effect was larger for the participants in the second study than in the first; this has important implications for the testing of the arguments set forth in hypothesis ten, as discussed later.

Hypothesis nine paralleled hypothesis three by proposing the full mediation of the direct effect of computer self-efficacy on task performance by the intervening construct of computer-supported task self-efficacy. This was also based on arguments by Bandura (1997) theorizing that when multiple self-efficacies come into play in predicting performance, it is expected that the more specific and proximal type would account for the direct effects on the dependent variable, in this case task performance. Results from both studies supported this position; in neither case did computer self-efficacy have significant effects on task performance beyond those accounted for by the mediating variable. Computer self-efficacy did, however, exhibit significant indirect effects on task-performance flowing through its effect on computer-supported task self-efficacy, in line with the statistical requirements for supporting the presence of a mediating role of one variable on the effects of another more distal predictor on a dependent variable of interest.

Finally, hypothesis ten stated that the strength of computer self-efficacy as a moderator of the relationship between task self-efficacy and computer-supported task self-efficacy would increase as the role of technology on the effectiveness of the task increased. In order to test this hypothesis at least two tasks where the use of technology would be argued to have differential impacts with regards to task effectiveness were required. To this end, two studies were conducted.

In the first one, participants employed spreadsheet technology to complete a financial budget task, which included various activities such as inputting missing values, assigning revenues and expenses to the appropriate time periods, calculating variances between budgeted and actual revenues and expenses, etc. This task was deemed to be representative of those included in the continuum shown in Figure 3. 2 under the label of 'Type I Tasks', e.g., those "*where the introduction of computer technologies into task performance did not significantly affect the outcome or effectiveness of the task, but rather made its execution more efficient, in terms of processing time, process automation, etc.*"

For the second study a marketing resource allocation task was chosen. In this scenario, participants played the role of a marketing manager charged with allocating a supplementary promotional budget to a subset of twenty customers, chosen freely by the subjects, that would make the most out of the limited resources available, expressed in terms of increased sales. The technology employed in this study was a Decision Support System, in particular a multinomial logit model which estimated the probabilities of future purchase based on past purchases and results from a customer

survey, that participants could use to help them in making their recommendation. Consistent with past research on DSS (Lilien et al., 2004; Sharda et al., 1988) which supports the effects of these technologies on decision effectiveness, this task was deemed representative of those labeled 'Type II Tasks' in Figure 3.2, that is, those tasks "*where the introduction of information systems both increased the efficiency with which the task could be implemented as well as qualitatively improved the output of the task, but in a rather incremental, even if significant, manner*".

Testing of hypothesis ten, then, entailed a comparison of the two moderating effects, represented by hypothesis eight, obtained from each of the two studies. The expectation in line with the hypothesis was that the moderating effect for the second study would be significantly larger in magnitude than that for the first one. Support was found for this assertion from a parametric test of the difference between the two unstandardized path coefficients, regardless of whether equality of variances was assumed or not. This result provide some degree of validation, albeit preliminary, to the other novel contribution of this research, namely that the nature of the task affects the magnitude of the tripartite relationship among task, computer, and computer-supported task self-efficacy constructs, even though it is argued that its structure remains the same. This finding highlights the importance, also suggested by authors in various lines of research (Goodhue & Thompson, 1995; Zigurs & Buckland, 1998), of considering the focal task of interest in conducting research on individual performance in technology-using contexts.

Integration with Past Research

The research reported here builds on and extends the basic model developed by Looney et al (2006), shown earlier in Figure 2.8, albeit with similarities and differences. On the first count, both models propose the existence of a joint self-efficacy, which combines and integrates the effects of computer and task self-efficacy constructs on more distal variables of interest, although based on different theoretical arguments. While Looney et al (2006) relied on the notion of encapsulation and domain overlap between technology and task, this research builds on Bandura's (1997) conceptualization of self-efficacy at diverse levels of generality, which has received empirical support in other literatures.

Both models also propose direct effects of task and computer self-efficacy on the intervening self-efficacy variable; the two studies conducted here, however, go beyond linear relationships and propose the existence of a moderating effect of computer self-efficacy on the relationship between task self-efficacy and computer-supported self-efficacy, and the two studies empirically support this contention. Also in both cases an argument is put forth about the full mediation by the intervening self-efficacy of the effects of computer and task self-efficacy on the ultimate dependent variables (see Model 4 in p. 229 of Looney et al, 2006; the authors called this "*full moderation*" [p. 230] but they most likely meant *full mediation*, which is consistent with their research model). Looney et al (2006), however, concluded for the presence of full mediation based on the insignificant direct effects of computer and task self-efficacy in the presence of the intervening variable, but went no further to confirm the

existence of an indirect effect to be moderated, as was done here in Chapters 4 and 5 – this constitutes an important methodological improvement over their previous research.

Finally, while Looney et al (2006) grounded the effects of their individual and joint self-efficacies on outcome expectations (both personal- and performance-based), the research reported here collected performance data as well as measured other known determinants of performance to better ascertain the incremental effects of computer-supported task self-efficacy on performance, which results in a more comprehensive test of the underlying theory than relying solely on expectations.

In addition to the theoretical and methodological extensions to past research described above, the nature of the task, and how this affects the strength of a key relationship in the model, the moderating effect of computer self-efficacy, was considered. To a large extent, past research on computer self-efficacy has not considered the study context beyond highlighting the need for computer self-efficacy measures to reflect the features of the underlying technologies (Marakas et al., 1998). Moreover, the measuring tradition that follows the early work of Compeau and Higgins (1995a, 1995b) does not even consider the focal technology and instead focuses on the possibility of accomplishing a nondescript task under various levels of external support. Given the maturity of research in self-efficacy in general, and computer self-efficacy in particular, awareness of task and technology contexts appears to be a natural extension of this literature into considering more detailed and complex models that may give rise to more targeted interventions and a better

understanding of the underlying relationships. This research attempts to provide a first step in that direction.

Contribution and Implications

Contributions to Social Cognitive Theory

This research has at least two important implications for the Social Cognitive Theory literature. First, it joins a small but growing cadre of research (Chen et al., 2001; Chen et al., 2000; Chen et al., 2002; Eden, 2001; Tierney & Farmer, 2002) that considers beliefs of efficacy simultaneously in either multiple domains or at different levels of generality, and thus provides a richer picture of the different generative forces at work underlying human action and performance.

Conducting this type of studies allows researchers to focus on the diffusion of efficacy beliefs about a particular domain into the specific contexts in which actions are performed, by considering levels of self-efficacy generality, or on the confluence of efficacies from multiple domains, several of which may simultaneously play a role in shaping thought and action, by including self-efficacy concepts from different domains of functioning. The research reported here contains elements of both.

Second, this research sheds some light on so-called "process" self-efficacy beliefs (Mone, 1994; Stotland & Zuroff, 1991), which have received little attention from mainstream self-efficacy research. Process self-efficacies, as opposed to outcome-oriented beliefs, are those that assess ca-capacity to perform subfunctions that lead to obtaining a certain performance, working through their effects on a

mediating operative self-efficacy, but not directly affecting performance. Considered in the broader context of computer-supported tasks, computer self-efficacy beliefs can be conceptualized under the umbrella of process efficacies, to the extent that their importance lies in mastery of a subfunction (the technology) that is relevant to obtaining a certain performance, but in a supporting role.

Whereas most researchers have focused on operative, or outcome-oriented self-efficacy beliefs, the inclusion of process-oriented beliefs will likely contribute to a better understanding of the mechanisms by which self-efficacy affects performance. While it cannot necessarily be expected that the structural relationship developed for computer self-efficacy and tested here will replicate for other process-oriented efficacy beliefs in different domains, it does provide a starting point to theorize about the relationship of these with other more focused, task-specific, beliefs of capability.

Contributions to the Computer Self-Efficacy Literature

This research contributes to the literature on computer self-efficacy by repositioning the construct into a broader nomological network that includes a more interesting dependent variable (task performance, as opposed to computer performance), better delineating its relationship versus other determinants of performance, as well as putting into evidence that tasks carried forward with the support of computer technology are not devoid of content. This represents a significant shift of attention from mainstream research involving this construct, which

has largely focused on more narrow conceptualizations of task and, by necessity, performance.

In addition, it proposes a new structural role for computer self-efficacy not only taking into account its direct effects, but also as part of an interactive relationship with perceptions of capability about performing a certain task, where high levels of both would be required to successfully perform such task with the support or through the use of information technology.

While the positioning of computer self-efficacy one degree of separation further away from performance could be interpreted as taking a more limited view of the importance of this construct for the latter, this research in fact provides a more detailed view of the mechanisms by which computer self-efficacy relates to computer-supported task performance, and thus provides additional support for the relevance of better understanding this important construct. Before this link was established, a number of researchers had shown that computer self-efficacy was related to performance in computer tasks, but the conduits by which it related to a more comprehensive view of 'task' had not been made evident. This research, while likely not definitive, provides a first glimpse into this relationship.

Contributions to the Training Literature

While the studies conducted here are not directly related to the training literature, nor deal with interventions or manipulation of the computer self-efficacy construct, they may prove nonetheless valuable for this stream of research by

providing a much needed connection between studies designed to foster perceptions of capability about using computer technology (Johnson & Marakas, 2000; Yi & Davis, 2003) and the effects of those undertakings on the ultimate dependent variable of interest, which is not performance in computer-only tasks, but on improving individual ability to perform a task which requires, among other things, proficiency in operating and understanding computer technology.

Sein, Bostrom and Olfman (1998) discussed the existence of six distinct and hierarchical levels of software knowledge, based on earlier work by Ye (1991), that advance the concept of knowledge beyond that about the tool, and into more sophisticated cognitive functions; these are, from lowest to highest: syntax (about the commands), semantics (about the meaning of those commands), task/functional (grouping commands into a task), conceptual (viewing the tool in the context of the entire system), inferential (further application of the tool in a variety of contexts), and motivational (how the tool fits with the goals of both individual and organization) [note that in this framework task refers to the grouping of commands into a discrete unit of work, such as creating a document in a word processing application, and thus has not the same meaning as has been ascribed before in this research].

The traditional training literature has stressed the first (or lowest) three levels of knowledge, whereas the context of current and future use of information technology in organizations requires that future training methods and techniques be adapted to foster an understanding that includes the conceptual, inferential, and motivational levels (Sein et al., 1998). The research conducted here provides evidence

of the interplay between computer self-efficacy and task self-efficacy that is required for performance of a task. This could provide a theoretical basis for the development of training methods, like those alluded to by Sein et al (1998), that would foster higher levels of understanding about the technology and how it fits with the organizational tasks the individual is expected to perform with it. A straightforward conclusion from these findings would be the need to incorporate interventions related to specific tasks the trainee will be performing in the future, in addition to interventions only about the specific technology, into training programs.

Limitations

The interpretation of results obtained from empirical studies should be approached by taking into consideration caveats that result from choices related to the research design, selection of study context and tasks, subjects who participated in the research, measures employed, and the statistical techniques used to analyze the data; and this research is no exception. This section discusses these issues and their effects on the interpretation of the results and contribution stated above.

Research Design and Internal Validity

Internal validity refers to whether the observed effects could have been caused by a set of either unmeasured or unhypothesized variables, or both (Straub, 1989). Given the correlational nature of the studies conducted here, which involved neither the manipulation of exogenous or intervening variables, nor random assignment of

participants, any implications of "causality", e.g., stating that the independent or intervening variable "caused" effects on the dependent variable, must be tempered. The use of more advanced statistical techniques, such as structural equation modeling, does not serve to ameliorate these problems. In these scenarios, any limited inferences about causality that one wishes to draw from the data and analyses must be supported by the strength of the theory used to derive the relationships, and past empirical research supporting the validity of that theory.

While the research conducted here, as noted above, provides evidence for some novel theoretical propositions regarding the positioning of the computer self-efficacy construct as well as the differential effects on this relationship that arise from the type of task under consideration, the basic structure of the research model shown in Figure 3.1 is heavily grounded on well supported theory, most notably Social Cognitive Theory and the work of Bandura and colleagues (Bandura, 1986b, 1997, 2006; Bandura & Jourden, 1991; Wood & Bandura, 1989b), as well as theories of goal setting (Locke & Latham, 1990, 2002), and work motivation (Eden, 1988, 2001). In addition, this research directly builds on and extends that of Looney et al (2006), which tested a model similar, albeit more circumscribed, in its structure and main relationships to the one developed in Chapter 3. To summarize, while the important threats to internal validity discussed in the preceding paragraph certainly cannot be ignored, building on accepted and validated theory does provide some assurance as to the validity of the relationships tested in this research.

A second important issue related to internal validity is that of common method variance, i.e., variance that is attributable to the measurement method rather than to the constructs the measures represent (Podsakoff, Mackenzie, Lee, & Podsakoff, 2003). Although interest in common method bias has been renewed in the organizational and psychology literature of late, other researchers have expressed doubts about both its omnipresence as well as magnitude, and thus relevance for empirical research. Spector (2006) reviewed a number of different studies whose outcomes directly contradict the assumption that common method variance is always present in empirical research; for instance, that all self-report measures are correlated.

If this were the case, then a baseline level of correlation should exist among all variables in a self-report survey, yet large sample studies indicate that in some cases correlations between self-reported items are not only non-significant, but also of a magnitude small enough to be inconsequential. Based on this and other evidence, Spector (2006) concludes the assumption that "*everything measured with the same method shares CMV* [Common Method Variance]" is an urban legend. In addition, methods alternative to self-report may be difficult to come by for measures dealing with aspects of the self that may not be easily observable by a third party; for instance, tapping into the level of self-set goals.

While attempting to resolve this controversy, if possible at all, is beyond the scope of this research, some of the prescriptions by Podsakoff, Mackenzie, Lee and Podsakoff (2003), to the extent that it was possible, were followed in this research to ameliorate any effects arising from the use of self-reported items for most of the

measures employed in this research. First, in the case of the relationship between task performance and its predictors, the measures were obtained from different methods, self-report in the case of the predictor, and either raters (for Study I where, as noted in Chapter 4, the grading was validated by an independent rater with a high degree of reliability) or formulaic calculations (for Study II, based on the actual outcome experienced by the manufacturing company on which the scenario was based).

Second, the existence of an ordering effect was tested during pilot for the task and measures employed in the first study. As mentioned in Chapter 4, the three self-efficacy measures (computer, task, and computer-supported task) were administered to a large sample of subjects from the same population of those from which data was later collected for the actual research, where the order of the three measures was varied in every possible combination, resulting in six different questionnaires. Analysis of this data revealed no ordering effects in the relationships between the three constructs.

External Validity and Generalizability

In their classic work, Campbell and Stanley (1963) distinguished between two types of validity: internal validity, as a characteristic of the experimental design, and external validity, which provides the basis for generalization of findings to other populations, settings, times, etc. The authors described internal validity as "*the basic minimum without which any experiment is virtually uninterpretable*" (p. 5); issues

related to internal validity found in the research reported here were discussed in the preceding section.

External validity was defined by Shadish, Cook and Campbell (2002) as the validity of inferences about whether the identified relationships can be maintained over other situations of interest, including variations in participants, time, context, or treatment variables. Cook and Campbell (1979) distinguished between "generalizations to" – those situations in which a random sample is obtained from a target population and thus any findings can be generalized to that population – and "generalizations across" – that is, generalizing across populations, which includes applying findings to populations, settings, etc. that were not represented in the original sample from which the data was collected. In most research situations, however, the samples are not obtained randomly from the target population and thus, strictly speaking, the findings are applicable only to that particular sample.

For the research reported here, three important limitations to generalizability of results to the population of interest – broadly defined as individuals who employ technologies in support of their work or personal activities – may arise as a result of the particular combinations of subjects, technologies, and task scenarios that were selected. Before delving deeper into these issues, it is important to highlight that tradeoffs between realism, on the one hand, and the practicalities involved in the conduct of research, on the other, are a constant source of tension in most published empirical research.

The adequacy of undergraduate college students as surrogates for other populations of interest has been the subject of much debate in management research (Gordon, Schmitt, & Schneider, 1984; Gordon, Slade, & Schmitt, 1986; Remus, 1986), starting with the observation by McNemar (1946) that "*the existing science of human behavior is largely the science of sophomores*" (p. 333), in reference to the largely established practice then, as is today, of obtaining data for psychological research (as well as management research in general, and information systems in particular) from college students, either required or voluntarily (or through the use of incentives such as extra credit towards a course grade). Lacking the ability to conduct primary research using actual subjects from the target population, researchers often caution about the need to replicate the results, in the case of management research, with knowledge workers or managers, but these prescriptions are rarely carried out.

This issue is certainly also present in the research reported here, and does pose an important limitation to the generalization of findings from the reported studies to the more broader population of interest. On the other hand, it could be argued that the ultimate target population for management and information systems researchers, knowledge workers, supervisors, managers, etc., are mostly college educated, and thus a major difference between business students and business professionals lies with the field experience that the former lack.

Great care was exercised to procure and adapt tasks that were representative of those faced by business professionals, even though the need to bound the time required for the exercise resulted in the removal of some of the complexity present in

the business world. For the first study, for instance, the budget task employed was representative of those performed on a daily basis by junior accountants and budget analysts. While the number of line items was limited to fit existing time constraints, the basic nature of the underlying tasks (e.g., assigning income and expense amounts to their appropriate time periods, summarizing with the use of totals and subtotals, calculating variances, etc.) remains close to the ones students would be called upon to perform upon graduation. In addition, the technology used to perform the task, i.e. spreadsheets (in particular Microsoft Excel, which is currently the most popular spreadsheet package) is widely used in business organizations today.

The participation of business students may have had more of an impact on the generalizability of the results obtained from the second study. While the task and technology employed there, a DSS based on a multinomial logit model that estimated future purchase probabilities based on past history and the results of a customer satisfaction survey, were an accurate replica of a real-life scenario reported by Gensch and colleagues (Gensch, 1984; Gensch et al., 1990), undergraduate students may be less than appropriate surrogates for managers than graduate students in the context of business decision making (Remus, 1989). Lilien et al (2004), who first used this task in the context of DSS research, noted that undergraduate students performed less proficiently than graduates. Pilot work for the second study reported here showed that the performance of undergraduate students was generally lower than that of the graduate students reported by Lilien et al (2004), but not significantly so. Whether this would result in the general structure of relationships in the model to be

any different is not evident. In any case, this is an important limitation to consider when attempting to interpret these results, and will be discussed again in the context of future research directions below.

Measurement

The validity of the measurement instruments used to collect data for each of the six constructs included in the research model shown in Figure 3.1 precedes other core validities, such as internal, external, and statistical conclusion (Cook & Campbell, 1979). Straub (1989) discusses many of these issues under the general heading of "Instrument Validation", particularly focusing on content and construct validity, as well as reliability.

In all cases the (composite) reliability of all measures was high and well above commonly accepted cutoffs, and all the statistical tests associated with convergent and discriminant validity were satisfactory; these are reported in Chapters 4 and 5 and will not be discussed here any further. Two other issues related to measurement, however, merit more attention. First, factorial structure of the goal commitment measure was disappointing, and did not conform to expectations, in both studies. This was rather surprising, given than the measure employed was itself the outcome of an extensive meta-analytic validation process (H. Klein et al., 2001). In both studies a differential pattern of loadings was evident between positively and negatively worded items (both datasets were carefully revised to eliminate the possibility of improper reverse coding). One and two factor models were fit to the

data, and a conclusion was reached that retaining the three positively worded items, which loaded strongly together and showed appropriate content validity with regards to the definition of the construct, was the best possible course of action.

Given that the three retained items appear to represent the construct of goal commitment fairly well (GC5 – I am strongly committed to pursuing this goal, GC7 – I think this is a good goal to shoot for, and GC8 – I am willing to put forth a great deal of effort beyond what I would normally do to achieve this goal) it is not clear that only using these indicators for the construct would bias any relationship between computer-supported task self-efficacy, as a predictor, and task performance, as a criterion. However, in light of these unexpected findings with regards to the factorial structure of the measure, obtained results should be interpreted with caution, and more research, both about the goal commitment measure, as well as a replication of these studies using alternative measures of the construct, is needed to provide additional evidence in support of the relationships mentioned above.

Second, while the measure for computer self-efficacy (spreadsheet self-efficacy more specifically) for the first study was adopted from previous research (Johnson & Marakas, 2000), brand new measures were developed for both task and computer-supported task self-efficacy in both studies, and for computer self-efficacy (e.g., DSS self-efficacy) for the second study. While all the measures used in the first study were piloted with a large sample and refined as a result, the development of a new measure always entails some uncertainty about the results obtained from its employment in a research endeavor.

Also, while many researchers have discussed the inherent advantages of adopting existing and validated measures, where appropriate (Straub, 1989), researchers in the Social Cognitive Theory literature (Bandura, 2006; Bong, 2006; Lent & Hackett, 1987) have stressed the need for measures of self-efficacy to be tailored in specificity to the domain and performance one seeks to predict. As a result, self-efficacy measures evolve over time and need to be revised to match the particular context and, in this case, technology of interest (Marakas et al., 2007). Thus, while all of the newly developed measures performed more than acceptably in tests of reliability, construct validity, their pattern of relationships with other measures in their nomological net was as would be expected, and exhibited high a priori face validity, a certain degree of caution is advised pending further validation of these measures with different populations, as well as replication of these results.

Directions for Future Research

This research has established the theoretical foundation and preliminary empirical validation of a research model with important implications for advancing the information systems literature on computer self-efficacy and its nomological net, the technology training literature, by emphasizing the importance of jointly considering both the technology and the task when designing training interventions, and for Social Cognitive Theory in general, by further developing the importance of process self-efficacy belief in addition to outcome-oriented ones, which have received the most attention up to date. A number of avenues for future research can be

envisioned that would improve on the internal and external validity of these studies, as well as extend the model to new domains and better integrate it with other related lines of investigation. Several of these are discussed next.

The internal validity of this research can be improved by testing for the presence of the interaction between computer and self-efficacy through the conduct of experiments involving random assignment of subjects to alternative conditions and the manipulation of the two main constructs. This would allow for a stronger statement of causality between task and computer self-efficacy and computer-supported task self-efficacy than was possible here, as well as validate and replicate the findings that stem from the two studies discussed above.

It would also be worthwhile to develop, and properly validate, shorter measures of the two main effect constructs, in order to test the interaction using structural equation modeling but alternative procedures to the LMS method (A. Klein & Moosbrugger, 2000) employed here, such as the ones proposed by Little et al (Little et al., 2006) by creating an interaction factor measured by a cross-product of all the indicators for each main effect, or the one suggested by Marsh, Wen and Zau (2004) involving the use of an indicator mean structure. For the measures used in this research, such alternatives become problematic due to the large number of cross-product indicators required.

For instance, in the first study the measures for the exogenous constructs had nine and seven indicators, resulting in an interaction factor with sixty three indicators, and associated structures for either correlated residuals or mean structures, depending

on the chosen alternative. An alternative approach may involve the reduction of items by means of constructing a smaller number of parcels; however, such approaches have shown to be somewhat problematic in the context of measurement invariance (Meade & Kroustalis, 2006), and more research would be required to ascertain whether such techniques would be appropriate for the testing of multiplicative interactions.

A straightforward avenue for enhancing the external validity and generalizability of the research model would be its replication with participants drawn from the professional domains of interest. Replication is an important part of the scientific method and thus conducive to the advancement of science and knowledge, and its importance is, at least at face value, well accepted among information systems researchers (Berthon, Pitt, Ewing, & Carr, 2002). That being said, actual research and publication practices parallel the distinction made by Argyris and Schön (1974) between theory-in-used and espoused theory: replication of past research is more frequently praised than actually conducted (and published), at least in information systems research (Berthon et al., 2002). In this regard, the discussion and framework provided by Berthon and colleagues provides both the justification for the need to conduct this type of research as well as an organizing structure to systematize its conceptualization.

The continuum proposed in Figure 3.2 relating to the effects on task effectiveness arising from the introduction of technologies into the performance of the task, was tested with only two of the three "types" of tasks presented there – recall

that these tasks were intended to anchor the continuum and help in its interpretation, but no arguments were made about the existence of only three different types of computer-supported tasks. While the conduct of a third study would have provided more support for the proposed continuum for the moderating relationship, several issues made this impractical at this stage in the research process, and these would need to be carefully addresses before embarking on such endeavor.

One of these issues relates to the required sample size for such a study. Given the degree of task specificity present in 'Type III' tasks (i.e., "*those tasks where the introduction of technology radically altered their outcome, or those that were not even possible before the technology was available. Examples include computer-based animation and large scale data mining, among others. Issues of efficiency in performing the task are not particularly relevant for this category, since there is no prior point of comparison*") the use of students as surrogates for professionals in these fields appears to be less appropriate and valid than in the two studies reported here. Thus, obtaining a sample size large enough to provide adequate power for the detection of interaction effects would be beyond the scope of this dissertation.

In addition, the measurement of task performance in these tasks is problematic and would need to be conceptualized in a different form than has been done in the literature. Given the high degree of specialization and technical prowess required in these professions, it is not evident that the necessary degree of variance would be present in performance to allow for co-variation between the computer-supported task self-efficacy construct and performance to occur. This is due to the possible operation

of selection mechanisms that prevents the presence of poor performers in highly specialized and competitive professions or industries, where deficiencies in performance are more rapidly evident and thus the majority of participants are more than adequate performers – this would also be the case in fields of medicine where the use of technology was either of paramount importance or outright required, which could otherwise have provided participants for the type of research described here.

Finally, the measurement of computer self-efficacy as distinct from task self-efficacy in this type of tasks may be problematic due to the phenomenon that Bandura (1997) labeled co-development. While noting that self-efficacy beliefs are multifaceted, Bandura (1997, 2006) identified several scenarios where self-efficacy beliefs would co-vary even though the domains of functioning were distinct. First, the different domains of activity are governed by the same of similar sub-skills so that the development of these sub-skills will result in higher efficacy beliefs for both domains. Second, even if different domains of functioning are not served by common or similar sub-skills, the same perceived efficacy can simultaneously occur in multiple domains if the development of competencies is structured so that abilities in different fields are developed together or at similar rates – the example given by Bandura (1997) refers to the development of similar perceptions of efficacy by school-age children, where dissimilar subjects such as mathematics and language are taught in discrete units that are interspaced and thus students tend to progress in both subjects at a similar rate. Finally, powerful mastery experiences that result in an increased self-awareness of one's capabilities can result in a transformational

restructuring of efficacy beliefs across a wide range of domains, also leading to co-variation across different spheres of activity.

In the example provided above, while co-development of efficacy perceptions occurs in tandem due to the social structuring of learning experiences, the two subject domains of mathematics and language remain conceptually and practically distinct from the perspective of students, and thus it is possible to assess their self-efficacy beliefs separately for each domain, even though there would be an expectation that those be correlated. However, if the logic behind the description of the task continuum, and the more extreme types of tasks, is valid, when the technology either creates the possibility of executing the task, or fundamentally restructures an existing task so that the new iteration cannot be performed without the focal technology, it is not evident that these two aspects of efficacy perceptions are at all distinct, and thus capable of being subject to independent measurement.

Two examples of these type of tasks noted in Chapter 3 were data mining and computer-based animation. While some form of animation had been successfully done prior to the advent of computer technology, the type of computer-generated graphics and animations that are common in the current entertainment environment cannot be possibly created without the use of technology; in the case of data mining, the sheer volume of data outright prevents the use of the associated statistical techniques without some form of automated data processing. In both cases, the technology and the tasks are inextricably linked to the extent that it is not clear that it would be possible to assess perceptions of efficacy separately for task and

technology, or even that those can be conceptually defined as distinct, and as a result the joint perception, computer-supported task self-efficacy, may be the only appropriate point of measurement. This issue represents an important methodological limitation that needs to be addressed prior to conducting research with tasks at the extreme of the continuum depicted in Chapter 3.

Undertaking additional validation of the same task ordering could be done in two different ways. First, the research model could be tested on alternative examples of the same type of tasks employed in the two studies conducted here, for instance, by choosing different DSS business and technology scenarios (for the second study), and by focusing on different tasks of the first type, such as calculating and filing taxes online or with the assistance of a tax preparation application. Further validation could be obtained from conducting research in contexts that fall between the anchors and examples used in this research (e.g., by testing the validity of interpolating between data points). In order to do so, however, a more comprehensive and detailed definition of the dimension or dimensions underlying the ordering of tasks proposed in Chapter 3.

Whereas the paradigmatic tasks employed in this research were apart enough in the continuum as well as, based on prior research, their effects on task effectiveness and performance expected to be of a different nature, so that their use to test the research model and associated hypotheses exhibited some degree of face validity, more detailed testing of the model with intermediate tasks does require the development of a scale on which the different contexts can be assessed and their

effects on performance relative to other tasks predicted prior to collecting data, i.e., it can be hypothesized where the strength of computer self-efficacy as a moderator of the effects of task self-efficacy would fall with respect to other tasks that have already been mapped. This represents another important avenue for future research that would contribute to the generalizability of the results obtained here.

The present studies have largely ignored the temporal development of self-efficacy beliefs and the possibility of different individual patterns underlying their growth. While this is a rather common limitation of this literature, which has largely focused on cross-sectional and between individual studies, rather than considering intra-individual variation, future research could study whether the development of the three efficacy constructs depicted in the research model occurs at different rates for different individuals, whether the individual temporal patterns of growth and development can be reduced to a limited number of archetypes, and these can be identified based on observable features so that targeted development interventions can be derived. This line of research would be of value not only to the information systems domain, but also to the general literature on efficacy beliefs and human development, and falls in line with recent calls to reconsider the importance of individual units of analysis in psychology (Molenaar, 2004)

Finally, the integration of computer self-efficacy research with other models of individual performance in the information systems could foster a more integrated and comprehensive view of the factors affecting the use and outcomes of computer-supported task performance. The research conducted here takes an important first step

by delineating the role that computer self-efficacy plays versus the task under consideration in affecting an holistic perspective on task performance, which represents a more natural perspective than focusing on the performance on the use of syntactic and more mechanic skills that has been the focus of most computer self-efficacy research to date. At least two other theoretical domains seem worth exploring further.

The first one is the literature on task-technology fit, started by Goodhue (Goodhue, 1998; Goodhue & Thompson, 1995), and adapted to group support systems by Zigurs and Buckland (1998; Zigurs, Buckland, Connolly, & Wilson, 1999). The main tenet of this literature is that "fit" between the task and the technology would have an impact on performance. While Goodhue and Thompson (1995) originally conceptualized of task-technology fit as the result of users' *perceptions* of both components and their adequacy, later work such as that of Zigurs and colleagues (1998; 1999) made the fit between a task and the technology employed a function of *objective* characteristics of both. The former conceptualization, based on individual user perceptions, can be related to self-efficacy concepts, and the link between both may be provided by the Internal-External Self-Efficacy (IESE) model developed by Eden (2001).

The distinction between internal and external sources of efficacy by Eden (2001; 2002), both of which have their own separate effects on task performance, goes beyond Bandura's work, which Eden relates to internal source of efficacy, and incorporates efficacy beliefs about the means that are used to perform a task, an

external source of efficacy, into the theory. In this model, then, and individual belief about perceived capability for performing a task is coupled with a separate belief about the efficacy of the tools or technology that are available, or have been provided, to perform such endeavor. The latter set of beliefs appear to be closely related to perceptions of task-technology fit, while the former are tied to more traditional notions of self-efficacy as an internal generative force driving human action. While the theory is relatively recent, and empirical validation is still undergoing, it may provide an overarching framework under which disparate lines of research in information systems such as computer self-efficacy and task-technology fit can be accommodated and integrated with each other.

Conclusion

Starting with the seminal work of Gist and colleagues (1987, 1989; Gist & Mitchell, 1992; Gist et al., 1989) and, later and within the information systems domain properly, that of Compeau and Higgins (Compeau & Higgins, 1995a, 1995b; Compeau et al., 1999) and Marakas and colleagues (Johnson & Marakas, 2000; Marakas et al., 1998), computer self-efficacy has become a prominent construct in the information systems literature, as evidenced by the attention it has commanded from researchers in areas such as technology acceptance, training interventions, construct measurement, as well as individual performance.

Most of the latter research, however, had up to now focused on a narrow conceptualization of performance that, while helpful in defining and understanding

the effects and implications of computer self-efficacy, had somewhat constrained the inclusion of the construct in models of broader interest. At the same time, while it was rather evident that there was more to task performance than beliefs of capability about computer skills, the nature of the relationship between computer self-efficacy and this larger domain of interest remained largely unexplored. More recently, research by Looney et al (2006) was the first to empirically explore the position of self-efficacy versus task and task performance. Even then, there was no consideration of how this relationship could vary across tasks and contexts different than those already studied.

The research conducted here attempts to further our understanding of the structural role of computer self-efficacy and proposes a moderating relationship that builds upon earlier research by Looney et al (2006). In addition, this research provides a more comprehensive validation of the newly proposed research model including both a measure of task performance (whereas Looney et al, 2006, only focused on expectations of future performance), as well as other known determinants of performance in order to better ascertain the contribution of the joint task-computer self-efficacy construct. Finally, a preliminary position on the importance of the nature of the task is stated, and a general ordering of these related to the effects on effectiveness caused by the introduction of technology is proposed, and a first validation of the proposition is obtained. These studies are by no means definitive and are not without limitations, but it is hoped will provide a basic framework on which future research in this area can be supported.

APPENDIX A. REFLECTIVE VS. FORMATIVE SPECIFICATION

Recent work by Marakas, Johnson and Clay (2007) specified computer self-efficacy using a formative, as opposed to reflective model. Up to this point, researchers using Social Cognitive Theory, and even within the domain of computing, had always used the latter form to posit the relationships between latent and manifest variables. The authors argued for this new conceptualization of computer self-efficacy by noting that indicators currently used to measure the construct did not necessarily follow any particular pattern of correlations, as required by the reflective mode of measurement. In particular, they proposed that a person answering positively to one item might not necessarily answer in a similar manner to a second one, e.g. "*It is possible, even likely in many cases, a person responding to the instrument might be capable of installing software, but not capable of accurately describing how a computer works*" (p. 21).

More properly, what latent variable models require is that population differences in position on the latent variable cause population differences in the expectation of the item responses, and not that any particular individual necessarily answer questions in a particular manner. Positing causality relationships at the individual, as opposed to between subject sense, becomes problematic because of the lack of covariance (Borsboom, Mellenbergh, & van Heerden, 2003). Moreover, if the authors thought a negative correlation between a pair of items was likely, per their statement, that would require reverse scoring of the particular question. In addition, alternatives other than postulating a formative model were available to them, such as

a spurious model with multiple causes (Edwards & Bagozzi, 2000), or even conclude that the measure was not appropriately tapping into the construct of interest and should be refined or scrapped altogether.

However, the road chosen by Marakas et al (2007) follows a literature that has so far been mainly concerned, and arguably to an excessive degree, with the issue of direction of causality between manifest and latent variables (Bollen & Lennox, 1991; Edwards & Bagozzi, 2000; Jarvis, Mackenzie, & Podsakoff, 2003; Mackenzie, Podsakoff, & Jarvis, 2005). As argued by Diamantopoulos and Siguaw (2006), it is not clear why researchers seem to argue that, following a process of measurement construction, the same items should have been selected to comprise either formative or reflective specifications. Pushing the issue a little further, it is also not clear why Diamantopoulos and Siguaw (2006) believe that the issue boils down to selecting different items from the same pool, as opposed to creating separate pools of items altogether. In all this literature, however, there is a more fundamental question that has so far been left unanswered, and from which all other considerations follow directly, namely *why would a researcher choose a reflective or formative specification in the first place?* Borsboom et al (Borsboom et al., 2003) propose that the answer depends on the ontological status of the latent variable being invoked in the research model.

In addition, a number of other important issues arise from the choice of specification, that extend beyond the mere direction of arrows in the graphical depiction of a causal model, such as the error-free nature of the manifest indicators.

Given the still nascent and fragmented nature of this literature, however, and in all fairness to the authors, it is not clear that all these were evident at the time their work was being developed.

While this discussion requires one or more treatises in its own right, this section will attempt to provide enough theoretical and practical grounding for the position taken regarding measurement of self-efficacy in this work. Thus, the remainder of this segment will be organized as follows. First, a more comprehensive introduction to the problem, current positions, and philosophical implications will be provided. Next, other relevant issues that follow from the choice of model specification will be discussed, and then a number of problems with current validation procedures for formative specifications will be raised. This section closes with a summary of the issue and a statement of position.

Choosing Between Specifications

Early on, it has been argued that theories can be divided into two distinct parts, one that specifies particular relationships between theoretical variables, and one, termed auxiliary, that specifies the relationships between those constructs and their observed measures (Blalock, 1968; Costner, 1969). While the latter have typically received less attention, they are of critical important since they constitute the bridge between abstract constructs and observable phenomena (Edwards & Bagozzi, 2000). Underlying classical test theory are reflective measures, e.g. those where the indicators are presumed to be caused by the latent variable, and generally termed

reflective. Formative specifications, on the other hand, posit that the measured indicators are exogenous variables that cause the latent composite of interest. In the interest of clarity, and following MacCallum and Browne (1993), the term *latent variable* is reserved for reflective specifications, and *latent composite* for formative ones. Figure A.1 depicts a graphical representation of these two alternatives.

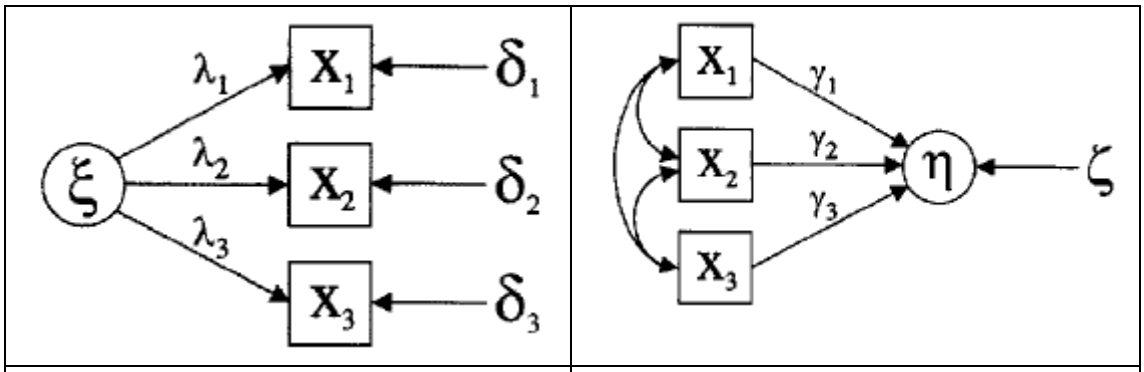


Figure A.1(a) – Reflective Specification	Figure A.1(b) – Formative Specification

Formally, if ξ is a latent variable and x_1, x_2, x_3 are a set of observable indicators, then the reflective specification implies the following (Diamantopoulos & Siguaw, 2006): $x_i = \xi \lambda_i + \delta_i$ where λ_i is the expected effect of ξ on x_i and δ_i is the measurement error for the *i*th indicator ($i = 1, 2, 3$). Additionally, it is also assumed that Cov (ξ, δ_i) = 0, Cov (δ_i, δ_j) for $i \neq j$, and E (δ_i) = 0. The formative specification, on the other hand, implies that $\eta = \gamma_1 x_1 + \gamma_2 x_2 + \gamma_3 x_3 + \zeta$, where γ_i is the expected effect of x_i on η, and ζ is a disturbance term, with Cov (x_i, ζ) = 0 and E (ζ) = 0 (Bollen & Lennox, 1991). The choice of mathematical model also implies a number of requirements and assumptions about the behavior of manifest indicators and their relationships with their latent variables or composites; these have been summarized by Jarvis, Mackenzie and Podsakoff (2003) and are reproduced in Table A.1 below (it

should be noted that there is at least one problematic statement in this table, formative indicators are required to share at least one common consequence, the latent composite of interest, as evidence by the formulation presented above):

Table A.1 – Distinguishing Characteristics from Jarvis, Mackenzie and Podsakoff (2003)

DECISION RULES FOR DETERMINING WHETHER A CONSTRUCT IS FORMATIVE OR REFLECTIVE

	Formative model	Reflective model
1. Direction of causality from construct to measure implied by the conceptual definition	Direction of causality is from items to construct	Direction of causality is from construct to items
Are the indicators (items) (*a*) defining characteristics or (*b*) manifestations of the construct?	Indicators are defining characteristics of the construct	Indicators are manifestations of the construct
Would changes in the indicators/items cause changes in the construct or not?	Changes in the indicators should cause changes in the construct	Changes in the indicator should not cause changes in the construct
Would changes in the construct cause changes in the indicators?	Changes in the construct do not cause changes in the indicators	Changes in the construct do cause changes in the indicators
2. Interchangeability of the indicators/items	Indicators need not be interchangeable	Indicators should be interchangeable
Should the indicators have the same or similar content? Do the indicators share a common theme?	Indicators need not have the same or similar content/indicators need not share a common theme	Indicators should have the same or similar content/indicators should share a common theme
Would dropping one of the indicators alter the conceptual domain of the construct?	Dropping an indicator may alter the conceptual domain of the construct	Dropping an indicator should not alter the conceptual domain of the construct
3. Covariation among the indicators	Not necessary for indicators to covary with each other	Indicators are expected to covary with each other
Should a change in one of the indicators be associated with changes in the other indicators?	Not necessarily	Yes
4. Nomological net of the construct indicators	Nomological net for the indicators may differ	Nomological net for the indicators should not differ
Are the indicators/items expected to have the same antecedents and consequences?	Indicators are not required to have the same antecedents and consequences	Indicators are required to have the same antecedents and consequences

Table A.1 highlights the extensive focus that this literature places on the direction of causality between manifest indicators and latent variables or composites, and assumes that it is the conceptual definition of the construct of interest what determines the most appropriate specification. This raises the question as to whether it is possible for a research to define a construct in alternative forms such that either a reflective or a formative specification can be deemed appropriate. It will be later argued that this is not the case. At the moment, however, the central issue in this stream of research revolves around the direction of causality. In this regard, socio-

economic status (SES) has become the quintessential example for the need to specify at least some constructs as formative composites, and for the purpose of this argument it can be defined as a combination of education, income, occupation and residence (Diamantopoulos & Winklhofer, 2001).

Clearly, researchers argue, it is changes in income what causes SES to vary, and not the other way around; a change in SES could not cause a change in income (or residence, or any other of its components). This shows a rather restrictive and limited unidirectional conceptualization of causality. It would quite straightforward to fabricate a counterexample where an individual, because of possessing or having a certain SES is invited to belong to a prestigious organization, say a country club or the like. Because of increased opportunities to socialize with more powerful members of the local establishment, this person is able to land a better position in a new organization. In this case, it can be argued that a certain socio-economic status causally preceded a change in income. On the other hand, attitude is commonly mentioned as a classic example of the appropriateness of reflective formulations for some constructs. However, as noted by Jarvis et al (2003), but not necessarily for the reasons stated by the authors, a careful reading of Fishbein and Ajzen (1975) reveals that the expectancy-value formulation of attitude is a clear example of a formative specification. The main reason why this has not been evident before is because the authors omit consideration of a disturbance term and assume equal weights for all the belief-evaluation products, on the premise that these represent the salient beliefs and

there is not theoretical reason to presume one would be more salient than another. Nevertheless, it should be recognized as such.

These two examples show that arguments about the direction of causality between manifest variables and constructs are less straightforward than the literature has assumed so far. Other authors have also posed important objections to this stream of research, not necessarily on the basis that it is incorrect, but rather that it might overstate the extent of model misspecification by incorrectly assuming that the same indicators would be used in formative or reflective specifications of constructs, as has been the case in extant research so far, e.g. Jarvis et al (2003), Mackenzie et al (2005). The latter propose a framework for scale development that prescribes the following nine steps:

1. Clearly define the construct domain
2. Evaluate the conceptual dimensionality of the construct
3. Generate set of measures to fully represent the construct's domain
4. Carefully consider the relationship between the construct and its measures
5. Specify measurement and structural relations to be tested
6. Collect data
7. Purify measures (different procedures for formative and reflective specifications)
8. Evaluate nomological, discriminant, and criterion-related validity
9. Cross-validate scales using new sample data

Following Diamantopoulos and Siguaw (2006), the Monte Carlo simulation conducted by Jarvis et al (2003) to assess the extent of the problems caused by model misspecification can be criticized on the basis that it assumes the only difference between correctly and incorrectly specified measures lies in the directionality of the arrows, but the items used to measure the constructs remain constant. The author argues, and it becomes clear from the framework presented above, that since the procedures to purify scales differ for each formulation, it is very likely (and from a statistical standpoint almost certain, as will be discussed later) that the resulting item set will be very different for each case, and thus it is not clear what the results of the simulation are showing.

Going one step further, it is also problematic that Diamantopoulos and Siguaw (2006) argue that the original pool of items would be the same, but later purification would lead to two different final instruments. While this is in accordance with the nine-step framework proposed by Mackenzie et al (2005), e.g. first generate a set of items and then proceed to reduce them according to prescribed procedures, this process appears to be inappropriate for a very important reason: the generation of the original item set should not follow the same underlying logic. While reflective measures are supposed to be generated according to the domain sampling model (Churchill, 1979; Nunnally, 1978), items comprising formative scales should represent a census of causes affecting the latent composite (Bollen & Lennox, 1991). As such, it would be highly unlikely that these two procedures would result in the same original pool of items.

Another inconsistency can be found in arguing that the definition of the underlying construct determines whether a reflective or formative specification is more appropriate, which underlies the work of Jarvis et al (2003) and Mackenzie et al (2005) on model misspecification, but then proposing that the domain of the construct be defined first and consideration of the relationship between the construct and its measures be considered later, per the framework shown above. Thus, the choice of specification is inextricably linked to the generation of manifest items, the direction of causality between these and constructs, development and validation procedures, and interpretation of results. Borsboom et al (2003) note that there is no clear a priori reason why researchers should prefer one model over the other, but in practice do opt for the reflective specification. They argue that "… *the choice of model depends on the ontology of the latent variables that it invokes*" (p. 208). Whereas the use of reflective models is consistent with a realist ontology, the use of formative ones is more consistent with a non-realist position, be it constructivism, operationalism, or an instrumentalist point of view.

In this line of thinking, the formal latent variable is a mathematical entity, fully defined by formulas and statistical theory, which state how parameters relating the latent variable to observed data would be generated if the data were generated under the particular mathematical model in question. An ontological view about the latent variable is needed to connect the formal side of the issue to the operational latent variable that arises from observed data. The authors convincingly argue that only a realist stance is compatible with the choice of a reflective specification, and conclude

that the choice of models is thus not philosophically neutral. They also note that it is not possible to defend causal structures invoking latent variables if one does not adopt a realist position about those latent variables, in the sense that those exist independent of measurement.

The formative specification, on the other hand, is more consistent with a philosophical position that denies the objective existence of the latent constructs involved in the formulation. If one were to interpret formative models from a realist point of view, this would give rise to the spurious model with multiple causes discussed by Edwards and Bagozzi (2000), where each of the formative indicators is re-specified as a first-order reflective construct in its own right. Borsboom et al (2003) also note that statistical practice involving the estimation of parameters, and the testing of hypotheses under the assumption that the null can be considered to be "true" or "false" also necessitates a commitment to a realist position. Referring to these issues, the authors note:

"*The evaluation of the position of a subject on the latent variable, the process of estimating parameters, and the conditional reasoning based on the assumption that a model is true are characterized by realist commitments. It would be difficult to interpret these procedures without an appeal to some sort of correspondence truth. However, what we have shown is only that the natural interpretation of what one is doing in latent variables analysis is a realist one, not that it is the only interpretation. It may be that the constructivist could make sense of these procedures without recourse to truth. For now, however, we leave this task to the constructivist and*

contend that theory realism is required to make sense of latent variable analysis" (p. 211)

The fundamental issue, then, is for the researcher to consider whether the latent entity being invoked does have a counterpart in the real world, that is whether there is such a thing as attitudes or self-efficacy, or whether these are social constructions employed by researchers in order to label and categorize phenomena, but which do not exist independently of the particular form of measurement employed. This consideration supersedes the focus on the direction of causality between constructs and indicators, which has been the main preoccupation in current research, given that the latter follows from the former. The relationship between manifest indicators and latent variables or composites becomes tautological once one specification has been chosen, given that they are derived from a mathematical formulation. Thus, it the researcher assumes the variable of interest is better represented through a formative model, by definition the manifest indicators become its causes. A latent variable exists independently of attempts to measure it; in contrast, formative indices do not exist independently of the researchers definition, e.g. do not reveal anything about reality but build upon other measurements, being in essence a linear combination of measures.

The important issue is whether the researcher agrees with the implications this has for the conceptualization of the latent variable or composite of interest. Partially because of this, expressions such as "measurement model" have been avoided so far in this section, given that if the researcher believes something does not really exist,

then there is nothing to be measured (Borsboom, Mellenbergh, & Van Heerden, 2004). In this light, formative models are not measurement specifications.

Other Important Considerations Related to the Choice of Models

Part of the problem in understanding this issue lies in that researchers employing a formative model have not accordingly redefined their conceptualizations of the construct of interest. Drawing an example from Marakas et al (2007), the authors defined Computer Self-Efficacy as "*an individual's perception of efficacy in performing specific computer-related tasks within the domain of general computing*" (p. 16). Assuming, for the sake of this argument, that this definition refers to their General CSE measure, then a more accurate (e.g. in accordance with the formative items) conceptualization of the construct would read something like "an individual's perception of efficacy in describing how a computer works, in installing new software applications on a computer, in identifying and correcting common operational problems with a computer, in unpacking and setting up a new computer, in removing information from a computer that is no longer needed, and in using a computer to display or present information in a desired manner".

Formative specifications, being a census of causes (Bollen & Lennox, 1991) essentially define the latent composite in terms of its component indicators. Thus, the new definition offered is a more accurate reflection of what the composite represents. Whether or not this was the intention of the authors is unclear from their writings, but is not suspected to have been so from other statements in that article. While the

postulation of a disturbance term in the formula for latent composites presented above prevents this situation from fully arising, e.g. the composite becoming a perfect linear combination of its components, this issue seems to have been lost in applied research. If the disturbance term is omitted in practice (as it is the case then Partial Least Squares is used to model the composites, as will be discussed later), then this six activities fully define the General Computer Self-Efficacy construct, and no other activity is presumed to have any influence on it.

In addition, given the formative constructs are not presumed to be counterparts to an entity having a realist existence, and following from the mathematical model underlying this specification, manifest variables are assumed to be error-free, in contrast to reflective measurement where the indicators do contain a certain amount of measurement error. In contrast to assertions by Jarvis et al (2003) and Edwards and Bagozzi (2000), Diamantopoulos (2006) clearly showed that the disturbance term present in formative composites does not represent measurement error at the construct level, but rather variance in the composite yet unexplained by the postulated causes, and argued for the value of this term in improving the definition and operationalization of latent composites. This follows from the fact that measures in formative models are by definition error-free, and thus it is simply not possible for the disturbance term to capture measurement error that is not there in the first place.

From a more theoretical standpoint, the rejection of the real existence of the latent variable implied by the researcher using a formative model makes the whole

notion of measurement error inappropriate, since it is not possible to deviate from the true score if there is not one to begin with. It should be again noted that employing PLS to model these de facto sets the disturbance term to zero (the disturbance term has been a major source of the identification problems discussed by MacCallum and Browne, 1993; this is the reason why it is possible to obtain results in PLS from models that are strictly underidentified).

Extant Issues with Current Validation Procedures for Formative Composites

In addition to foundational issues and the substantive interpretation of formative constructs, there appears to be a number of limitations associated with current validation procedures for these latent composites. First, there is no agreed procedure as to which items should be retained in the final measure, and positions in this issue vary along a continuum. On one extreme, some authors argue that only those items that show significant relationships with the latent composite should be retained in the final instrument. In favor of this position is the underlying rationale in conventional measure development that the data is the ultimate judge as to the appropriateness of included items. On the other hand, given the items in formative composites have an role equivalent to predictors in a multiple regression, items would be retained according to their role in explaining variance in the composite, and not necessarily with any theoretical consideration.

In addition, if the manifest variables are highly correlated, the stability and accuracy of the regression coefficients may become problematic due to

multicollinearity. It should also be noted that, even if authors in this area address the issue of removing an item as having a potential impact on the substantial interpretation of the composite, there is nothing potential about it; removing a predictor from a regression will always have some impact on the dependent variable, the two variables are altogether not correlated, which is not a common case.

On the other side of the argument, other authors (e.g. Rossiter, 2002) argue that maintenance of content integrity is of primary importance, which is established by expert agreement and interviews with target raters. While this approach ensures that the final set of items reflects the original definition of the composite intended by the research, it may excessively rely on subjective judgments from the part of the researcher. About thirty years ago, Jacoby (1978) complained that "*most of our measures are only measures because someone* ***says*** *they are, not because they have been shown to satisfy standard criteria*" (p. 91, emphasis on the original). Somewhere in between is the position adopted by Marakas et al (2007), where the authors retain all that are related to the composite beyond accepted thresholds for chance, and in addition those that are believed necessary for the theoretical completeness of the construct. It is not clear what the rationale for such a procedure would be.

The modified multitrait-multimethod approach developed by Loch, Straub and Kamel (2003), used by Marakas et al (2007) to assess discriminant and convergent validity, imposes a particular pattern of correlations on the items composing each of the formative constructs (it should be noted that multiplying the original item by its weight, obtained from the PLS procedure, does not in any manner affect the

correlation between two items; as such, the correlations used in their procedure are the same as the original ones present in the data). In particular, the authors argue that all items should be more highly correlated with items within the construct that with items from other constructs. Given that, by their very nature, causal indicators of formative constructs are not expected to display any particular patterns of covariation, share any antecedents or consequents (aside from, as noted above, the focal composite of interest), and need not be interchangeable or share any common theme (per Table A.1 above), it is not clear why Loch et al (2003) argue for the need to establish certain patterns if an indicator is assumed to be a valid cause of the latent composite. Indeed, these procedures were developed with the more classic reflective specification in mind, and are not necessarily transferable to the formative domain.

Aside from general objections to the concept of nomological validity in general (Borsboom et al., 2004), the validation of formative constructs as dependent variables of other constructs (either reflective or formative) poses another conceptual problem. Formative constructs are presumed to be cause by their manifest variables. When omitting the disturbance term (as in PLS modeling) they become linear composites of this indicators, and are thus fully defined by them. Thus, if no other possible causes of the composite are postulated, any other entities affecting the composite should operate through their effects on the indicators, and not on the composite itself. Otherwise, the predictor becomes an additional cause of the latent composite that was not included in its formulation. Even if the statistical method does produce a result, it is not clear conceptually how to interpret this influence.

Summary and Position Taken

This section noted that current computer self-efficacy research has turned to formative specifications of the latent construct, and reviews these and their reflective counterparts. While the literature has so far been concerned primarily with the direction of causality, Borsboom et al (2003) convincingly argue that the decision to use one or the other specification of the relationship between constructs and manifest variables rests on the ontological status of the latent variable being invoked, in this case computer self-efficacy. Whereas reflective models, and arguably the general framework of hypotheses testing require a commitment to a realist ontology, formative model are more compatible with a non-realist one, such as constructivism. Other important issues, such as the direction of causality, the error-free nature of the manifest variables, and the use of one or other procedures to validate the instruments, all follow from the underlying choice of model. Ultimately, this position requires the researcher to make a philosophical commitment as to the existence of the latent variable involved in the research model. While implementation of either alternative can be reviewed and criticized (e.g. as to whether validation was appropriate, reliability coefficients are high enough, etc.), the decision to choose one reflects the understanding of the researcher about the phenomena under investigation. Given a strong belief in the reality of computer self-efficacy, this work takes the position that it would be better conceptualized as a reflective, latent variable, and thus develops its measures accordingly.

APPENDIX B. SUPPLEMENTAL MATERIALS FOR STUDY I

B.1 – Instructions to Participants

Perform all entries and calculations using the capabilities of Excel. All calculations should be performed using a formula wherever possible. **Be sure to save your work regularly.**

1. The actual income and expenses for October, November, and December (as found in your spreadsheet) are incomplete. Use the information provided below to create an accurate picture of actual income and expenses for the quarter.:
    a. November sales were composed of 150 Products A at $35 each, 75 Products B at $52 each, and 34 Products C at $71 each.
    b. The cost of Parts and Supplies for October equaled 74% of the actual revenues from Parts and Supplies for that same month.
    c. The company ran an advertising campaign in the local newspaper for $330 that appeared in October, but was not paid until November. The remaining newspaper campaign ads (paid for in the same month they appeared) were for $340 in November and $420 in December.
    d. The TV campaign for October cost $685 and was paid in the same month, as was the one for November for $850. Of the total budget for TV advertisement in December, only $980 was spent.
    e. Phone bills were $95 for October, $110 for November, and $100 for December. The phone bills received in October and December were

both paid in those same months, while the one for November was not paid until December.

f. The actual expense for Licenses and Permits was $35 higher in December than was budgeted for that month because of a fine.

2. Total Budget and Total Actual is lacking totals for the quarter.
    a. For the "Total Budget" and "Total Actual" columns, calculate quarterly totals for income and expenses in each category.
    b. Add subtotals and totals as appropriate.
    c. Calculate net income (or loss) for the quarter.
    d. Show all subtotals and totals in Bold.
3. The difference between budget and actual income and expenses is missing.
    a. In a new column, calculate the difference between budget and actual income and expenses for the quarter.
    b. In a column next to the one you created to calculate the difference between budget and actual, calculate the differences as a percentage of budget.
    c. Add subtotals and totals where appropriate.
    d. Create appropriate labels for both columns.
    e. Show all subtotals and totals in Bold.
4. Format all dollar amounts in the spreadsheet with a $ sign and no decimals.
5. Format all percentages in the spreadsheet with a % sign and two decimals.

6. Format quarterly variances appropriately such that variances equal to or greater than zero are displayed in green and variances less than zero are displayed in red. Do this by using the Conditional Formatting tool previously discussed in the tutorial sessions.
7. In a new column, create a formula using a conditional statement such that:
    a. If the company was over budget, the text "Over" will be displayed
    b. If the company was under budget, the text "Under" will be displayed
    c. If the company was on budget, the text "Equal" will be displayed
    d. Replicate this formula for each income and expense line, including subtotals and totals, shown in the spreadsheet.
    e. Label this column "Over/Under Budget".
8. In a new column, create a formula such that it will display "TRUE" if either of the two following conditions apply, otherwise it will display "FALSE":
    a. The percentage variance is more than 5%
    b. The percentage variance is less than – 5%
    c. Replicate this formula for each income and expense line, including subtotals and totals, shown in the spreadsheet.
    d. Label this column "Large Variances".

B.2 –Task Materials Provided to Participants

	Budget				Actual			
	October	November	December	Total Budget	October	November	December	Total Actual
Revenue								
Parts and Supplies	11500	12300	11900		12150		12810	
Installation	3700	4200	3950		3830	3975	4045	
Total Revenue	**15200**	**16500**	**15850**		**15980**	**3975**	**16855**	
Cost of Sales								
Parts and Supplies	8430	7390	8720			7270	8635	
	8430	**7390**	**8720**		**0**	**7270**	**8635**	
Salaries and Commissions								
Salaries	1395	1480	1275		1455	1570	1305	
Sales Commissions	230	246	238		243	250	256	
	1625	**1726**	**1513**		**1698**	**1820**	**1561**	
Advertising								
Newspaper	350	320	400				420	
Television	700	850	1100			850		
	1050	**1170**	**1500**		**0**	**850**	**420**	
Utilities								
Electricity	140	150	120		150	145	115	
Phone	90	100	90		95			
Water	80	80	80		75	85	80	
Natural Gas	90	110	150		95	115	130	
Broadband	45	45	45		45	45	45	
	445	**485**	**485**		**460**	**390**	**370**	
Other Expenses								
Insurance	220	220	220		220	220	210	
Administrative Supplies	140	140	140		130	150	140	
Property Taxes	350	350	350		330	350	350	
Licenses and Permits	280	280	280		270	270		
	990	**990**	**990**		**950**	**990**	**700**	
Total Expenses	**12540**	**11761**	**13208**		**3108**	**11320**	**11686**	
Net Income / Loss	**2660**	**4739**	**2642**		**12872**	**-7345**	**5169**	

B.3 – Solution Key

	Budget				Actual								
	October	November	December	Total Budget	October	November	December	Total Actual	Var ($)	Var (%)	Over/Under	Large Variances
Revenue												
Parts and Supplies	$ 11,500	$ 12,300	$ 11,900	$ 35,700	$ 12,150	$ 11,564	$ 12,810	$ 36,524	$ (824)	-2.31%		
Installation	$ 3,700	$ 4,200	$ 3,950	$ 11,850	$ 3,830	$ 3,975	$ 4,045	$ 11,850	$ -	0.00%		
Total Revenue	**$ 15,200**	**$ 16,500**	**$ 15,850**	**$ 47,550**	**$ 15,980**	**$ 15,539**	**$ 16,855**	**$ 48,374**	**$ (824)**	**-1.73%**		
Cost of Sales												
Parts and Supplies	$ 8,430	$ 7,390	$ 8,720	$ 24,540	$ 8,991	$ 7,270	$ 8,635	$ 24,896	$ (356)	-1.45%	Over	FALSE
	$ 8,430	**$ 7,390**	**$ 8,720**	**$ 24,540**	**$ 8,991**	**$ 7,270**	**$ 8,635**	**$ 24,896**	**$ (356)**	**-1.45%**	Over	FALSE
Salaries and Commissions												
Salaries	$ 1,395	$ 1,480	$ 1,275	$ 4,150	$ 1,455	$ 1,570	$ 1,305	$ 4,330	$ (180)	-4.34%	Over	FALSE
Sales Commissions	$ 230	$ 246	$ 238	$ 714	$ 243	$ 250	$ 256	$ 749	$ (35)	-4.90%	Over	FALSE
	$ 1,625	**$ 1,726**	**$ 1,513**	**$ 4,864**	**$ 1,698**	**$ 1,820**	**$ 1,561**	**$ 5,079**	**$ (215)**	**-4.42%**	Over	FALSE
Advertising												
Newspaper	$ 350	$ 320	$ 400	$ 1,070	$ -	$ 670	$ 420	$ 1,090	$ (20)	-1.87%	Over	FALSE
Television	$ 700	$ 850	$ 1,100	$ 2,650	$ 685	$ 850	$ 980	$ 2,515	$ 135	5.09%	Under	TRUE
	$ 1,050	**$ 1,170**	**$ 1,500**	**$ 3,720**	**$ 685**	**$ 1,520**	**$ 1,400**	**$ 3,605**	**$ 115**	**3.09%**	Under	FALSE
Utilities												
Electricity	$ 140	$ 150	$ 120	$ 410	$ 150	$ 145	$ 115	$ 410	$ -	0.00%	Equal	FALSE
Phone	$ 90	$ 100	$ 90	$ 280	$ 95	$ -	$ 210	$ 305	$ (25)	-8.93%	Over	TRUE
Water	$ 80	$ 80	$ 80	$ 240	$ 75	$ 85	$ 80	$ 240	$ -	0.00%	Equal	FALSE
Natural Gas	$ 90	$ 110	$ 150	$ 350	$ 95	$ 115	$ 130	$ 340	$ 10	2.86%	Under	FALSE
Broadband	$ 45	$ 45	$ 45	$ 135	$ 45	$ 45	$ 45	$ 135	$ -	0.00%	Equal	FALSE
	$ 445	**$ 485**	**$ 485**	**$ 1,415**	**$ 460**	**$ 390**	**$ 580**	**$ 1,430**	**$ (15)**	**-1.06%**	Over	FALSE
Other Expenses												
Insurance	$ 220	$ 220	$ 220	$ 660	$ 220	$ 220	$ 210	$ 650	$ 10	1.52%	Under	FALSE
Administrative Supplies	$ 140	$ 140	$ 140	$ 420	$ 130	$ 150	$ 140	$ 420	$ -	0.00%	Equal	FALSE
Property Taxes	$ 350	$ 350	$ 350	$ 1,050	$ 330	$ 350	$ 350	$ 1,030	$ 20	1.90%	Under	FALSE
Licenses and Permits	$ 280	$ 280	$ 280	$ 840	$ 270	$ 270	$ 315	$ 855	$ (15)	-1.79%	Over	FALSE
	$ 990	**$ 990**	**$ 990**	**$ 2,970**	**$ 950**	**$ 990**	**$ 1,015**	**$ 2,955**	**$ 15**	**0.51%**	Under	FALSE
Total Expenses	**$ 12,540**	**$ 11,761**	**$ 13,208**	**$ 37,509**	**$ 12,784**	**$ 11,990**	**$ 13,191**	**$ 37,965**	**$ (456)**	**-1.22%**	Over	FALSE
Net Income / Loss	**$ 2,660**	**$ 4,739**	**$ 2,642**	**$ 10,041**	**$ 3,196**	**$ 3,549**	**$ 3,664**	**$ 10,409**	**$ (368)**	**-3.66%**	Over	FALSE

B.4 – Grading Criteria

Budget Analysis (___ / 30 points)

"Income and Expenses" (Task 1) (___ /4.5 points)

0.75 pts	1.a November sales
	=150*35 + 75*52 + 34*71
0.75 pts	1.b Costs for October
	=I6*0.74
0.75 pts	1.c Newspaper advertising campaign
	October = 0
	November = 330 + 340
	December = 420
0.75 pts	1.d TV advertising campaing
	October = 685
	November = 850
	December = 980
0.75 pts	1.e Phone bills
	October = 95
	November = 0
	December = 110 + 210
0.75 pts	1.f Licenses and permits
	December = E37 + 35

"Totals Budget and Actual" (Task 2) (___ / 7 points)

3 pts 2.a Quarterly Totals

1.5 pts for Total Actual Column

1.5 pts for Total Budget Column

Either SUM() or A+B+C is OK

2 pts 2.b Subtotals

1 pt for Total Actual Column

1 pt for Total Budget Column

Either SUM() or A+B+C is OK

2 pts 2.c Net Income / Loss

1 pt for Total Actual Column

1 pt for Total Budget Column

"Budget / Actual Differences" (Task 3) (___ / 5.5 points)

2 pts 3.a Difference in dollars

Check - should be Budget - Actual

2 pts 3.b Difference in percentage

Check - should be (Budget - Actual) / Budget

1 pt 3.c Subtotals

0.5 pts 3.d Column labels

"Conditional Statement" (Task 7) (___ /6.5 points)

5 pts 7.a,b,c Nested IF formula

=IF(O12<0,"Over",IF(O12>0,"Under","Equal")) or any variation that achieves the same result 1 pt if done in two cells (e.g. with two IF statements) - partial credit

1 pt 7.d Copy formula

0.5 pts 7.e Label column

"OR Statement" (Task 8) (___ / 6.5 points)

5 pts 8.a,b

=OR(P12>0.05,P12<-0.05)

1 pt of partial credit if only one of the two conditions is included, or done in two different cells with IF statements

1 pt 8.c Copy formula

0.5 pts 8.d Label column

B.5 – Measurement Instrument

Computer Self-Efficacy (Johnson and Marakas, 2000):	
CSE1	I believe I have the ability to manipulate the way numbers appear on a spreadsheet
CSE2	I believe I have the ability to use and understand the cell references in a spreadsheet
CSE3	I believe I have the ability to enter numbers into a spreadsheet
CSE4	I believe I have the ability to use a spreadsheet to communicate numeric information to others
CSE5	I believe I have the ability to write a simple formula in a spreadsheet to perform mathematical calculations
CSE6	I believe I have the ability to summarize numeric information using a spreadsheet
CSE7	I believe I have the ability to use a spreadsheet to share numeric information with others
CSE8	I believe I have the ability to use a spreadsheet to display numbers as graphs
CSE9	I believe I have the ability to use a spreadsheet to assist me in making decisions

Task Self-Efficacy	
TSE1	I believe I have the ability to correctly distinguish between income and expenses
TSE2	I believe I have the ability to correctly allocate income or expenses to the appropriate time period
TSE3	I believe I have the ability to distinguish between budgeted income and expenses and actual income and expenses
TSE4	I believe I have the ability to calculate the variance between budgeted income and expenses and actual income and expenses
TSE5	I believe I have the ability to calculate subtotals and totals where appropriate
TSE6	I believe I have the ability to correctly group income and expenses into categories
TSE7	I believe I have the ability to distinguish between favorable and unfavorable variances

Computer-Supported Task Self-Efficacy	
CSTSE1	I believe I have the ability to distinguish between income and expenses and enter these amounts into the appropriate cells in a spreadsheet
CSTSE2	I believe I have the ability to correctly allocate income and expenses to the appropriate time period by entering these amounts into the appropriate cells in a spreadsheet
CSTSE3	I believe I have the ability to distinguish between budgeted income and expenses and actual income and expenses and enter these amounts into the appropriate cells in a spreadsheet
CSTSE4	I believe I have the ability to calculate the variance between budgeted income and expenses and actual income and expenses by writing a formula in the appropriate cells in a spreadsheet
CSTSE5	I believe I have the ability to calculate subtotals and totals where appropriate by writing a formula to summarize this information using a spreadsheet
CSTSE6	I believe I have the ability to group income and expenses into categories and thus summarize this information using a spreadsheet
CSTSE7	I believe I have the ability to distinguish between favorable and unfavorable variances and control the way these variances appear on a spreadsheet

Personal Goal
For the assignment that you will be performing today, please indicate what is your personal goal in terms of the percentage of total points that you want to achieve. - Response format: 0-39 percent of the points, 40-49 percent of the points, 50-59 percent of the points, 60-69 percent of the points, 70-79 percent of the points, 80-89 percent of the points, 90-100 percent of the points.

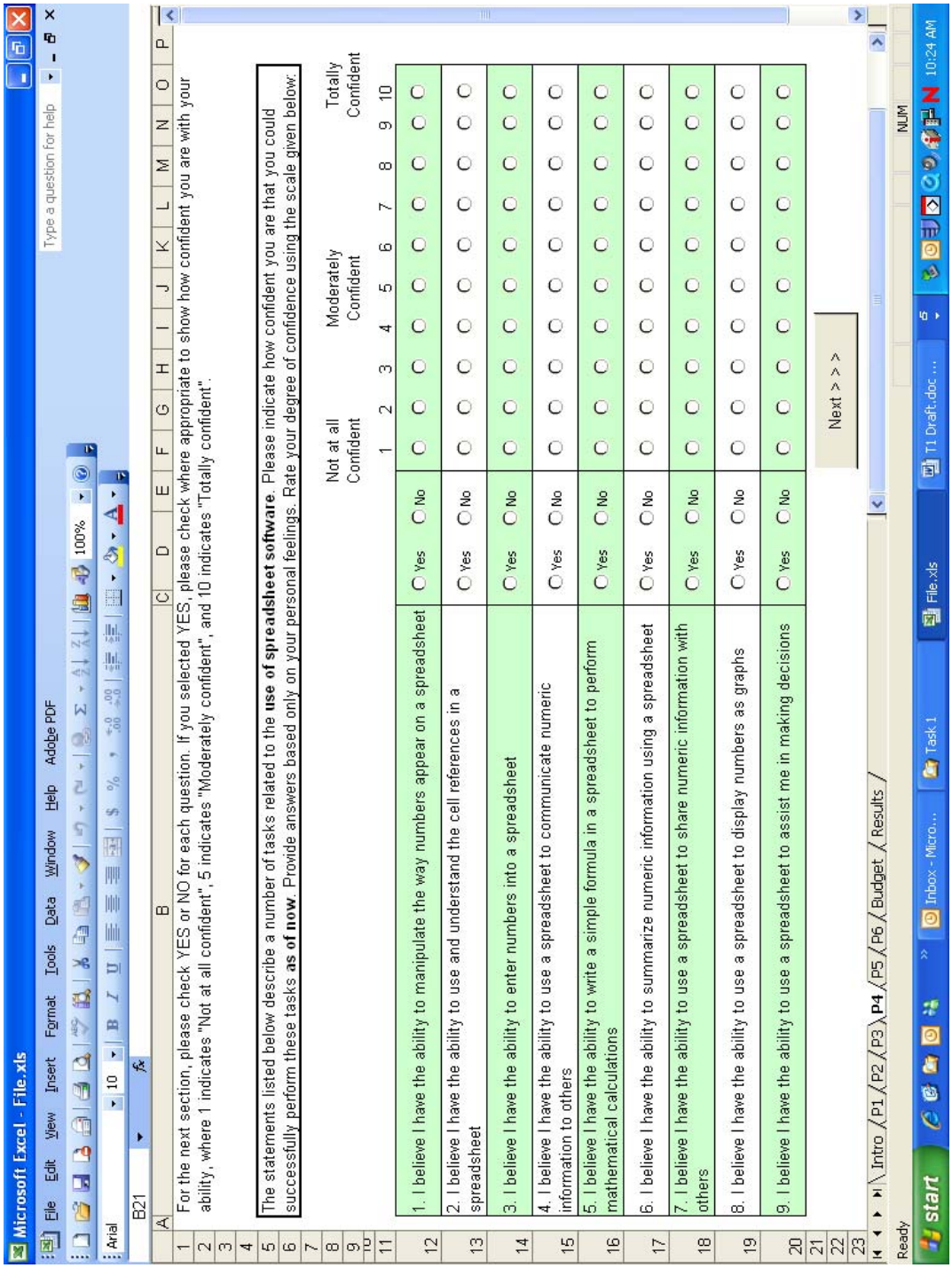
Goal Commitment (items with * included in the final analysis)	
GC1	It is hard to take this goal seriously
GC2	It is unrealistic for me to expect to reach this goal
GC3	It is quite likely that this goal may need to be revised, depending on how things go
GC4	Quite frankly, I do not care if I achieve this goal or not
GC5*	I am strongly committed to pursuing this goal
GC6	It would not take much to make me abandon this goal
GC7*	I think this is a good goal to shoot for
GC8*	I am willing to put forth a great deal of effort beyond what I would normally do to achieve this goal
GC9	There is not much to be gained by trying to achieve this goal

Performance
Performance was assessed by comparing the solution submitted by the participants to a previously developed standard key answer. Points were deducted based on the difficulty associated with each of the tasks included in the exercise. The range for this variable goes from 0 to 30.

B.6 – Structure of Correlated Residuals

Pairs of Residuals		***Shared Content***
TSE1	CSTSE1	"I believe I have the ability to correctly distinguish between income and expenses"
TSE2	CSTSE2	"I believe I have the ability to correctly allocate income or expenses to the appropriate time period"
TSE3	CSTSE3	"I believe I have the ability to distinguish between budgeted income and expenses and actual income and expenses"
TSE4	CSTSE4	"I believe I have the ability to calculate the variance between budgeted income and expenses and actual income and expenses"
TSE5	CSTSE5	"I believe I have the ability to calculate subtotals and totals where appropriate"
TSE6	CSTSE6	"I believe I have the ability to correctly group income and expenses into categories"
TSE7	CSTSE7	"I believe I have the ability to distinguish between favorable and unfavorable variances"
CSTSE1	CSTSE2	Entering amounts into the appropriate cells in a spreadsheet
CSTSE1	CSTSE3	Entering amounts into the appropriate cells in a spreadsheet
CSTSE2	CSTSE3	Entering amounts into the appropriate cells in a spreadsheet
CSE1	CSTSE7	Manipulate the way numbers appear on a spreadsheet
CSE3	CSTSE1	Entering amounts into the appropriate cells in a spreadsheet
CSE3	CSTSE2	Entering amounts into the appropriate cells in a spreadsheet
CSE3	CSTSE3	Entering amounts into the appropriate cells in a spreadsheet
CSE5	CSTSE4	Writing a simple formula in a spreadsheet to perform mathematical calculations
CSE5	CSTSE5	Writing a simple formula in a spreadsheet to perform mathematical calculations
CSE6	CSTSE5	Summarizing numeric information using a spreadsheet
CSTSE4	CSTSE5	Writing a simple formula in a spreadsheet to perform mathematical calculations
CSE6	CSTSE6	Summarizing numeric information using a spreadsheet
CSTSE5	CSTSE6	Summarizing numeric information using a spreadsheet

B.7 – Screenshot of Data Collection Spreadsheet



For the next section, please check YES or NO for each question. If you selected YES, please check where appropriate to show how confident you are with your ability, where 1 indicates "Not at all confident", 5 indicates "Moderately confident", and 10 indicates "Totally confident".

The statements listed below describe a number of tasks related to the **use of spreadsheet software**. Please indicate how confident you are that you could successfully perform these tasks **as of now**. Provide answers based only on your personal feelings. Rate your degree of confidence using the scale given below:

			Not at all Confident			Moderately Confident					Totally Confident
			1	2	3	4	5	6	7	8	9	10
1. I believe I have the ability to manipulate the way numbers appear on a spreadsheet	○ Yes	○ No	○	○	○	○	○	○	○	○	○	○
2. I believe I have the ability to use and understand the cell references in a spreadsheet	○ Yes	○ No	○	○	○	○	○	○	○	○	○	○
3. I believe I have the ability to enter numbers into a spreadsheet	○ Yes	○ No	○	○	○	○	○	○	○	○	○	○
4. I believe I have the ability to use a spreadsheet to communicate numeric information to others	○ Yes	○ No	○	○	○	○	○	○	○	○	○	○
5. I believe I have the ability to write a simple formula in a spreadsheet to perform mathematical calculations	○ Yes	○ No	○	○	○	○	○	○	○	○	○	○
6. I believe I have the ability to summarize numeric information using a spreadsheet	○ Yes	○ No	○	○	○	○	○	○	○	○	○	○
7. I believe I have the ability to use a spreadsheet to share numeric information with others	○ Yes	○ No	○	○	○	○	○	○	○	○	○	○
8. I believe I have the ability to use a spreadsheet to display numbers as graphs	○ Yes	○ No	○	○	○	○	○	○	○	○	○	○
9. I believe I have the ability to use a spreadsheet to assist me in making decisions	○ Yes	○ No	○	○	○	○	○	○	○	○	○	○

Next > > >

B.8 – Indicator Loadings, Standard Errors, and T-Values

Computer Self-Efficacy (CSE)				
Indicator	***Loading***	***S.E.***	***T-Value***	***Std. Loading***
CSE1	2.005	0.120	16.739	0.831
CSE2	1.971	0.119	16.545	0.882
CSE3	1.519	0.157	9.660	0.741
CSE4	1.992	0.119	16.785	0.914
CSE5	1.948	0.126	15.509	0.865
CSE6	2.006	0.113	17.730	0.904
CSE7	1.973	0.103	19.243	0.918
CSE8	1.898	0.129	14.734	0.824
CSE9	1.836	0.103	17.877	0.851

Task Self-Efficacy (TSE)				
Indicator	***Loading***	***S.E.***	***T-Value***	***Std. Loading***
TSE1	1.787	0.142	12.617	0.843
TSE2	2.092	0.127	16.440	0.914
TSE3	2.129	0.132	16.084	0.911
TSE4	2.168	0.126	17.136	0.842
TSE5	2.047	0.134	15.228	0.910
TSE6	1.997	0.124	16.148	0.907
TSE7	2.118	0.129	16.395	0.750

Computer-Supported Task Self-Efficacy (CSTSE)				
Indicator	***Loading***	***S.E.***	***T-Value***	***Std. Loading***
CSTSE1	0.725	0.086	8.442	0.894
CSTSE2	0.828	0.104	7.930	0.918
CSTSE3	0.795	0.110	7.240	0.908
CSTSE4	0.807	0.114	7.087	0.884
CSTSE5	0.772	0.105	7.339	0.914
CSTSE6	0.796	0.112	7.136	0.898
CSTSE7	0.842	0.111	7.560	0.796

Goal Commitment (GC)				
Indicator	***Loading***	***S.E.***	***T-Value***	***Std. Loading***
GC5	1.643	0.097	17.019	0.899
GC7	1.651	0.102	16.113	0.924
GC8	1.415	0.100	14.204	0.827

Personal Goal (PG)				
Indicator	***Loading***	***S.E.***	***T-Value***	***Std. Loading***
PG	0.582	0.053	10.988	1.000

Performance (PERF)				
Indicator	***Loading***	***S.E.***	***T-Value***	***Std. Loading***
PERF	5.931	0.214	27.769	1.000

APPENDIX C. SUPPLEMENTAL MATERIALS FOR STUDY II

C.1 – The ABB Electric Case

ABB Electric is a recently founded company that sells medium-sized power transformers, breakers, switchgear, relays and the like to electric utilities in the North American market. Customers in this business consist of investor-owned electrical utilities, rural electrification cooperatives, municipalities, and industrial firms who purchase equipment for the purpose of generating their own electrical power. As a new firm in an industry dominated by General Electric, Westinghouse, and McGraw-Edison, ABB needs to identify ways to win customers from these major competitors or it will be difficult for ABB to be a successful business.

In its third year of existence, ABB Electric was approaching the break-even point when industry overcapacity and increased deregulation resulted in a 50 percent drop in total sales of industry equipment. The consumption of electricity in the United States has experienced an annual growth rate of less than 3% for the last decade. The electrical equipment industry is a mature industry in which total annual sales follow a cyclical pattern, but have a linear trend value that equals the annual growth rate in the consumption of electricity.

Recent events in the energy markets ended an era of cheap energy. Public service commissions in many areas of the country responded by changing the game rules for

utilities. This change, plus the utilities sharply reducing their estimates of the increase in annual electric energy left many utilities with substantial inventories of spare electrical equipment. In addition, weak new housing construction estimates further contributed to a gloom future for the energy generation industry.

One year ago, ABB Electric engaged a consulting firm to upgrade its information and help it gain insights about its customers. Working together, they isolated a set of attributes they believe customers use to select from amongst alternative suppliers, and contracted the services of a marketing research firm to survey all current and potential customers of ABB Electric. The data obtained reported how each of these customers rated the four existing suppliers (including ABB) on criteria such as price, technical aspects of the products, availability of spare parts, warranty, etc. The consultants then used the information to create a statistical model that assigned probabilities of purchasing from each supplier of electrical equipment — including from ABB Electric.

While the company has always targeted its marketing programs at its largest customers, the consultants introduced the concept of targeting customers by "switchability". The new idea is to target those customers whose likelihood of purchase indicates they are "sitting on the fence" with respect to purchasing from ABB (i.e. where ABB is either a narrow first choice or is the second choice by a narrow margin), and pay less attention to those customers who were already either

loyal to competitors or were loyal to ABB. However, this new idea conflicts with prior marketing strategy. In the words of a senior district sales manager: "Our goal is to grow the company by landing more big contracts. You've got to fish where the big fish are. Some might suggest just picking the 20 biggest contract-proposals and go after those folks with the new program. I don't know if this is the optimal strategy or not. I will leave that in your hands. Our resources are limited so I am certain we can only afford to target 20 companies so we must pick the right 20. If we can get a few more of those big fish to bite, the CEO and the board will be really happy!"

After assessing its market resources and capabilities, management at ABB has determined that, while it has a sufficient marketing budget to market to all 88 of the customers in the survey, it would prefer to substantially target 20 out of the 88 customers included in the survey, and keep marketing efforts aimed at the remaining customers at a maintenance level. They believe making a focused effort on a set of targets highly likely to make substantial purchases will result in better future sales as opposed to spreading the marketing budget evenly over the whole survey list. However, they are unsure as to which customers should be targeted, and have contracted your services to help them reach a decision.

You have been provided with the results of the survey conducted by the consulting firm, which also includes information about the supplier from which each customer purchased last year, and how much each company expects to spend on electrical

equipment this year. The consultants have also made available to you the choice probability model developed from the survey result; although ABB does not require that you use it, you are welcome to do so to inform your recommendation. You are free to make your recommendation using any information and procedure you deem relevant and appropriate.

C.2 – Description of the Decision Support System

The consulting company, retained by ABB Electric, developed a customer preference decision support system employing the underlying principles of choice-based market segmentation. When segmenting a market, consultants divide it into distinct subsets of customers, where each market subset is expected to react to messages and product offerings differently – that is, each market segment has different needs. Marketing opportunities, and their potential effectiveness, increase when a firm recognizes these differences and measures them. An increasingly common approach to segmentation, especially in direct marketing, is choice-based segmentation. Under this approach, a statistical technique summarizes past preference and purchase data to estimate the likelihood that a particular customer will make its next purchase from a specific supplier.

In this case, data from the survey conducted by the consulting company, coupled with knowledge about the last purchase made by each customer, were used to estimate future purchase probabilities from each of the four different suppliers in the electrical equipment industry — including ABB Electric. Figure 1 below shows a sample report with estimated preference data for three fictitious customers.

Estimated Customer Preferences Report						
		Estimated Future Purchase Probabilities				
Customer ID	Annual Purchase Volume	A (ABB)	Firm B	Firm C	Firm D	Last Purchased From
7	$980	16.00%	69.00%	14.00%	1.00%	B
23	$175	42.00%	18.00%	15.00%	35.00%	D
51	$462	33.00%	17.00%	9.00%	41.00%	A

Figure 1. Sample Estimated Customer Preferences Report

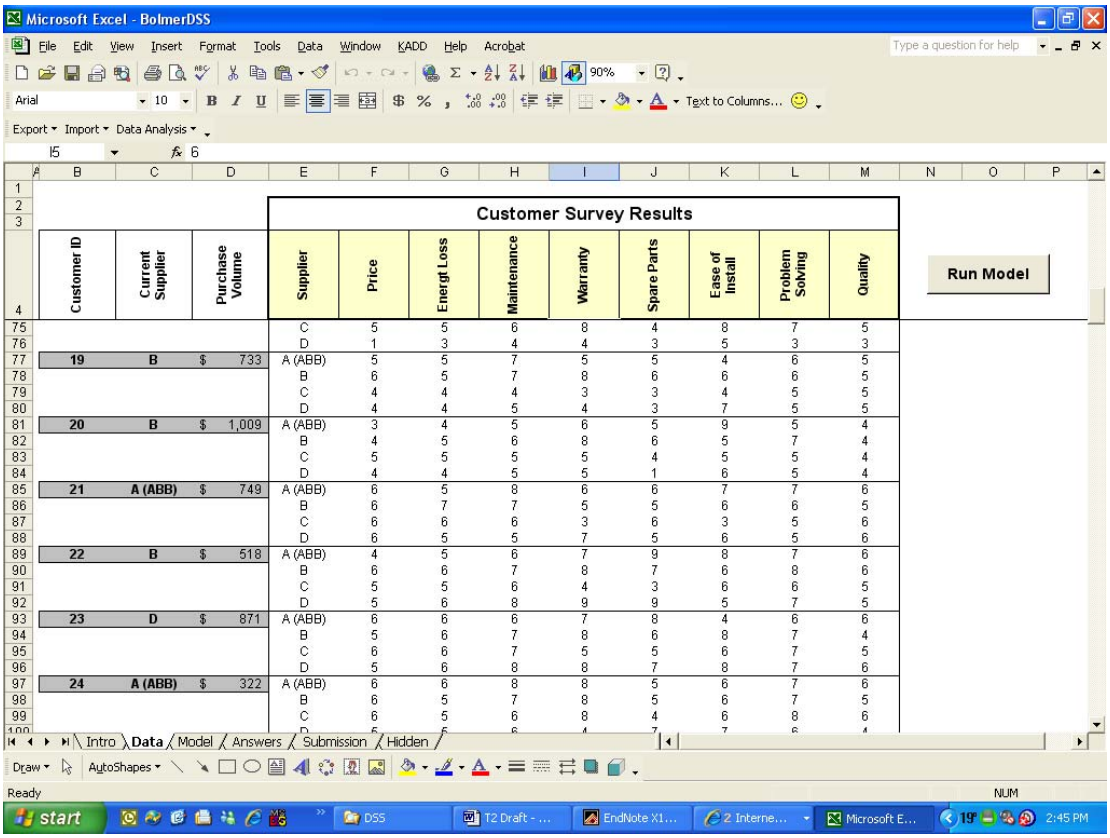
In this example, Customer 7 is projected to spend $980 (thousand) dollars on electrical equipment next year. This customer last purchased from Supplier B (recall that ABB is labeled as Supplier A). According to the model, there is a 16% probability that the customer will purchase its equipment from ABB next year, a 69% probability that it will do so from Firm B, a 14% from Firm C, and just a 1% probability that it will do so from Firm D.

In the second case, Customer 23 is expected to spend $175 (thousand) dollars on equipment next year, and made its last purchase from Supplier D. For this customer, the model estimates a likelihood of making its next purchase from Supplier A (that is, ABB) at 42%, from Supplier B at 18%, from Supplier C at 15%, and from Supplier D at 35%.

After running the model, you are free to manipulate the results in any way you deem appropriate taking full advantage of the capabilities provided by MS Excel. For

instance, you can sort the results, use them as inputs into formulas, etc. As stated before, you are free to make your recommendation using any information and procedure you deem relevant and appropriate.

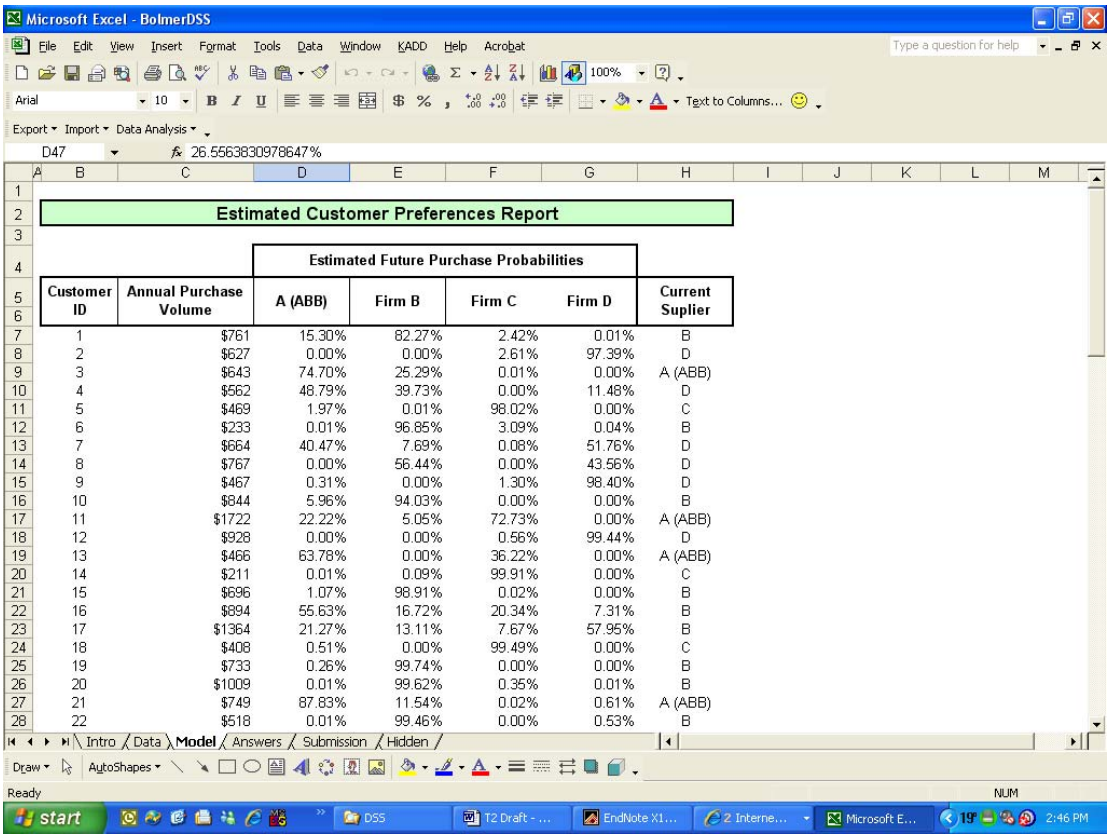
C.3 – Screenshot of Customer Survey Results



Customer Survey Results

Customer ID	Current Supplier	Purchase Volume	Supplier	Price	Energt Loss	Maintenance	Warranty	Spare Parts	Ease of Install	Problem Solving	Quality
			C	5	5	6	8	4	8	7	5
			D	1	3	4	4	3	5	3	3
19	B	$ 733	A (ABB)	5	5	7	5	5	4	6	5
			B	6	5	7	8	6	6	6	5
			C	4	4	4	3	3	4	5	5
			D	4	4	5	4	3	7	5	5
20	B	$ 1,009	A (ABB)	3	4	5	6	5	9	5	4
			B	4	5	6	8	6	5	7	4
			C	5	5	5	5	4	5	5	4
			D	4	4	5	5	1	6	5	4
21	A (ABB)	$ 749	A (ABB)	6	5	8	6	6	7	7	6
			B	6	7	7	5	5	6	6	5
			C	6	6	6	3	6	3	5	6
			D	6	5	5	7	5	6	5	6
22	B	$ 518	A (ABB)	4	5	6	7	9	8	7	6
			B	6	6	7	8	7	6	8	6
			C	5	5	6	4	3	6	6	5
			D	5	6	8	9	9	5	7	5
23	D	$ 871	A (ABB)	6	6	6	7	8	4	6	6
			B	5	6	7	8	6	8	7	4
			C	6	6	7	5	5	6	7	5
			D	5	6	8	8	7	8	7	6
24	A (ABB)	$ 322	A (ABB)	6	6	8	8	5	6	7	6
			B	6	5	7	8	5	6	7	5
			C	6	5	6	8	4	6	8	6

C.4 – Screenshot of Decision Model



Estimated Customer Preferences Report

Customer ID	Annual Purchase Volume	Estimated Future Purchase Probabilities				Current Suplier
		A (ABB)	Firm B	Firm C	Firm D	
1	$761	15.30%	82.27%	2.42%	0.01%	B
2	$627	0.00%	0.00%	2.61%	97.39%	D
3	$643	74.70%	25.29%	0.01%	0.00%	A (ABB)
4	$562	48.79%	39.73%	0.00%	11.48%	D
5	$469	1.97%	0.01%	98.02%	0.00%	C
6	$233	0.01%	96.85%	3.09%	0.04%	B
7	$664	40.47%	7.69%	0.08%	51.76%	D
8	$767	0.00%	56.44%	0.00%	43.56%	D
9	$467	0.31%	0.00%	1.30%	98.40%	D
10	$844	5.96%	94.03%	0.00%	0.00%	B
11	$1722	22.22%	5.05%	72.73%	0.00%	A (ABB)
12	$928	0.00%	0.00%	0.56%	99.44%	D
13	$466	63.78%	0.00%	36.22%	0.00%	A (ABB)
14	$211	0.01%	0.09%	99.91%	0.00%	C
15	$696	1.07%	98.91%	0.02%	0.00%	B
16	$894	55.63%	16.72%	20.34%	7.31%	B
17	$1364	21.27%	13.11%	7.67%	57.95%	B
18	$408	0.51%	0.00%	99.49%	0.00%	C
19	$733	0.26%	99.74%	0.00%	0.00%	B
20	$1009	0.01%	99.62%	0.35%	0.01%	B
21	$749	87.83%	11.54%	0.02%	0.61%	A (ABB)
22	$518	0.01%	99.46%	0.00%	0.53%	B

C.5 – Measurement Instrument

Computer Self-Efficacy:	
CSE1	I believe I have the ability to effectively use the decision model provided by the consultants to assist in my decision-making
CSE2	I believe I have the ability to understand the results provided by the decision system
CSE3	I believe I have the ability to accurately interpret the probabilities calculated by the model
CSE4	I believe I have the ability to manipulate the results of the model
CSE5	I believe I have the ability to investigate different alternatives using the decision system
CSE6	I believe I have the ability to make a better recommendation by using the decision model
CSE7	I believe I have the ability to understand and use the information provided by the model
CSE8	I believe I have the ability to write simple formulas to perform calculations on the results of the decision model

Task Self-Efficacy	
TSE1	I believe I have the ability to identify the customers with the most potential to purchase from the company
TSE2	I believe I have the ability to select the best group of customers to be targeted
TSE3	I believe I have the ability to distinguish between high potential and low potential customers based on survey results
TSE4	I believe I have the ability to choose receptive customers from the customer list
TSE5	I believe I have the ability to make an appropriate recommendation regarding which potential customers to target
TSE6	I believe I have the ability to identify customers that would purchase from the company in the future
TSE7	I believe I have the ability to provide the company with an informed recommendation regarding which customers to target

Computer-Supported Task Self-Efficacy	
CSTSE1	I believe I have the ability to use the decision model to identify the customers with the most potential for future purchases
CSTSE2	I believe I have the ability to select the best group of customers to be targeted by using the results of the decision model
CSTSE3	I believe I have the ability to interpret the results of the decision model to distinguish between high and low potential customers
CSTSE4	I believe I have the ability to use the decision model to identify customers that would purchase from the company in the future
CSTSE5	I believe I have the ability to manipulate the results of the decision model to identify receptive customers from the customer list
CSTSE6	I believe I have the ability to use the information in the decision model to make an effective recommendation regarding which customers to target

Personal Goal
For the assignment that you will be performing today, please indicate what is your personal goal in terms of the percent increase in sales that you want to achieve: . - Response format: 0-10 percent increase, 11-20 percent increase, 21-30 percent increase, 31-40 percent increase, 41-50 percent increase, 51-60 percent increase, 61-70 percent increase

Performance
Performance was measured by the dollar increase in sales that resulted from the customers being recommended by the subject. This increase is a function of the underlying type of customer which was targeted, with different categories of customers resulting in different increases in sales, and in cases no increase whatsoever.

Goal Commitment (items with * included in the final analysis)	
GC1	It is hard to take this goal seriously
GC2	It is unrealistic for me to expect to reach this goal
GC3	It is quite likely that this goal may need to be revised, depending on how things go
GC4	Quite frankly, I do not care if I achieve this goal or not
GC5*	I am strongly committed to pursuing this goal
GC6	It would not take much to make me abandon this goal
GC7*	I think this is a good goal to shoot for
GC8*	I am willing to put forth a great deal of effort beyond what I would normally do to achieve this goal
GC9	There is not much to be gained by trying to achieve this goal

C.6 – Indicator Loadings, Standard Errors, and T-Values (Measurement Model)

Computer Self-Efficacy (CSE)				
Indicator	***Loading***	***S.E.***	***T-Value***	***Std. Loading***
CSE1	0.996	0.066	15.120	0.754
CSE2	1.103	0.064	17.155	0.821
CSE3	0.996	0.054	18.297	0.856
CSE4	0.954	0.061	15.675	0.773
CSE5	1.041	0.061	17.039	0.818
CSE6	1.066	0.055	19.453	0.888
CSE7	1.042	0.067	15.482	0.767
CSE8	0.989	0.065	15.192	0.757

Task Self-Efficacy (TSE)				
Indicator	***Loading***	***S.E.***	***T-Value***	***Std. Loading***
TSE1	1.007	0.065	15.451	0.765
TSE2	1.086	0.060	17.968	0.846
TSE3	1.259	0.066	19.129	0.879
TSE4	1.007	0.070	14.333	0.725
TSE5	1.195	0.061	19.578	0.891
TSE6	1.060	0.063	16.740	0.808
TSE7	1.028	0.069	14.866	0.745

Computer-Supported Task Self-Efficacy (CSTSE)				
Indicator	***Loading***	***S.E.***	***T-Value***	***Std. Loading***
CSTSE1	1.740	0.083	21.052	0.925
CSTSE2	1.701	0.082	20.803	0.919
CSTSE3	1.669	0.078	21.327	0.932
CSTSE4	1.707	0.081	21.153	0.927
CSTSE5	1.735	0.082	21.149	0.927
CSTSE6	1.715	0.079	21.591	0.938

Goal Commitment (GC)				
Indicator	***Loading***	***S.E.***	***T-Value***	***Std. Loading***
GC5	1.204	0.065	18.661	0.878
GC7	1.301	0.066	19.570	0.906
GC8	1.144	0.066	17.408	0.839

Personal Goal (PG)				
Indicator	***Loading***	***S.E.***	***T-Value***	***Std. Loading***
PG	1.635	0.067	24.454	1.000

Performance (PERF)				
Indicator	***Loading***	***S.E.***	***T-Value***	***Std. Loading***
PERF	0.995	0.041	24.454	1.000

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