6-2012

Mechanisms of Transfer: Modeling Motivational and Self-Regulatory Processes that Promote Transfer of Learning

John A. Gonzalez
Syracuse University

ABSTRACT

A critical goal of many school and training interventions is to provide learners with the strategies and foundational knowledge that will allow them to tackle novel problems encountered under circumstances different than the learning situations. This is also quite often referred to as the ability to transfer learning. Theories of transfer posit that providing learners with ways to make connections between learning experiences and possible transfer tasks, accumulating domain and strategic and knowledge, and encouraging diverse abstractions of concepts might help promote transfer to new situations. Notably missing among these theories is the role various motivational tendencies play in helping promote transfer. This dissertation describes the development of a new theoretical model linking transfer, self-regulation, motivation, and prior knowledge. Based on extensive empirical and theoretical evidence, the model posits that motivation plays an indirect role in promoting transfer of learning exerting its effect through increased self-regulation. This effect, along with a strong direct effect exerted by prior knowledge, describes the major motivational mechanism by which transfer occurs. The theory also proposes an underlying latent variable structure that groups interest, self-efficacy, and goal orientation as major indicators that measure motivation. Similarly, domain and strategic knowledge are posited as dimensions that encompass prior knowledge. Self-regulated learning is made up of a motivational and cognitive component. The cognitive components model key processes of the cognitive architecture that explains the general learning process. An effort to validate this theory through structural equation modeling (SEM) is described. This includes comparisons to alternative models and discussions about methodological issues related to model fit. The dissertation also features in-depth discussions about the appropriateness of the proposed latent structure as well as a comprehensive exposition of the validity of estimated parameters under conditions where model fit is considered unacceptable. The dissertation concludes with a set of derived conclusions and recommendations that advance the theoretical model towards a more encompassing and rigorous methodology calling for the development of more sensitive and adaptive measurement instruments.

Keywords: **Transfer of Learning, Structural Equation Modeling, Motivation, Prior Knowledge, Self-Regulation, Mathematical Problem-Solving, Knowledge Transfer.**

MECHANISMS OF TRANSFER: MODELING MOTIVATIONAL AND SELF-REGULATORY PROCESSSES THAT PROMOTE TRANSFER OF LEARNING

By

John A. Gonzalez

B.S. Rochester Institute of Technology, 2002
M.S. City University of New York Brooklyn College, 2006

DISSERTATION

Submitted in partial fulfillment of the requirement for the degree of Doctor of Philosophy (PhD) in Instructional Design, Development, and Evaluation in the Graduate School of Syracuse University

June, 2012

ACKNOWLEDGEMENTS

First, I am grateful and indebted to my committee members. Marilyn Arnone has been a constant source of support, knowledge, and kindness. Her scholarship in the areas of motivation and learning provided tremendous insights into my work. Jim Bellini is a gifted methodologist and who always looked at my work keenly and analytically. I am grateful to Jim for his mentorship, support, advice, and teaching. The development of my analytical abilities is largely due to his influence. My advisor, Tiffany A. Koszalka, has been a source of knowledge, advise, support, and mentorship since I first arrived on campus. Tiffany expertly guided me through the many phases of my doctoral work. Much of my development as a scholar in the learning sciences is due to Tiffany's patient teaching, provoking questions, and timely insights.

The faculty and students of the Instructional Design, Development, and Evaluation Department, the School of Education, and Syracuse University in general have been instrumental to my success. Nick Smith is one of my intellectual heroes and an amazing teacher. Chuck Spuches was endless pillar of support encouraging me through the toughest times. Many thanks also go to Alan Foley, Jing Lei, Rob Pusch, Jerry Edmonds, and Jerry Klein for their teaching and indulgence. A million thanks also go to Linda Tucker for her constant help, support, and warmth. Without Linda and her expert guidance navigating the doctoral process I would have made it through. Patricia Stith provided me with invaluable advice about my studies, career and was always there in times of need. She has been a wonderful mentor.

I must also give thanks to my fellow students and friends. Yin-Wah Kreher, Nilay Yildirim, Yiyan Wu, Theresa Gilliard-Cook, and Kal Srinivas, among many, they have been an endless source of support, friendship, intelligence, and joy.

My wife Lisa deserves at least half of the credit for this dissertation. Without her support, positive demeanor, and belief, this wouldn't have been possible. And I owe to her the great joy of our two children, Jack and Audrey, whom also share in this accomplishment. No words will ever be enough to convey my feelings of gratitude for their presence in my life.

My deepest thanks go to my parents, Maria and Gerardo, for their sacrifices and unwavering belief in my abilities and potential. I hope I have made them proud.

TABLE OF CONTENTS

LIST OF ILLUSTRATIVE MATERIALS

THIS PAGE INTENTIONALLY LEFT BLANK

CHAPTER ONE: INTRODUCTION

Transfer, the deployment of content and strategic knowledge stored in long-term memory to solve never-before encountered problems that share structural and conceptual similarities with previous learning, has been a central focus of educational psychology for over a century. Despite this focus, the study of transfer of learning has produced unclear and conflicting results. In the midst of these results, a number of criticisms have emerged typically followed by frequent recommendations to shift the focus of transfer research. Some have gone as far as to question the viability of the transfer construct (Carraher & Schliemann, 2002), while others have questioned the epistemological and philosophical roots carried over from behavioral and cognitive psychology (Beach, 1999; Lave, 1988; Lobato, 2006). This criticism has been advanced by critiques of the methodologies (i.e. randomized experiments) typically employed to study transfer (Ellis, 2007; Lobato, 2006; Wagner, 2006), and the ways transfer of learning is operationalized and measured (Barnett & Ceci, 2005; Lave, 1988; Lobato, 2003; Schwartz, Bransford, & Sears, 2005).

As a result, the focus of transfer research has shifted to include more realistic settings, to use multiple holistic assessments, to employ qualitative and naturalistic inquiries (Lave, 1988; Ellis, 2007; Tuomi-Grohn & Engestrom, 2003; Wagner, 2006), and to explore multiple explanatory mechanisms (Nokes, 2009). Despite these renewed approaches, the transfer literature continues to rely heavily on cognitive elements and processes, and is especially concerned with testing hypotheses that identify the effectiveness of various instructional treatments. Notably missing from the literature is a focus on the motivational factors that shape transfer. Furthermore, little is known about the underlying motivational mechanisms that describe and explain these processes. Given the impact of motivation on the learning process, it is reasonable to expect motivational forces to have an impact on transfer. The purpose of this dissertation is to identify and validate a model that describes the role motivational constructs play in promoting transfer of learning.

To frame the issue of transfer of learning in terms relevant to instructional design and the learning sciences, it is useful to state our assumptions about training and instruction. Nearly all interventions are designed with the purpose of promoting skills and knowledge that can be applied beyond training and instructional settings to new situations. The compulsory schooling system in the United States, for example, is built partly on the assumption that learners will be able to use what they learned in school to successfully transition to post-secondary education or a career. Corporations and governments spend billions of dollars each year providing training and professional development to their employees with the implied expectation of improved performance. The success or failure of these efforts varies depending on the design of the instructional program, the degree of difficulty of the domain, and the learning characteristics of the individuals involved. What is empirically clear, however, is that designing and teaching with these goals in mind has traditionally produced mixed results with no clear consensus that a particular mode of instruction, or the use of particular instructional strategies are more beneficial than others in promoting the application of prior learning to new situations (Carraher & Schliemann, 2002; Cox, 1997; Lave 1988; Lobato, 2006).

The transfer literature has been pragmatically focused on an approach that examines malleable cognitive and instructional factors that can be altered to produce or improve transfer. There is, for example, a large body of literature exploring the effectiveness of analogical instruction as a strategy to promote transfer (Bulgren, 2000; Gick & Holyoak, 1980, 1983 Gentner, Loewenstein, & Thompson, 2003; Gentner & Kurtz, 2006; Nokes, 2009; Novick, 1988). Another body of literature addresses the generation of self-explanations by learners as a technique to promote transfer (Ainsworth & Loizou, 2003; Bielaczyc, Pirolli, & Brown, 1995; Chi, 1989; Chi et al., 1994; Hausmann & VanLehn, 2007; Renkl, 2002; van Merrienboer, 1997). In some cases, the transfer literature has sought to identify possible ways to develop general cognitive skills applicable across contexts through the exploration of metacognitive skills that may affect transfer of learning (Adey & Shayer, 1993; Berry, 1983; Georghiades, 2000; Halpern, 1998; Osman, 2008; Veenman, Prins, & Elshout, 2002; Veenman, Van Hout-Wolters, & Afflerback, 2006).

As these approaches have shown mixed results, some researchers have shifted their focus to provide multiple representations of the content covered as to improve the depth and quality of the structural connections made by learners (Ainsworth, 2006; Goldman, 2003; Kozma, 2003; van Der Meij & De Jong, 2006). These studies highlight the clear focus of testing for the effect of a treatment. However, not much time has been spent figuring out *how* these instructional interventions actually go about promoting (or failing to promote) transfer of learning. Moreover, a majority of these studies are largely concerned with identifying cognitive elements involved in transfer of learning, and thus fail to address the contextual components of transfer. Chief among these omitted components is the role of motivation in promoting transfer of learning.

Problem Statement

The concern with motivation's role on transfer of learning is by no means a novel one. In her astute analysis and critique of transfer research as a decontextualized, isolated, and culturally constructed activity that did not reflect the everyday practices of people, Lave (1988) acknowledged the critical—yet understated—role played by motivation in our study of transfer. It is worthwhile to include an entire paragraph in Lave's critique for it not only points out the missing link between motivation and transfer, but also offers a direct prescription to address motivation theory in the context of transfer of learning.

> A major factor missing from experimental investigations of problem solving and transfer is an account of what motivates people to recognize and undertake problems when not required to do so. The question need not arise when subjects have tacitly agreed to comply with an experimenter's requests, problem solving is often not controlled by others, nor is it determined by some general eagerness or reluctance to solve problems. *To analyze problem solving in everyday activity, in short, we shall need a theory of motivation*. For whether to have a problem or not, and the specification of what constitutes the problem, are commonly choices made by problem solvers. And we shall need to inquire into questions of how problem-solving activity impels or gives meaning to what happens next (p. 42, emphasis added).

Lave is hardly alone in pointing out this shortcoming of the transfer literature. Baldwin and Ford (1988) identified the need to "develop a research framework for conducting research on the effects of trainee characteristics on transfer" (p. 82). In arguing for consideration of the "spirit" of transfer, Haskell (2001) pointed out the long accepted belief that emotions, personality, and motivation are critical to learning and transfer. This belief, however, is often a forgotten implication not addressed in computational and cognitive models of transfer. This implies current accounts are incomplete representations of the transfer mechanism. For "it is the personal meaning that information holds for us that affects the way we encode, retrieve, and relate information" (Haskell, 2001, p. 121).

What seems missing, then, is a theoretical framework that spells out the motivational factors responsible for transfer, and further explicates how this system of variables affects the cognitive functions that facilitate storing, encoding, retrieval, and usage of prior learning. The purpose of this dissertation is to outline one such theoretical framework, and to provide empirical evidence supporting its validity in the domain of mathematical problem solving.

Focus

Specifying a theoretical model requires identification of relevant constructs, operational definition of those constructs, and their sub variables, and a hypothesis of the nature of the relationships among such constructs (Shoemaker, Tankard, & Lasorsa, 2004). Fortunately, the transfer literature has a rich tradition of empirical work providing an excellent starting point for theory building. What is needed is then is a cohesive model that unifies prior empirical work into a set verifiable and testable hypotheses.

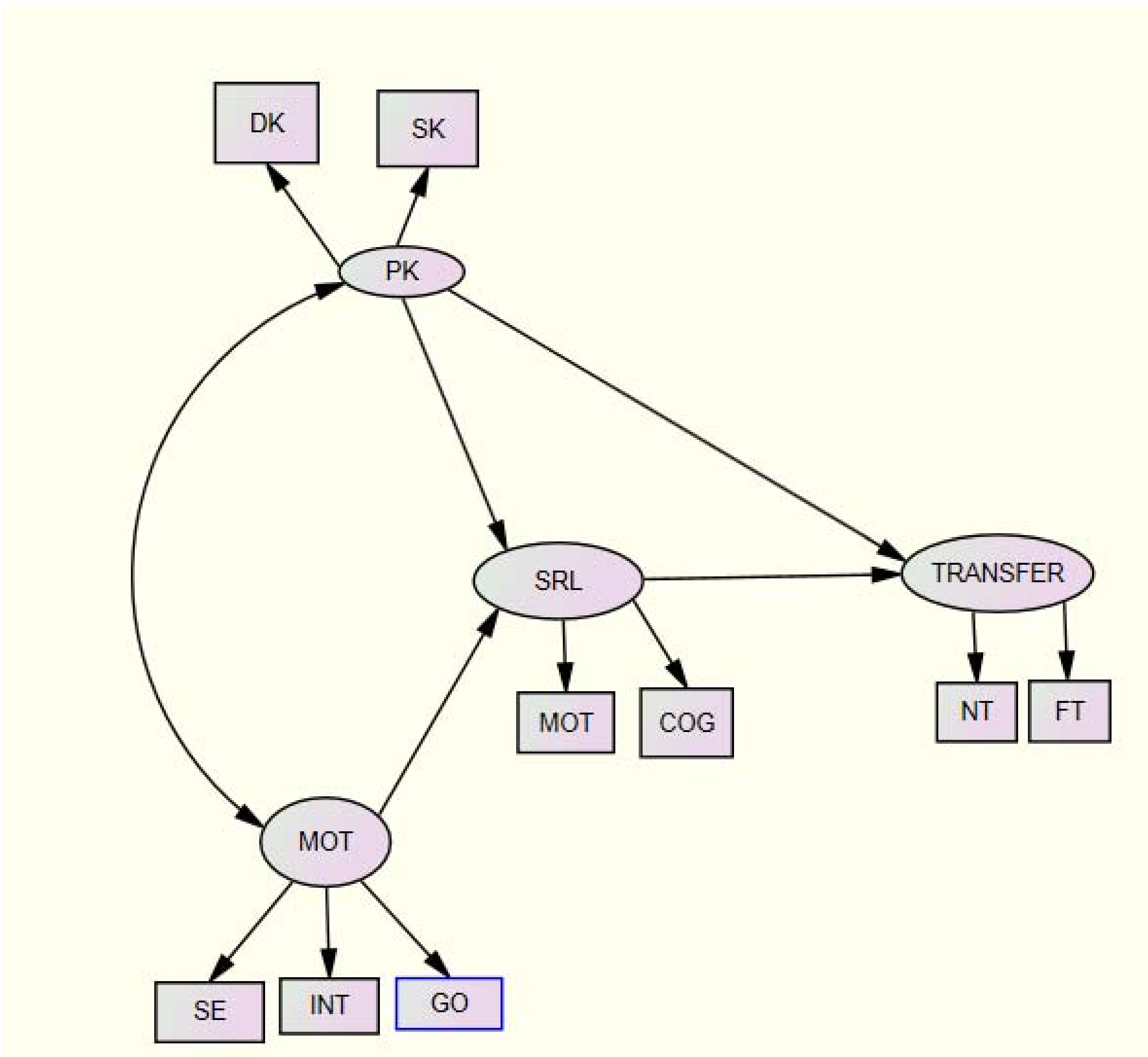


Figure 1. Theoretical model of motivation and transfer proposed in study. PK = Prior Knowledge, DK=Domain Knowledge, SK=Strategic Knowledge, MOT=Motivation, SE= Self-Efficacy, INT=Interest, GO=Goal-Orientation, SRL=Self-Regulated Learning, MOT = Motivational SRL, COG= Cognitive SRL, NT = Near Transfer, FT = Far Transfer.

The model is specified in figure 1. It settles upon two major predictor variables—motivation and prior knowledge—that are posited to indirectly influence transfer through increased self-regulation. Self-regulation, in turn, is posited to directly influence transfer of learning. The model specifies prior knowledge as a direct predictor of transfer acting as a control to the alternative hypothesis that motivated learners are more likely to transfer because they have higher levels of prior knowledge. The selection of these variables and the hypotheses developed about the relationships among the entire system of variables are based on a review of the existing literature. These choices are also based on our current knowledge about learning. While learning and transfer are often operationalized in different ways, we can argue that initial learning is a requirement for transfer. Without initial, deep learning, future transfer of learning is impossible (Bransford, 2000). And while many different types of factors can be said to contribute to learning, a few authors have attempted to narrow down these variables to a smaller set of factors that might play a significant role in influencing transfer. Mayer (1998), for example, identified a set of variables responsible for the development of academic achievement. He concluded

> There are three primary ingredients that contribute to students' academic achievement that configure in different ways over the course of domain learning. They are domain knowledge, motivation (e.g., interest), and general strategic ability (p. 567).

Mayer's conclusion is consistent with other conceptualizations of transfer components (Baldwin & Ford, 1988; Bransford, 2002; Burke & Hutchins, 2007; f & Bergin, 2006). In the context of this model, domain knowledge is defined as prior knowledge while general strategic ability is broken down into a prior-knowledge component and a self-regulatory component. Motivation remains the same and is further operationalized to be consistent with the motivation and transfer literature.

Extensive evidence is presented in the next section to justify the inclusion and operationalization of the constructs and variables as included in the model. First, however, a formal definition of transfer is provided.

Transfer of Learning. Transfer is defined as the deployment of content and strategic knowledge stored in long-term memory to solve never-before encountered problems that share structural and conceptual similarities with previous learning. Multiple conceptualizations of transfer exist in the literature. Differing definitions typically carry embedded implications about the underlying mechanisms responsible for transfer. Three different transfer perspectives are highlighted below.

- Transfer is a result of shared common elements or features between the learning situation and the transfer situation where an old response, or piece of knowledge, is used in a new context. Originally, Thorndike conceived this view under the theory of cognitive elements (Cox, 1997; Lobato, 2006). Cognitive psychologists, however, used the language of symbolic connections and mental schema proposing a similar view under analogical encoding (Gick & Holyoak, 1980, 1983; Gentner, Loewenstein, & Thompson; 2003).
- Transfer is preparation for future learning (Bransford & Schwartz, 1999; Schwartz, Bransford, & Sears, 2005). Under this view, transfer does not take place in a sequestered problem-solving environment but is supported by environmental resources. This view takes into account what learners “transfer in” to a learning situation and seeks to examine how that learning impacts future learning opportunities.

- Transfer is an actor-oriented activity that is learner-centric (Ellis, 2007; Lobato, 2003). Under this view, transfer is a generalization of learning that depends on connections made between prior learning activities and new learning situations. While this is similar to the common elements approach, it differs radically in its *ex post facto*, reflective assessment of the transfer process. Transfer situations are analyzed retrospectively to identify learning activities that might have been responsible for promoting those instances of transfer.

These multiple interpretations showcase the lack of agreement in the transfer literature. While these different conceptualizations are useful tools to advance transfer theory, they force a researcher to adopt a singular view of transfer without the necessary depth of empirical evidence to validate and justify the adoption of such view. As such, this study takes a generic view of transfer most closely aligned with the classical transfer view. That focus is taken as most of the evidence reviewed to specify and justify the model is based on a similar transfer view. When at all possible, however, this study avoids imposing a particular view of transfer on learners instead choosing to observe and record the performance of learners with instruments already used in the classroom context where formal learning is taking place.

A useful conceptualization of the transfer literature that is employed in this study is that of far and near transfer. Historically, this distinction has been given different names by different researchers. Gagne (1985) was among the first in describing different types of transfer. He outlined the difference between *vertical* and *lateral* transfer. Lateral transfer referred to learning that transfers across similar situations with a reasonably equivalent level of complexity. Vertical transfer, as viewed from the perspective of a skill hierarchy, involved using a lower level skill (or skills) in combination to achieve a higher-level skill or behavior. Salomon and Perkins (1989) created a similar dichotomy distinguishing between *low* and *high-road* transfer where high-road transfer was characterized by a conscious attempt to formulate abstractions and make connections as compared to the more automatic and repetitious low-road transfer (p. 118).

Most recently, Barnett and Ceci (2002) distinguished between *far transfer*—transferring to a dissimilar context—and *near transfer*—transferring to a similar context. These three approaches share many commonalities. For the purpose of this study, lateral, low road, and near transfer are merged under the umbrella of near transfer. Vertical, high road, and far transfer are merged under the umbrella of far transfer. The near transfer approaches are characterized by the use of prior learning within the same domain where difficulty levels remain relatively stable and learners are using what they have learned in a very similar context to what they experienced in the learning situation. An example might be a learner using the Pythagorean Theorem to solve a problem finding the shortest distance between two points. Far transfer, on the other hand, is characterized by using prior learning in completely unfamiliar contexts and using previously learned materials in different ways than originally learned. An example is a learner using that same Pythagorean Theorem to estimate the height of a building given the top of the building casts a shadow on the ground and the distance from the shadow to the building can be measured.

Settling on a definition of transfer helps narrow down the possible factors that can influence it. Moreover, such clarification makes it easier to select evidence supporting the inclusion of the proposed elements of the model. The first candidate is motivation.

Motivation. Motivation, in its various forms, has been shown to affect learning through multiple processes. An initial motivational mechanism has been shown to directly affect what learners attend to and thus play a large role in shaping the knowledge components learners are capable of storing in long-term memory (Pintrich & DeGroot, 1990; Pintrich & Schunk, 2002). An alternative mechanism links motivation to persistence. Under this scenario, increased time-on-task directly shapes learning and long-term retention (Larson, 2000; Vollmeyer & Rheinberg; 2000; Wigfield, 1994). We know that learning is a complex process influenced not only by cognitive processes but also by social and instructional factors (Pintrich et al., 1986), and thus can reasonably infer that a similar relationship exists between motivation and transfer.

But to explore this relationship, it is necessary to identify specific motivational indicators that as a whole represent the motivation construct. Pintrich (1988, 1989) outlined an expectancy-value model of motivation consisting of three major components. The first component, the expectancy component, covers a learner's belief about their ability to achieve and succeed. This component can be formally operationalized as self-efficacy, a person's belief about their ability to control levels of functioning and achievement (Bandura, 1993). A second component of motivation outlined by Pintrich is the value component. This includes a learner's goal orientation towards a task and their interest on performing that task. A third component concerns learners' affective and emotional reactions towards a task. This could include emotions such as guilt, pride, or fear, but in school settings it is often manifested in classrooms as test anxiety (Pintrich & De Groot, 1990, p. 34). This three-component model has been validated extensively and used frequently in educational research (Duncan & McKeachie, 2005), and thus serves as the basis for operationalizing motivation in this study.

The outlined model settles upon three motivational indicators: self-efficacy, goal-orientation, and interest. These indicators cover the expectancy and value components outlined above while omitting the emotional/affective motivational components. This deliberate omission results from a lack of empirical evidence demonstrating a direct or indirect relationship between emotional orientation and transfer. Additionally, test anxiety is a trait often associated with high-stakes testing, which is not present in this study. Lastly, as it will be shown in the next section, motivation seems to exert its indirect influence on transfer through increased self-regulation. This mediating relationship seems consistent with the motivational literature (Dweck & Leggett, 1988; Pintrich 1999). However, there seems to be little evidence that decreased test anxiety or negative emotions increase self-regulation. Of course, the presence of these factors is detrimental to learning and to self-regulated behaviors, but their absence does not necessarily imply increased self-regulation, retention, or transfer. As such, it makes little sense to include these types of variables as part of the model.

Self-efficacy and Transfer. Bandura (1993) described self-efficacy as “people’s beliefs about their capabilities to exercise control over their own level of functioning and over events that affect their lives” (p. 118). Two forms of scholarly inquiry traditionally cover self-efficacy research. The first form seeks to evaluate the relationship between self-efficacy and performance by measuring levels of self-efficacy at some point during a study (or multiple points) and correlating results with measures of performance. In these cases, self-efficacy is not manipulated. There is strong evidence supporting a positive correlation between self-efficacy levels and transfer (Holladay & Quinones, 2003; Kozlowski et al, 2001).

In an integrated review of the transfer literature, Burke and Hutchins (2008) highlight several lines of inquiry that support these findings (i.e. Harrison et al., 1997; Mathieu, Martineau, & Tannenbaum, 1993).

The second form of inquiry seeks to increase self-efficacy beliefs through targeted interventions. Many of these studies take the view that increased self-efficacy leads to increased transfer. An entire line of inquiry by Gist and her colleagues have found significant differences due to self-efficacy interventions in the context of business negotiations (Gist, 1989; Gist, Stevens, & Bavetta, 1991; Stevens & Gist, 1997). Elsewhere, Eden and Aviram (1993) have explored the effects of self-efficacy training on speeding up reemployment finding positive significant results. Within the math domain, Pajares and Miller (1994), Pajares (1996), Hall and Vance (2010), Hoffman and Spatariu (2008), and Marsh et al. (1997) have shown a significant relationship between increased self-efficacy and increased problem-solving performance.

These significant findings, which converge to a similar conclusion through independent lines of inquiry, provide support for the initial hypothesis that self-efficacy is a strong predictor of transfer. Learners who believe in their ability to successfully navigate a task are more likely to excel at that task and at tasks that call upon the learners to use what they have learned in prior situations.

Goal Orientation and Transfer. The goals set by learners when engaged with instruction have shown to affect academic achievement and transfer. The goal orientation literature has identified two broad classes of goals: performance and mastery (also known as learning) goals (Grant & Dweck, 2003; Kaplan and Maehr, 2007). Performance goals are typically set by a learner to validate their ability to perform a task or in some cases to avoid the appearance of inability to perform certain tasks. Mastery goals, on the other hand, are set by learners to strive towards mastering a particular skill or competency. They can also include a learner's desire to master a particular skill or goal as a learning challenge. There is evidence linking both types of goal orientation to positive outcomes such as improved self-efficacy and self-regulation, academic achievement, and positive emotions (See Kaplan & Maehr's review, 2007).

However, a number of studies in the literature have associated performance goal orientation with decreased performance outcomes as they shift the learner's attention away from the task, decrease effort, and are not effective in promoting self-regulated behaviors (Kozlowski et al., 2001; Newman & Schwager, 1995; Stevens & Gist, 1997). Furthermore, Brophy (2005) advices focusing away from performance goals because they are seldom generated by learners and often lead learners to adopt a performance-avoidance approach aimed at appearing competent to others. A normative view of performance leads students to set lower bars and focus simply on doing better than their peers.

Given such evidence, it appears a focus on mastery goal is appropriate. There is a limited amount of evidence linking mastery goals to transfer of learning (Grant & Dweck, 2003; Fisher & Ford, 1998; Ford et al., 1998). Some of the strongest evidence is provided by Berevy-Mayer and Kaplan (2005) who explored the direct link between mastery goal orientation and transfer of problem-solving strategies in a logical task. They found subjects assigned to a mastery-goal orientation condition scored higher on a transfer task than those assigned to a performance-orientation condition.

Evidence for an indirect link between mastery goal orientation and transfer appears to be more prevalent. A number of studies have found strong correlations between mastery goal orientation and self-efficacy. In addition, there is strong evidence suggesting a link between mastery goals and self-regulation. This relationship is explored briefly in the section presenting evidence on the link to self-regulated learning, and explored in more depth in chapter 2.

Interest. Interest as a psychological state manifests itself through attention to material and putting forth effort to engage in activities (Ainley, Hidi, & Berndorff, 2001). The interest literature has identified two main types of interest: individual and situational interest. *Individual* *interest* is an internal personal disposition that remains constant throughout different tasks and situations. *Situational interest*, in contrast, is specific to a task and is a response to the features of a learning environment. It may or may not be sustained over time (Ainley et al., 2001; Hidi & Renninger, 2006; Krapp, Hidi, & Renninger, 1992; Schiefele, 1991). Engagement and attention to a task means a learner is more likely to persist until the task is successfully completed. Interested learners spend more time thinking about a task and as a result are able to process learning materials more deeply. Interest has been shown to positively impact cognitive performance, integration of information with prior knowledge, persistence and effort, and levels of learning, among other factors. The combination of these factors also confirms a positive impact on overall levels of learning (see Hidi & Renninger, 2006 and Schiefele, Krapp, & Winteler, 1992 for a summary of evidence linking interest to all these constructs).

A link between interest and a set of variables associated with increased learning also suggests a link between interest and transfer of learning. Alexander and Murphy (1999) have used cluster analysis to create profiles of student performance on an analogical reasoning task. Both before and after instruction, the profiles with the highest levels of interest performed best on an analogical reasoning task. Mayer (1998) highlights the work of Anand and Ross (1987) and Ross et al., (1985) in providing evidence for the positive influence of personalized math instruction (as a proxy to improved interest) on mathematical transfer performance. Ku and Sullivan (2002) further validate these results showing positive transfer results for students receiving personalized math instruction.

These examples provide clear evidence of the role interest plays on promoting transfer in math settings, but as Mayer (1998) puts it, "... researchers have not yet been able to clearly specify the mechanism by which interest affects what is learned, or even to clearly specify what interest is" (p. 58). Much of the research on interest over the last few years has focused on clarifying and clearly operationalizing interest. Little attention, however, has been paid to the mechanisms responsible for explaining interest's effect on transfer and increased performance. To begin to answer that question, we must first outline the mediating mechanism between interest and transfer. The next section, which highlights the effect of self-regulation on transfer and the evidence linking previously outlined motivational indicators, attempts to clarify that concern.

Self-Regulated Learning, Motivation, and Transfer. A critical part of outlining a model of motivation of transfer is describing the causal mechanism by which motivation affects the cognitive transfer processes. This suggests that beyond having a direct effect on transfer, the motivational factors outlined above also exert their impact on transfer through a mediating mechanism.

Self-regulated learning is a prime candidate for this role. Pintrich (1999) defines self-regulation as "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior" (p. 453). Pintrich's framework of self-regulated learning spans across the traditional areas of psychological functioning: cognition, motivation, and behavior (Snow, Corno, & Jackson, 1996). Context is added in to account for environmental factors such as classroom culture.

Empirical evidence and theoretical conjecture support self-regulation as a mediating mechanism. On the theoretical front is the underlying assumption that self-regulated learning is a mediating factor in learning and achievement. Pintrich (2004) points this out while outlining the major assumptions of self-regulated learning:

> It is not just individuals' cultural, demographic, or personality characteristics that influence achievement and learning directly, nor just the contextual characteristics of the

> classroom environment that shape achievement, but the individuals' self-regulation of their cognition, motivation, and behavior that mediate the relations between the person, context, and eventual achievement (p. 388).

Individually, there is empirical and theoretical evidence linking the previously outlined components of motivation to self-regulated learning and transfer. Pintrich's (2004) framework for assessing self-regulated learning, which is based on Zimmerman's (2000, 2008) model of development for self-regulation, forms the theoretical basis used here.

The first phase of self-regulated learning includes planning and activation activities. On the cognitive area of psychological functioning, these activities entail the setting of target goals closely linking goal orientation to self-regulated learning processes. Empirical evidence supports the claim that developing a mastery goal orientation enhances self-regulated learning (Ames & Archer, 1988; Elliot et al., 1999; Elliot & McGregor, 2001; Greene & Miller, 1996; Schraw et al., 1995; Dweck; 2003; Pintrich & De Groot, 1990; Wolters, 2004), and that this increases the possibility of transfer (Bereby-Meyer & Kaplan, 2005; Koslowski et al., 2001).

On the motivational area of psychological functioning, self-regulated learning calls for efficacy judgments. This closely links self-efficacy to self-regulated learning. Empirically, the effects of self-efficacy on self-regulated learning are well documented (Bandura & Wood, 1989; Zimmerman, 2000; Zimmerman & Martinez-Pons, 1990). The evidence for the direct effect of self-efficacy on transfer is equally strong (Holladay & Quinones, 2003; Kozlowski et al., 2001; Harrison et al., 1997; Mathieu et al., 1993; Pajares & Miller, 1994; Hoffman & Spatariu, 2008).

On both the motivation and context areas of psychological function, interest is well linked to self-regulated learning through processes of interest activation and the development of task perceptions. Empirically, there is also support for the notion that increased interest in a topic allows learners to develop deeper knowledge of a topic (Ainley, Hidi, & Berndorff, 2002;

Alexander & Murphy, 1999; Hidi, 2001; Krapp, 1999). These empirical findings are summarized in table 1.

Multiple sources of evidence point to self-regulation as a mediating factor between motivation and transfer. Empirical evidence shows a direct relationship between motivation and self-regulated learning as well as a direct relationship between self-regulated learning and transfer.

Table 1. Evidence supporting link between motivational constructs, self-regulated learning, and transfer.

Motivational construct	**Description**	**Sources linking construct to self-regulated learning**	**Sources linking construct to transfer**
Goal Orientation	The goals set by learners when engaged with instruction.	Ames & Archer, 1988; Elliot et al., 1999; Elliot & McGregor, 2001; Greene & Miller, 1996; Schraw et al., 1995; Grant & Dweck, 2003; Pintrich & De Groot, 1990; Wolters, 2004.	Berevy-Mayer and Kaplan, 2005; Dupeyrat & Marine, 2005; Fisher and Ford, 1998; Ford et al., 1998.
Interest	A psychological state that manifests itself through attention to material and putting forth effort to engage in activities.	Ainley et al., 2002; Hidi, 1990; Sansone et al., 1992; Schiefele et al., 1992.	Alexander and Murphy, 1999; Anand and Ross, 1987; Ross et al., 1985; Ku and Sullivan, 2002.
Self-Efficacy	The belief is one's ability to perform the necessary steps to accomplish a desired goal or action.	Bandura & Wood, 1989; Pintrich & De Groot 1990; Zimmerman, Bandura, & Martinez-Pons, 1992.	Holladay and Quinones, 2007; Kozlowski et al., 2001; Harrison et al., 1997; Mathieu et al., 1993; Pajares and Miller, 1994; Pajares, 1996; Hall and Vance, 2010; Hoffman and Spatariu, 2008.

These findings establish not only a relationship among these constructs, but also suggest a temporal order that helps to specify the structural model presented here. Having established the viability of a model linking motivation to transfer through the mediating mechanism of increased self-regulation, the final step is to counter the alternative hypothesis that motivation is a factor that affects transfer only because motivated learners are learners with high prior knowledge. This requires us to include prior knowledge as part of the model, and to present justification for its inclusion as the main predictor of transfer.

Prior Knowledge and Transfer. Over the last three decades, prior knowledge has emerged as an enduring and critical construct in the study of learning. It is possible that no other construct has gathered such consistent empirical support in the education and psychology literature. Despite this success, the formalized study of prior knowledge as a factor in learning has been plagued by poorly operationalized definitions, an inability to separate different aspects of prior knowledge, and a tendency to merge and confound into different types of knowledge (Dochy, Moerkerke, & Martens, 1996).

Fortunately, prior knowledge researchers have attempted to address these issues by creating frameworks that separate and operationalize the different components of prior knowledge. First, Dochy, Moerkerke, and Martens (1996) defined prior knowledge as "the whole of a person's knowledge. As such, prior knowledge is dynamic in nature; available before a certain learning task; is structured; can exist in multiple states (i.e., declarative, procedural, and conditional knowledge); is both explicit and tacit in nature and contains conceptual and metacognitive knowledge components" (p. 5). Both Alexander and Judy (1988) and Dochy and Alexander (1995) settle upon a broad, two-dimension framework of prior knowledge that includes domain knowledge and strategic knowledge. Domain knowledge is defined as "the declarative, procedural, or conditional knowledge one possesses relative to a particular field of study (Alexander & Judy, 1988, p. 376). Separated from domain knowledge is strategic knowledge. This is knowledge of "goal-directed procedures that are planfully or intentionally evoked either prior to, during, or after the performance of a task" (Alexander & Judy, 1988, p. 376). These two components make up the relevant factors that may influence transfer of learning.

Evidence linking prior domain knowledge, strategic knowledge and transfer are extensive and can be found across different areas of research. The first research area is that of expertise development. Experts provide optimal examples for the study of transfer because expertise is often a result of being able to apply knowledge and strategies learned under one context to completely new situations. Alexander's (2003) Model of Domain Learning (MDL), for example, posits that expertise is a result of the interrelation between domain knowledge, strategic knowledge, and interest. Similarly, Ericsson and Smith (1991) and Hatano and Oura (2003) identified domain knowledge and strategic knowledge as key requirements in the development of expertise. These findings are important in establishing problem-solving skills as domain specific and often correlated highly with in-depth domain knowledge.

A second area of research where the role domain and strategic knowledge in promoting transfer of learning is investigated is the study of educational outcomes and performance. Dochy, Moerkerke, and Martens (1996) reviewed the literature on the subject and found evidence pointing to prior knowledge as a significant covariate in post-test learning performance in intervention studies, and as a significant predictor in causal modeling correlational studies (p. 7-8). Since then, a variety of studies have linked prior knowledge to positive learning outcomes and transfer (Ben-David & Zohar, 2009; Brand-Gruwel & Stadtler, 2011; Chang, 2010; Hailikari & Nevgi, 2010; Kilpatrick, Swafford, & Findell, 2001; Lee & Chen, 2009; Rittle-Johnson, Star, & Durkin, 2008; Schwartz, Bransford, & Sears, 2005; Star & Rittle-Johnson, 2007; Wong, Lawson, & Keeves, 2002). Table 2 outlines these studies and provides relevant information on the research design employed, the type of prior knowledge explored, and the knowledge domain covered in the study.

The third area where support for prior knowledge influencing transfer can be found is theoretical. The current and widely accepted view of the human cognitive architecture (Sweller, 2008; Sweller & Van Merrienboer, 1998) outlines a human information processing system directed by three main processes: assimilation, processing, and use (Sweller, 2008, p. 370). In this process, assimilation is dependent upon stored long-term knowledge. This knowledge forms the basis by which all new knowledge is developed (Bartlett, 1995). Thus, prior knowledge is likely to be the most important determinant of new learning and so it stands to reason that it also has a big impact on a learner's ability to transfer learning to newer circumstances.

Table 2. Evidence connecting prior knowledge and transfer.

Article	Research design	Knowledge type	Domain
Star & Rittle-Johnson, 2007	Experimental	Strategic	Math
Wong, Lawson, & Keeves, 2002	Path Analysis	Domain	Math
Rittle-Johnson, Star, & Durkin, 2008	Experimental	Domain	Math
Lee & Chen, 2009	Experimental	Domain	Math
Chang, 2010	Correlational	Domain	Science
Brand-Gruwel & Stadtler, 2010	Correlational	Both	Information seeking /web
Ben-David & Zohar, 2009	Experimental	Strategic	Scientific inquiry
Kilpatrick, Swafford,& Findell, 2001	Lit Review	Both	Math
Schwartz et al., 2006	Experimental	Both	Data analysis
Hailikari &Nevgi, 2010	Correlational	Both	Math

The more knowledge available—both in terms of domain knowledge and strategies to appropriately use that knowledge—the higher the probability learners will properly select and use the appropriate knowledge needed to solve new problems.

There is also evidence suggesting prior knowledge influences self-regulated learning, which justifies the inclusion of not only a direct relationship between prior knowledge and transfer, but also an indirect one. In outlining the components of self-regulation, Boekaerts (1996, 1997) showed that self-regulated learners typically rely on domain-specific knowledge and cognitive strategies to enhance performance. This led her to develop a six-component model of self-regulated learning that included regulating strategies along cognitive, motivation, belief, and affective dimensions, in addition to the two dimensions of prior knowledge. Pintrich (1999) arrived at a similar conclusion by outlining the role of cognitive learning strategies (rehearsal, elaboration, and organizing strategies) that along with metacognitive strategies help students control their learning. Since then, empirical findings have further validated the role of prior knowledge on self-regulated learning (Greene et al., 2010; Moos & Acevedo, 2008; Moos & Acevedo, 2009; Muis, 2007; Pieschl, Stahl, & Bromme, 2008).

The evidence points to a clear system of relationships among prior knowledge, motivation, self-regulated learning, and transfer. More than a control in the relationship between motivation, self-regulation, and transfer, prior knowledge is a key component of the system of relationships that explain the transfer process. This evidence, and the rationale supporting such evidence, provides sufficient justification—empirically and theoretically—for outlining the proposed model. The main assumptions of the model, which were outlined and graphically presented in previous sections, are summarized below:

1. Motivation—composed of a learner’s goal orientation, learner’s self-efficacy, and learner’s interest—indirectly affects transfer of learning through self-regulated learning.
2. Prior knowledge—composed of strategic and domain knowledge—affects transfer directly and indirectly through self-regulated learning.
3. Self-regulated learning directly affects transfer of learning.
4. Motivation and prior knowledge are significantly correlated. That is, motivated learners are typically learners with high prior knowledge.

Of course, the argument for the inclusion of these constructs is in itself not an argument to omit related constructs. As this study goes, the selection of these specific variables has been based on the quality of empirical and theoretical evidence justifying the posited relationships. These omitted variables are covered in more detail in the next chapter.

The next section argues that this proposed model can make a significant contribution to the transfer and motivation fields of research by concurrently investigating how motivational forces and prior knowledge interact with self-regulation to promote transfer of learning.

Significance of the Study

The proposed study argues that empirical evidence suggests an extension to the scope of the study of transfer beyond cognitive elements to encompass a set of affective components hypothesized to influence transfer of learning. Whereas both the transfer and motivation literature have identified antecedents and outcomes related to each, as Pugh and Bergin (2006) point out, “…conspicuously lacking is an analysis of the relation between motivation and transfer” (p. 147).

The analysis of this relationship through empirical means is the main focus of this study. The lack of a unified theoretical framework, however, makes this endeavor somewhat difficult.

As such, a main point of interest in the study is in better understanding the mechanism by which motivation affects transfer. That understanding can provide a theoretical starting point for future work wishing to explore the effects of motivational techniques on learning transfer.

Beyond theoretical goals, a better understanding of the causal mechanisms of a phenomenon allows us to capture the complexity of such phenomena, and in turn create more targeted interventions to change it. If we understand the mechanism by which motivation affects transfer, we can design learning interventions that better address that process. Furthermore, we can derive a set of instructional principles that target motivational factors and mediating causes to improve transfer of learning. Replication of such work in different contexts, with different content, and under different learning circumstances may allow us to come up with a comprehensive set of instructional principles that can be effectively applied to a variety of instructional situations. This is, after all, a principal focus of instructional scientists. As Reigeluth (1983) reminds us:

> Instructional scientists are not just interested in knowing that one method variable has better results than any other under given conditions – we are not just interested in single strategy components and isolated principles of instruction. What instructional designers and teachers need to know is a what *complete set* of strategy components has better results (for desired outcomes) than any other set under given conditions: We are interested in complete models and theories of instruction (p. 21).

As such, understanding the system of variables and the mechanisms that drive the processes of learning, which are targeted by our interventions, plays a major role in the eventual design of instruction.

Research Questions

The proposed model posits that motivation and prior knowledge have a direct effect on self-regulation. Self-regulation, in turn, affects, transfer of learning. Prior knowledge is also posited to have a direct effect on transfer of learning as supported by prior empirical studies (Brown, 1990; Gick & Holyoak, 1983; Nokes 2009; Schwartz, Bransford, &Sears, 2005; Wong et ale, 2002). Motivation encompasses goal orientation, interest, and self-efficacy. Prior knowledge includes knowledge of the domain and knowledge of learning strategies. Self-regulation is made up of both cognitive and motivational components that work together to influence deep-level processing associated with transfer. With regards to the transfer of learning phenomena, the following questions are addressed in this study:

- R1: Does prior knowledge significantly increase transfer performance? What is the magnitude of the relationship?
- R2: Does self-regulation significantly increase transfer performance? What is the magnitude of the relationship?
- R3: Does self-regulation significantly mediate the relationship between prior knowledge and motivation? What is the magnitude of the relationship?
- R4: Does self-regulation significantly mediate the relationship between prior knowledge and transfer of learning? What is the magnitude of the relationship?

As this study employs SEM to model the relationships among construct, a number of questions about model fit must also be addressed (Bollen & Long, 1993):

- R5: Does the specified model reasonably fit the data according to fit standards (x^2, CFI, RMSEA, AIC, etc.).
- R6: Which of the specified models (M1, M2, M3, M4, M5) best fit the data?
- R7: What modifications, if any, are proposed to improve the model's data fit?

Limitations

Although correlational studies examining the relationships between transfer of learning and the outlined constructs exist, there are no studies that simultaneously explore these relationships. The use of Structural Equation Modeling (SEM) as an analytical technique is appropriate for the types of inquiry investigating systems of variables and their relationships (Schumaker & Lomax, 2004).

The use of this technique, however, brings about a series of limitations. MacCallum and Austin (2000) identify several of these limitations. Applicable to this study are limitations about generalizability of findings, concerns about confirmation bias, and difficulty establishing the temporal order of the variables posited in the model, which seriously limits causality inferences.

First, as an initial exploration into the motivational factors of transfer of learning, it is expected that future, iterative validation will take place and that subsequent research will be carried out under different contexts and with different populations. The present study, however, will have limited generalizability beyond college students. This is not a limitation of SEM, but rather a limitation of the sampling technique used here. The sample is this study can be considered a convenience sample as subjects have been selected from an available pool of volunteers (Krathwohl, 1998). This non-probability sampling technique limits the scope of the inferences to be made to other populations, and has the potential to affect internal validity if the sample suffers from extreme homogeneity. Care will be taken to minimize these threats. A more detailed discussion of sampling can be found in chapter 3.

A second issue is that of confirmation bias. Confirmation bias refers to a prejudice towards a model being evaluated without consideration for alternative models that might fit data to the same degree, or better, than the proposed model (MacCallum and Austin, 2000, p. 213). This limitation can be addressed by progressively fitting nested models (equivalent models with different assumptions about correlations or direct and indirect effects) or by creating multiple *a priori* models. Given the time and resource limitations, these approaches might prove unfeasible, but a limited amount of model fitting consistent with SEM best practices is expected to take place. Specific techniques employed to minimize these concerns are discussed in chapter 3.

The third issue relevant to this is study is that of time. In correlational and observational studies such as this, there are issues establishing directional influences among variables and thus our ability to imply causation is restricted. How do we know, for example, that self-regulated learning strategies aren't influencing motivational forces? The temporal order is important because it is likely to influence the statistical estimates generated by the analysis, but most importantly because if the hypothesized variable relationships are wrong, the whole model rests on faulty logic. Addressing this issue requires complex considerations.

First, selection of the variables must rely on strong theoretical and empirical evidence that establishes the proposed temporal order. As shown before, the theoretical and empirical evidence clearly supports the temporal order proposed in this model.

Second, a temporal order is a necessity to establish causation, but it is not by itself sufficient for causation claims. Shadish and Cook (1999) discuss the logic of causation and remind us that causation is a more a matter of logic than a matter of statistics. Beyond temporal precedence, this requires us to rule out alternative causes. Thus, the danger of omitted variables lurks, as a third variable might be responsible for the outlined effects.

Once again, theory, empirical evidence, and common sense must be strongly considered in specifying the model. In the words of Shadish and Cook (1999), "design rules, not statistics", and thus mechanisms to address these issues must be built into the design of the study. This chapter described the careful logic for selecting and specifying the model. The next chapter discusses the evidence in more detail, and outlines the efforts to eliminate other plausible variables. Chapter 3 describes the methodological and design choices taken to minimize these inherent limitations.

Summary

For more than one hundred years, the study of the conditions and strategies that promote transfer of learning has taken a central role in the psychology and education literature. Over the last twenty years, this central focus has merged with a nascent interest in exploring the role of personal and motivational beliefs. Yet, despite a wealth of evidence linking individual motivational and belief characteristics to self-regulated learning and transfer, there are only a handful of studies attempting to advance a theoretical integration of these areas through quantitative or qualitative validation.

This study lies at a critical intersection of these fields, and attempts to fill a gap in our theoretical understanding of the motivational mechanisms of transfer. To accomplish this, the proposed model seeks validation in predicting prior knowledge and motivation as mechanisms that influence transfer of learning through increased self-regulation. An expectancy-value model of motivation spells out three major indicator variables—goal orientation, interest, and self-efficacy—that correlate closely with prior knowledge, both in terms of domain knowledge and strategic knowledge. These constructs are posited to directly and indirectly influence transfer of learning. A case has been made for the inclusion and operationalization of these variables as outlined in the proposed model. That case is extended, and further developed in the next chapter by summarizing the relevant literature, revisiting each argument and logical justification in detail, and proposing a research design and analytical methodology suited for validating the theoretical and empirical relationships outlined in this chapter.

CHAPTER 2: LITERATURE REVIEW

The purpose of this dissertation is to identify and validate a model that describes the role of motivation on transfer. Chapter 1 described the nature of the problem and provided justification for the proposed study by outlining a gap in the transfer and motivational literature. In this chapter, this rationale is expanded and the distinct components of the motivational model of transfer are discussed in detail.

It is no easy feat to summarize more than 100 years of theoretical and empirical work into a succinct and cohesive chapter. Light and Pillemer (1984) argue that the literature review is a necessary step in ensuring science is a cumulative endeavor that draws from prior work. Further, the authors argue that this process is not merely about selecting and synthesizing a narrow set of studies. Rather, the process is a systematic attempt to structure a research endeavor review while aggregating and integrating conflicting information. This review follows this sound advice by establishing clear criteria for selection and inclusion of literature in this review. Furthermore, this review addresses a set of issues that have been identified as weakening the existing evidence, and by extension limiting the scope of the foundational evidence that supports new empirical work.

Light and Pillemer (1984) identified five critical issues to be addressed in any systematic literature review (p. 12). These are:

1. Identifying a question the review is trying to answer.
2. Determining whether the review is exploratory or built around specific, testable, hypotheses.
3. Determining studies to be included.

4. Determining to which population the main findings can be generalized.
5. Describing important differences in the ways the studies were done.

The first three issues are addressed at a global level while issues four and five are addressed with regards to each study covered in this review.

First is the issue of identifying a set of answerable research questions. Booth, Colomb, and Williams (2003) warn that plunging into a search without identifying a question and plausible answer is essentially the same as leaving the review up to chance. Instead, a logical chain must be followed from the identification of the problem to the formulation of questions to the validation of the plausibility of the answers hypothesized for those questions, and finally to the verification of those answers through data collection. That chain of reasoning is followed in this study.

Chapter 1 established a gap in the transfer literature, which has conspicuously ignored the role of motivation in promoting transfer of learning. From that gap followed a set of questions that laid the foundation for this chapter. These questions, and potential answers were supported with empirical and theoretical evidence. In this chapter, that evidence is further described and expanded upon, its limitations are highlighted, and its logical relationship to this study is established.

From these questions, followed clear, testable hypotheses operationalized in the form of a theoretical model in need of validation. While there are some exploratory aspects—namely with regards to testing various models to determine best fit—these alternative models are specified *a* *priori*. They follow, once again, from the empirical and theoretical evidence that drives the research questions posed.

The final global issue is that of establishing inclusion criteria for the studies reviewed, and discussing the implications that criteria will have on the review and the study in general. Light and Pillemer (1984) suggest the easiest alternative is to include all available studies. This is a problematic strategy in a domain where an established tradition of empirical work exists. Sheer volume makes it difficult to cover all studies under a limitation of time and space, as is the case in this study. Given that limitation, a more feasible approach is followed in this study and thus the following criteria for inclusion are established:

1. *Include published and unpublished quantitative, qualitative, and mixed-methods studies.* While acknowledging that most of the studies included in this review will be drawn from published work in journals and books, this study will also draw on unpublished dissertations and technical reports that exhibit sound methodology and either support or provide a departing point to the hypotheses posed in this study.
2. *Include all empirical work related to a topic.* The focus of this study shall be on empirical work. That is, work that employs systematic data collection and analysis techniques. Work that reviews, summarizes, and amalgamates a body of work will be included when systematic procedures (i.e. meta-analysis procedures) for selection and analysis of studies are provided by the authors.
3. *Include only conceptual work when establishing theoretical foundations and frameworks.* Conceptual/theoretical work provides a major starting point for this study because it is important to establish the theoretical foundation under which the

study operates. Beyond that, however, conceptual work will not be considered to support claims of significant relationships or effects of a variable upon another. This leads to the next point.

4. *Give preference to studies consistent with theoretical framework selected for this study.* Construct operationalization requires selection of a theoretical framework (Creswell, 2003; Babbie, 2008). The rationale for the theoretical frameworks chosen is detailed in this chapter. Based on that rationale, studies are selected for theoretical congruence to facilitate operationalization and interpretation.
5. *Include all relevant literature domains beyond education and psychology.* Many of the constructs included in this study have been covered in other fields. This review expands its scope, when appropriate, to include studies from multiple disciplines as to provide a wider, more comprehensive view of the relationships proposed.
6. *When possible, include only studies covering the domain of mathematical problem solving.* Despite the concern for comprehensiveness, however, the study also seeks to establish depth in a particular content domain—that is mathematical problem solving. As such, the study attempts to include mostly studies covering this domain. It is speculated processes of transfer might be unique to the domain they concern (Bransford, 2000; Nokes, 2009). An exception to this rule arises when a study in a different content domain can offer supporting evidence for an overall process that is generalizable to multiple content domains (as it is the case with the relationship between prior knowledge and transfer of learning).
7. *Include studies covering all populations unless the processes described are unique to that population.* Although this study relies on a sample of university students,

inclusion is justified when empirical evidence suggests the processes can be replicated across multiple populations.

The criteria specified above forms the basis for study inclusion in this review. This systematic review begins with an overview of the transfer of learning.

The Multiple Perspectives of Transfer of Learning

Psychology, education, and their surrounding subsets have been concerned with transfer of learning since the very beginning. This concern has resulted in contentious findings and somewhat contradicting conceptualizations. As Haskell (2001) affirms, "…the term transfer appears nearly omnimeaningful, with no systematic taxonomical framework to guide its multiple definitions and uses" (p.78). To illustrate this point, historical definitions of transfer as they have evolved in the literature are highlighted below.

- ***Transfer as identical elements:*** "The influence of improvement in one mental function upon the efficiency of other functions (I)" (Thorndike & Woodworth, 1901, from title).
- ***Transfer as analogy:*** "The central idea is that an analogy is an assertion that a relational structure than normally applies in one domain can be applied in another domain" (Gentner, 1983, p. 156).
- ***Transfer as socio-cultural activity:*** "The central idea is that 'the same' activity in different situations derives structuring from, and provides structuring resources for, other activities. This view specifically opposes assumptions either that activities and

settings are isolated and unrelated, or that some forms of knowledge are universally insert able into any situation" (Lave, 1988, p. 122).

- ***Transfer of learning:*** "Stated most simply, in our work, we mean understanding; and understanding is indexed by the ability of learners to *explain* the resources (knowledge and processes) they are acquiring and to make flexible use of them. (Campione, Shapiro, & Brown, 1995, p. 39).
- ***Transfer as consequential transitions:*** "Transfer involves the movement of a person, a transaction, or an object from one place and time to another in our daily lives" (Beach, 1999, p. 101).
- ***Transfer as an actor (i.e. learner)-oriented activity:*** "…Transfer as the personal creation of relations of similarity, or how the 'actors' see situations as similar" (Lobato, 2003, p.18).
- ***Transfer in granular pieces:*** "Processes by which ideas once cued only in particular contexts can be actively and flexibly developed, combined, and coordinated such that they are more likely to be used in an increasingly wider span of situations" (Wagner, 2006, p. 6).

At first glance, it would seem these definitions are quite similar. They all involve the application or usage, in some manner, of previous experiences (in most cases learning experiences) under a new context. A closer look, however, reveals deeply embedded psychological and methodological assumptions that have been the subject of disagreement since the early 20th century when Thorndike first began the tradition of transfer research in psychology (Baldwin & Ford, 1988; Detterman & Sternberg, 1993; Lobato, 2006). Thorndike's definition, for example, was situated within the behaviorist paradigm of psychology that acknowledged mental “function” but focused only on observable behavior.

More than 80 years later, Gentner’s definition came in the midst of a cognitive revolution that sought to map out cognitive processes through formal definition of schematic mental structures. Subsequent definitions stressed flexibility in using knowledge but held on to the epistemological view that learners were “receivers” of knowledge rather than active participants in its construction (Lave, 1988; Lobato, 2006). Lave (1988) challenged this view in proposing transfer as malleable activity embedded in, and shaped by, personal dispositions, culture, and context. Lave’s reconceptualization spawned a series of critiques that saw an abandonment of experimental procedures to study transfer of learning and instead moved into observations of transfer is more realistic, situated settings (i.e. Beach, 1999; Ellis, 1997; Lobato, 2003; Tuomi-Grohn & Engestrom, 2003; Wagner, 2006).

Table 3. Classic vs. learner-oriented view of transfer (adapted from Lobato, 2003).

Dimension	Classical Transfer View	Actor-Oriented View
Definition	The application of knowledge learned in one situation to a new situation.	The personal construction of relations of similarity across activities, (i.e. seeing situations as the same).
Perspective	Observer’s (expert’s) perspective.	Actor’s (learner’s) perspective.
Research method	Researchers look for improved performance between learning and transfer tasks.	Researchers look for the influence of prior activity on current activity and how actors construe situations as similar.
Research questions	Was transfer obtained? What conditions facilitate transfer?	What relations of similarity are created? How are they supported by the environment?
Transfer tasks	Paired learning and transfer tasks have structural features but differ by surface features.	Researchers acknowledge that what experts consider a surface feature may be structural substantive for a learner.
Location of invariance	Transfer measures a psychological phenomenon.	Transfer is distributed across mental, material, social, and cultural planes.
Transfer processes	Transfer occurs if two symbolic mental representations are identical or overlap, or if a mapping between them can be constructed.	Multiple processes, such as attunement to affordances and constraints, assimilation, language use, and “focusing phenomena,” influence transfer.
Metaphor	Static application of knowledge.	Dynamic production of “sameness.”

This brief historical overview illustrates the evolving nature of the transfer phenomena. Moreover, it highlights the need for transparency and clarity from a researcher in specifying the theoretical underpinnings and assumptions they are adopting. This study adopts a traditional view of transfer. Table 3 provides a summary overview of those assumptions and a contrast to the actor-oriented view of transfer—a conceptualization resulting from Lave's critique.

Lobato's overview of assumptions is a logical extrapolation of most of the transfer literature, which up to Lave's critique had done little to acknowledge the role of culture, context, and individual dispositions on transfer. These studies—consciously or unconsciously—have replicated many of these assumptions without considering the problematic implication of their adoption.

The current study operates under a traditional view of transfer while acknowledging, and in many ways integrating, the theoretical and practical contributions made by the authors that have offered alternative views of transfer. Lobato's assumptions of the classical view of transfer as a rigid and uniform structure are rejected in favor of a more integrated approach. This integrated approach is an amalgamation of theoretical and empirical evidence. To be clear, the approach is described in terms of Lobato's suggested categories and is provided in contrast to the rigid opposing views offered above. The approach is summarized on table 4.

The formal outlining of these assumptions frames this study within the larger transfer literature. It frames the study as one departing from assumptions long considered to be lacking while still maintaining those aspects of the classical view of transfer that have pushed the literature forward for over a century. Two important departures differentiate this study from the majority of transfer studies found in the educational and psychology literature. First is the inclusion of contextual variables—in this case motivational dispositions—into a framework that explores the role of those variables on transfer of learning. Second is the concurrent analysis of the impact of multiple variables upon transfer. Having established that frame of reference, this chapter turns to describing the factors that are known to influence transfer, including the role of motivation.

Table 4. Assumptions about the transfer construct adopted in this study.

Dimension	**View adopted in this study**
Definition	The application of knowledge learned in one situation to a new situation.
Perspective	Observer's (expert's) perspective with the caveat that we don't have a full view of what the learner knows. As such, the transfer task is designed to allow learners to access resources and other materials as to show what they have "transferred in" (Schwartz, Bransford, and Sears, 2003).
Research method	Researcher begins by defining a transfer task and working backwards to analyze the knowledge components necessary to accomplish that task. Researcher then uses advanced modeling techniques to validate hypothesized relationships among those components.
Research questions	Was transfer obtained? What conditions facilitate transfer? What relations of similarity are created? How do learner characteristics influence transfer?
Transfer tasks	Transfer tasks have structural features similar to what we assumed the learner knows. The task, however, is open enough to allow learners to showcase their knowledge in more than one way.
Location of invariance	Transfer measures a psychological phenomenon that is profoundly influenced by a learner's disposition, intentions, emotions, etc.
Transfer processes	Multiple processes, such as attunement to affordances and constraints, assimilation, language use, and "focusing phenomena," influence transfer. Moreover, motivational processes influence these cognitive processes significantly.
Metaphor	Dynamic assembly of multiple knowledge components that require regulatory processes for successful assembly.

Factors Influencing Transfer of Learning

The concern with transfer found in the early psychological literature did not necessarily lead to a formal explication of the factors known to influence transfer. Instead, the initial focus rested on experimental manipulation. This early experimental work helped outline the singular factors that influenced transfer. These efforts, however, were marked by a focus only on factors that were malleable and therefore appropriate for experimental manipulation. These factors, for most of the 20th century, took the form of a particular training or learning intervention designed to alter cognitive or behavioral structures. Little attention was paid to personal characteristics, as these were considered stable, and fairly difficult to manipulate via experimental intervention.

Ellis (1965) was one of the first to formally outline transfer factors that went beyond the manipulation of a task or instructional intervention. He acknowledged that the extent to which a learner is able to master a new task "…depends to some degree upon individual learner characteristics" (p. 36). He posited these factors were mediational processes "to be regarded as mechanisms for producing transfer" (p. 36). Ellis' list is limited referencing "past experiences of the learner and how those experiences are utilized in the present task" (p. 36). This vague statement must be unpacked based on the evidence presented by Ellis in the subsequent pages of the chapter. In the studies cited as evidence for this claim, Ellis is likely referencing prior domain knowledge. When describing how a learner goes about using that knowledge in the present transfer task, Ellis is referencing strategic knowledge as well as self-regulated behaviors that would allow a learner to monitor the state of their knowledge, select and implement strategies to solve the problem, and carry out that plan with minimal mistake.

Remarkably, without having the language and terminology of socio-cognitive psychology, Ellis had pinpointed the role motivational processes and prior knowledge play in promoting transfer. Ellis identified other factors influencing transfer. They're included in table 5.

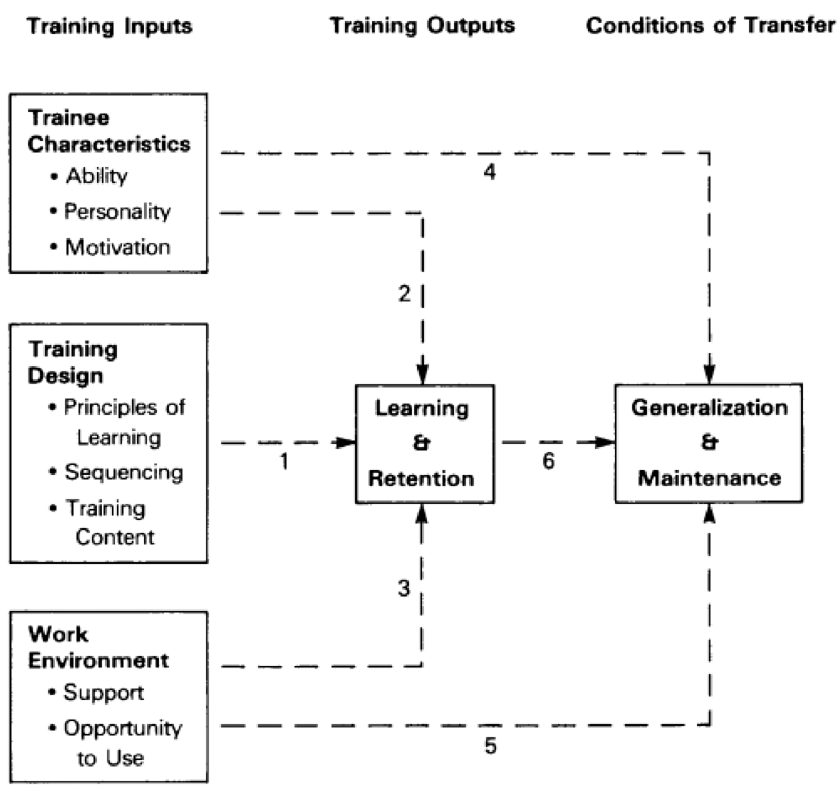


Figure 2. A model of the transfer process from Baldwin and Ford, 1988, p. 65.

More than twenty years after Ellis' review of the transfer literature, a comprehensive look at transfer influences was provided by Baldwin and Ford (1988). The authors developed a framework concerned with outlining the overall forces responsible for promoting transfer of training. Their framework included a series of inputs, outputs, and conditions that as a whole described the transfer process. Once again, the results were similar in identifying learner characteristics, characteristics of training/instruction, and environmental variables. Baldwin and Ford's framework is displayed in figure 2.

Motivation and other learner characteristics are correctly identified as influencing both initial learning, and the "generalization and maintenance" required to be able to transfer. Despite this identification, much of the focus of the review is the training design aspect of the framework as the available evidence is most extensive in that area. As the authors point out: "There are fewer such studies, but they are more recent that those focusing on training-design characteristics" (p. 75). A complete list of the variables summarized by Baldwin and Ford are provided in table 5.

The latest review outlining what we know about the variables influencing transfer was provided by Bransford, Brown, and Cocking (2000). In this comprehensive treatise of learning, Bransford and his colleagues had the benefit of more recent research on transfer focusing on a transformed view that included motivation, metacognition, and contextual variables in addition to training design characteristics. They conclude:

> Several critical features of learning affect people's abilities to transfer what they have learned. The amount and kind of initial learning is a key determinant of the development of expertise and the ability to transfer knowledge. Students are motivated to spend the time needed to learn complex subjects and to solve problems that they find interesting. Opportunities to use knowledge to create products and benefits for others are particularly motivating for students. (p. 77).

Table 5 summarizes and compares these variables to previously proposed models of transfer. The series of variables included in these reviews reflect the evolving nature of our understanding of the transfer phenomena. Motivation, prior knowledge, and self-regulated behaviors were included in reviews as early as the 1960s reflecting the view that these factors are important pieces of the processes that influence transfer. That recognition, however, has resulted in few studies formally exploring the process by which motivation and prior knowledge affect transfer. That is the focus of this study. It is thus appropriate to now turn to motivation, its formal definition, and the evidence supporting its influence of transfer of learning.

Table 5. A Comparison of Factors Influencing Transfer of Learning.

	Ellis (1965)	Baldwin and Ford (1988)	Bransford, Brown, and Cocking (2000)
Training/instructional characteristics	• Time interval between tasks • Variety of previous tasks • Task difficulty • Task similarity	• Principles of Learning • Sequencing	• Understanding versus memorizing • Time to learn • Deliberate practice • Problem representations • Relationships between learning and transfer conditions
Learner Characteristics	• Prior experiences • Degree of original learning • Learning to learn	• Ability • Personality • Motivation	• Metacognition • Prior knowledge • Motivation
Context Characteristics		• Support • Opportunity to transfer	• Context (i.e. where learner is being asked to transfer) • Cultural practices

Motivation

As these reviews show, the concern with motivation as an influence force in promoting transfer of learning is by no means a novel one. As early as 1965, Ellis asserted: “To the extent that motivational variables influence learning, they are also likely to influence transfer” (p. 65). Ellis cites studies by Spence (1964) exploring the effect of anxiety on performance and transfer. Given the nascent nature of the motivation construct at the time, its recognition as an essential variable in the transfer process is remarkable.

Historically, motivation did not enter the language of psychology until the 1950s. Gollwitzer and Oettingen (2000) cite Atkinson’s work (1957) as first in exploring expectancy-value theories of motivation that shifted the view of human beings as reactive organisms that were compelled to act by external faces rather than internal dispositions. The new view assumed "…that people choose goals in a rational way, based on the comprehensive knowledge of the probability of goal attainment and the goals' expected value" (p. 1011). These early concerns with motivation and transfer have carried over as researchers have continued to refine their understanding of the role of motivation on learning and transfer.

Self-Determination Theory. The selection and operationalization of a framework is complicated by the widespread number of theories addressing motivation, behavior, and performance. During the course of this literature review, two competing framework emerged as suitable candidates for the present study. One of the most prominent candidates referenced in the motivation literature was Deci and Ryan's (2000) Self-Determination Theory (SDT).

Unlike motivational theories such as Pintrich's expectancy-value model, which focus on goal-directed behaviors consciously set by learners, Deci and Ryan affirm a differentiator of their theory is a focus on needs.

> Since the time of the shift toward cognitive theories, most motivation theorists remained unwilling to consider needs, focusing instead on goal-related efficacy. SDT has, in contrast, maintained that a full understanding not only of goal-directed behavior, but also of psychological development and well-being, cannot be achieved without addressing the needs that give goals their psychological potency and that influence which regulatory processes direct people's goal pursuits (p. 228).

Needs are "innate, organismic necessities rather than acquired motives" (p. 229). According to SDT, there are three basic psychological needs—autonomy, competence, and relatedness—that must be satisfied for human beings to function optimally. Autonomy is the "organismic desire to self-organize experience and behavior and to have activity be concordant with one's integrated sense of self" (p. 231). Competence is "a propensity to have an effect on the environment as well as to attain valued outcomes within it" (p. 231). Relatedness is a human and social need, a "desire to feel connected to others—to love and care, and to be loved and cared for" (p. 231). When these needs are not satisfied, SDT predicts significant psychological costs.

This focus on needs allows the authors to expand the scope of their motivational theory to all endeavors of human behavior. It has been used, for example, to explain behavior and performance in sports-related settings (Vansteenkiste & Deci, 2003; Gagne, Ryan, & Bargmann, 2003), to propose solutions to promote health behavior changes (Ryan et al., 2008; Niemiec et al., 2010), to investigate perceptions of discrepancy between managers and employees in organizational settings (Kasser, Davey, & Ryan, 1992; Llard et al., 1993), and to suggest more targeted psychotherapeutic interventions (Ryan, Plant, & O'Malley, 1995; Zeldman, Ryan, & Fiscella, 2004).

In the realm of education, SDT has far reaching implications. It has been used to explain performance of undergraduate students in a variety of cultures and contexts (Filak & Sheldon, 2003; Jang et al., 2009; Levesque et al., 2004; Niemiec et al., 2006), to predict academic performance with children (Grolnick, Ryan, & Deci, 1991; Patrick, Skinner, & Connell, 1993; Ryan, Stiller, & Lynch, 1994), and as an analytical tool to examine medical students' motivations (Williams et al., 1994; Williams et al., 1996; Williams et al., 1997).

The breadth of the theory makes it well suited to explain a variety of human behaviors in a variety of contexts. This, however, does not mean that it is well suited to explain transfer. For one, the limited evidence supporting the effect of various motivational aspects on transfer has been mostly based on socio-cognitive and goal-oriented theories of motivation rather than need-driven theories such as SDT. Secondly, the mechanisms of transfer have been described under multiple perspectives as the definitions previously highlighted show. These mechanisms, however, have never been directly mapped to the SDT processes that spell out how intrinsic, extrinsic motivation and goals help human beings fulfill their basic needs.

For these reasons, namely a lack of theoretical and empirical foundation establishing SDT as a suitable theory to explain or predict transfer and its mediation processes, this motivational theory is not considered as the foundation for this study. For this same reason, many of the variables operationalized within SDT—namely volition and locus of control—are also omitted despite possible links to transfer. This is done for purposes of theoretical congruence but also because these variables are likely to be captured by the variables specified under the expectancy-value model of motivation employed in this study.

The Expectancy-Value Model. Having ruled out Self-Determination theory, this study relies on Pintrich's (1988, 1989) expectancy-value model of motivation as a theoretical framework of motivation. The framework consists of three major components that have direct correspondence to the known transfer mechanisms. First, it should be acknowledged that a single mechanism is not responsible for promoting transfer. Instead, multiple mechanisms, and a combination of mechanisms can be employed to produce transfer (Nokes, 2009; Salomon & Perkins, 1989).

These variations are dependent on a number of design, individual, cultural, and conditional factors, but according to Salomon and Perkins (1989), they can be roughly classified within two separate mechanisms: a mechanism to predict *low road*, or near transfer, and a mechanism to predict *high road*, or far transfer. In chapter 1, a discussion of near transfer and its equivalent conceptualizations led to the conclusion of near transfer as characterized by the use of prior learning within similar domains under difficulty levels that remained fairly close to the initial learning context. The near transfer mechanism is simply an extension of the overall learning mechanism specified in the information-processing model (Huitt, 2003).

Near transfer occurs when a new concept, fact, or procedure is learned and practiced in a variety of contexts allowing multiple schematic representations so that future retrieval and application is flexible. When a learner encounters a transfer task, they are able to transfer if the surface features (the face characteristics of the task as perceived by the learner) of the task resemble the features stored in long-term memory that were encountered in previous problems. This is an automatic process made possible by varied practice (Salomon & Perkins, 1989). This mechanism is similar to the analogical reasoning mechanism specified elsewhere in the literature as being an essential mechanism of transfer (Gick & Holyoak, 1980, 1983; Gentner, Loewenstein, & Thompson, 2003; Novick, 1988). Nokes (2009) showed the analogical reasoning mechanism to be most effective in explaining near transfer.

Far transfer, on the other hand, was characterized by the use and adoption of previously mastered knowledge components to newly encountered problems. Salomon and Perkins (1989) posited far transfer occurred as a result of three interwoven processes: abstraction, mindfulness, and mindful abstraction. Abstraction refers to a process, and also eventual outcome, where a learner engages a task/problem, and through a variety of information-processing techniques proceeds to create a generic representation of that problem so that it can be cross-referenced to existing knowledge components. This is followed by mindfulness, which is "the volitional, metacognitively guided employment of nonautomatic ('controlled') processes typical of 'deeper processing', of great mental effort expenditure, and of the 'conscious manipulation of the elements of one's environment" (p. 125-126).

A combination of the two prior processes follows this to help learners make conscious choices about a suitable principle, strategy, or procedure to tackle the problem at hand. The point of the process is to sufficiently decontextualize knowledge components so that they are generically represented in schema. This allows future, flexible retrieval of these knowledge components to address a variety of newly encountered problems. Mindful abstraction is clearly a process requiring willful, intentional, and ideally self-regulatory effort to move from an abstraction to the selection and implementation of a proper strategy to solve a problem. This willful action implies motivational processes play a role in the efficiency and effectiveness of the transfer processes that require mindful action. This naturally leads to a question about how motivational processes map onto the mechanisms of near and far transfer.

Mayer (1998) examined the role of cognition and motivation on transfer. He described three theoretical and empirical approaches emphasizing the role of motivation—interest theory, self-efficacy theory, and attributional theory. These motivational processes are posited to influence transfer by affecting cognitive processing, much the same way Salomon and Perkinson (1989) describe it. Interest theory suggests if a learner is interested in a task, they will exert more effort promoting deeper learning and enhancing transfer (Ainley, Hidi, & Berndorff, 2002; Mayer 1998). Self-efficacy theory predicts that when learners judge themselves as capable of solving a problem, they set challenging goals for themselves and commit to achieving those goals. Bandura (1993) asserts: "There is a marked difference between possessing knowledge and skills and being able to use them well under taxing conditions" (p. 119).

The evolving view of human performance as capability depending not just on knowledge but on managing regulatory processes that allow learners to use that knowledge makes self-efficacy an influential motivational factor upon transfer of learning. Attribution theory predicts that when learners attribute academic success and failure to their own efforts, they're more likely to succeed than when they attribute success or failure to innate ability (Weiner, 1985). These three components of motivation are consistent with other models of motivation (Pintrich 1988, 1989; Dweck, 1986; Dweck & Leggett, 1988).

The first component, the expectancy component, covers a learner's belief about his/her ability to achieve and succeed. This corresponds to Mayer's self-efficacy dimension as well as the attribution component. A second component is the value component, which includes a learner's goal orientation towards a task and their interest on performing that task. This is similar to Mayer's notion of motivation as interest. A third component concerns learners' affective and emotional reactions towards a task. This could include emotions such as guilt, pride, fear, but in school settings it is often manifested in classrooms as test anxiety (Pintrich & De Groot, 1990, p. 34). This emotional and affective component has no match in Mayer's model, in part because of the effect of anxiety on transfer has not been explored widely in the literature. For those reasons, and because in the context of a low-stakes task outside of the classroom, text anxiety and task anxiety seem less likely, this component is left out of the motivation model used in this study.

From these multiple theoretical frameworks emerges a conceptualization of motivation that includes three distinct components: self-efficacy, goal-orientation, and interest. Empirical support linking each of these components to transfer of learning is reviewed next, along with a description of the ways the variables are conceptualized and measured.

Self-Efficacy. Self-efficacy has been defined as “people’s beliefs about their capabilities to exercise control over their own level of functioning and over events that affect their lives” (p. Bandura, 1993, 118). In what often becomes a self-fulfilling prophecy, learners with a strong belief about their abilities to complete a problem are more likely to perform better in problem solving tasks (Hall & Vance, 2010; Holladay & Quinones, 2003; Pajares & Miller, 1994; Pajares, 1996; Hoffman & Spatariu, 2008; Marsh et al., 1997).

One of the first studies exploring the link between transfer and problem solving performance under social cognitive theory was conducted by Pajares and Miller (1994). The authors conducted a correlational study with 350 undergraduate students. In the study, the authors posited both a direct and indirect link between self-efficacy and mathematical performance as measured by a problem-solving task. The authors modeled this relationship with self-efficacy as a mediator variable between learner characteristics (gender, and prior knowledge conceptualized essentially as educational experience in math), and other belief variables (self-concept and perceived usefulness). The initial model also included anxiety but the variable was removed in the final model as no significant relationships were found between it and the mediating and predictor variable. The final model is shown in figure 3.

Under this model, both self-efficacy and self-concept are found to be mediator variables, and both are found to directly predict performance. The strongest direct effects, however, are those of self-efficacy with standardized path coefficients of .545 compared to .163 for self-concept. The learner characteristic variables, which are used here as control variables, account for similarly modest total effects with the exception of math high school experience which has a total effect of .375 on performance, although a large part of that effect is manifested through self-efficacy.

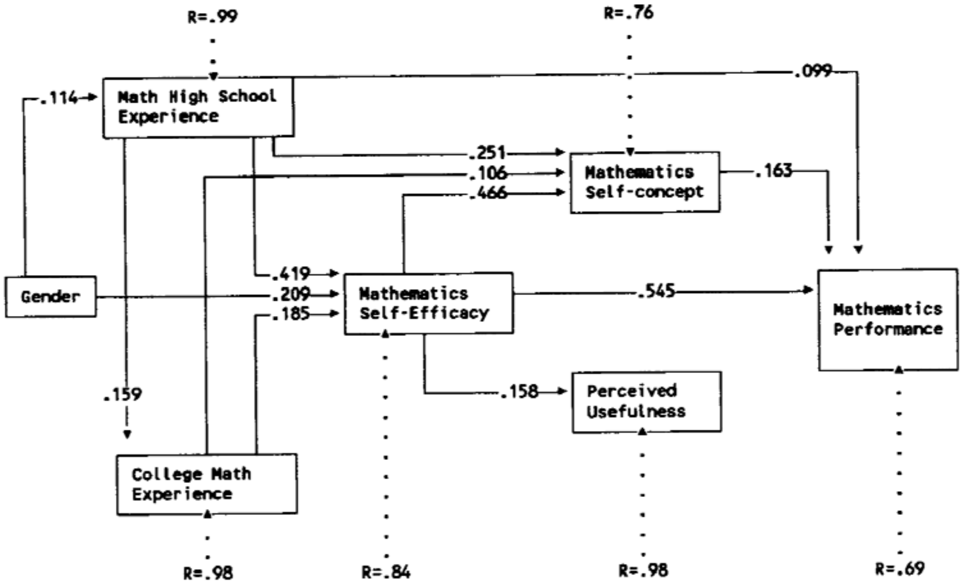


Figure 3. Modeling the effects of self-efficacy on performance. Reproduced from Pajares and Miller, 1994.

Overall, the study suggests that under this system of variables, self-efficacy is an important predictor of mathematical performance. It is a bit more difficult to interpret the fact that in the model self-efficacy indirectly influences math performance through self-concept. As operationalized in this study, self-concept refers to more generic perceptions of capability rather than context specific judgments of ability as in the case of self-efficacy.

Given the nature of the study (non-experimental), it is difficult to establish a temporal order in this relationship beyond what should obviously be a strong correlation. What is clear is that this set of independent variables provide reasonable predictive power for math performance (R^2 = .52), but leave open the possibility that there is much left to explain.

The previously described study established a framework for future studies concentrating on the role of self-efficacy and mathematical transfer. Subsequent studies focus on establishing antecedents of self-efficacy maintaining the meditational role of self-efficacy.

Holiday and Quinones (2003) explored a similar line of inquiry specifically concerned with transfer of learning. They measured both the intensity of self-efficacy as well its 'generality'; a measure of the consistency of self-efficacy ratings across a number of tasks, which the authors suggest was more likely to accurately reflect the learner's overall self-efficacy. They hypothesized that practice variability in training was likely to influence both aspects of self-efficacy, which in turn would influence both near and far transfer. Further, the authors isolated self-efficacy generality, as a main predictor of far transfer while self-efficacy level was a main predictor of near transfer. Their findings supported both the hypothesis that practice variability increased self-efficacy along both dimensions, and also that increased self-efficacy generality was a strong predictor of far transfer (p. 1099). Once again, self-efficacy was viewed as a meditational process without regard for the potential mechanisms existing between self-efficacy and transfer.

Hoffman and Spatariu (2008) conducted a similar correlational study with 81 undergraduate students enrolled in psychology course. The authors sought to determine the influence of metacognitive prompts on transfer positing self-efficacy as a mediating mechanism between the two. They fit a regression model with a number of controlling variables, including prior knowledge. Mathematical performance was assessed by a number of measures that included performance accuracy, difficulty level, time, and efficiency (accuracy/time). Their findings suggested both self-efficacy and metacognitive prompting affected performance accuracy and efficiency. No evidence was found suggesting prompting was more effective on learners with certain levels of self-efficacy. In this case, no tests of mediation were conducted despite the previous attempts to establish self-efficacy as a meditational mechanism of performance.

Hall and Vance (2010) continued this tradition of inquiry by creating an experiment to tease out the effects of self-explanations on problem-solving scores. A total of 138 students enrolled in a large business course participated. Their findings suggested groups trained to self-explain (n=68) influenced self-efficacy beliefs, which in turn influenced problem-solving scores. This inference was supported by the absence of this same relationship in the group that was not trained to self-explain (n=68).

These studies do quite a bit in establishing a model of self-efficacy processes that influence transfer. There is reasonable empirical and theoretical evidence to justify the stated relationships, but at a macro-level, these relationships appear to be missing key learning processes. There are multiple meditational processes that influence mathematical performance. When modeling these, the key is not necessarily to include them all, but to ensure the most influential ones are represented.

The variables included in these studies pose granular hypotheses concerned with explaining the relationship between self-efficacy and mathematical performance. But in doing so, these authors have left out a major link between self-efficacy and performance. This link is established in the theoretical basis of self-efficacy, which is described as a capability influential in organizing and executing behaviors and actions necessary to attain certain performances (Bandura, 1986). This regulatory mechanism is the main mediator between self-efficacy and performance. Failure to include components of the mechanism has the potential to distort the strength and direction of the relationships posited in the model. This is the all-common omitted variable bias described in virtually every multivariate statistics textbook (see Baron & Kenny, 1986; Clarke, 2005; Kim & Frees, 2006; Kline, 2010 for some examples). The lack of justification for the omission of these variables makes it even more problematic.

The inclusion of the self-regulatory mechanism in the present study is a direct response to this flaw in the literature. The present study departs from this current line of inquiry by choosing to model a more generic process focusing on global motivational processes rather than micro processes related to self-efficacy. It improves upon previous studies by using SEM instead of path analysis, which allows us to more closely address issues of measurement error and construct validity and thus obtain more accurate estimates. Lastly, the present model relies on a theoretical framework specific to transfer of learning rather than just performance. As such, it leaves out variables such as self-concept that are present in the self-efficacy literature but are likely to be closely correlated and covered within measures of self-efficacy in more generic models.

Thus, this leads us to converge on self-efficacy as a strong predictor of transfer because it provides a monitoring and feedback mechanism that helps learners keep tabs on their potential ability. This is especially true when learners receive self-efficacy training, but it is also supported by lines of inquiry employing correlational techniques to establish a relationship between prior levels of self-efficacy and eventual transfer abilities (as in Marsh et al., 1997; Finney and Schraw, 2003; and multiple studies cited by Usher & Pajares, 2008). This further suggests a link between self-efficacy and the cognitive and motivational monitoring and feedback processes, which are encompassed under self-regulated learning.

These significant findings found throughout separate lines of inquiry in self-efficacy research provide support for the initial hypothesis that self-efficacy is a strong predictor of transfer. Learners who believe in their ability to successfully navigate a task are more likely to excel at that task and at tasks that call upon the learners to use what they have learned in prior situations. Having established a strong link between this aspect of motivation and transfer, it is now time to turn our attention to the issue of goal orientation.

Goal Orientation and Transfer. The goals set by learners when engaged with instruction have shown to affect academic achievement and transfer. As discussed in chapter 1, the goal orientation literature has identified two broad classes of goals: performance and mastery (also known as learning) goals (Grant & Dweck, 2003; Kaplan & Maehr, 2007). There is evidence linking both types of goal orientation to positive outcomes such as improved self-efficacy and self-regulation, academic achievement, and positive emotions (See Kaplan & Maehr's review, 2007).

However, a number of studies in the literature have associated performance goal orientation with decreased performance outcomes as they shift the learner's attention away from the task, decrease effort, and are not effective in promoting self-regulated behaviors (Kozlowski et al., 2001; Newman & Schwager, 1995; Stevens & Gist, 1997). This, along with critiques that point out the possibility of performance goals leading learners to adopt a performance-avoidance approach marked by a focus on competition that can be detrimental to learning (Brophy, 2005), makes mastery goals a preferable candidate as a key predictor of transfer over performance goals.

There exists some evidence that links mastery goals both directly and indirectly to transfer of learning (Berevy-Mayer & Kaplan, 2005; Dupeyrat & Marine, 2005; Fisher & Ford, 1998; Ford et al., 1998).

Ford and his colleagues (1998) conducted a correlational study with 98 undergraduate psychology students. They sought to examine how differences in goal orientation affected training and transfer performance. Guided by social cognitive theory, the authors posited self-efficacy as a mediating mechanism to be influenced by goal orientation as well as the learning strategies applied by learners. The results, depicted graphically in figure 4, show mastery orientation indirectly influencing transfer performance through increased success in metacognitive strategies training and increased self-efficacy. Performance orientation is shown to have a negative effect on transfer. These results are interesting in that they establish self-efficacy, once again, as suitable mediating mechanism that influences transfer. A possible reason for this finding relates to the analytical technique employed.

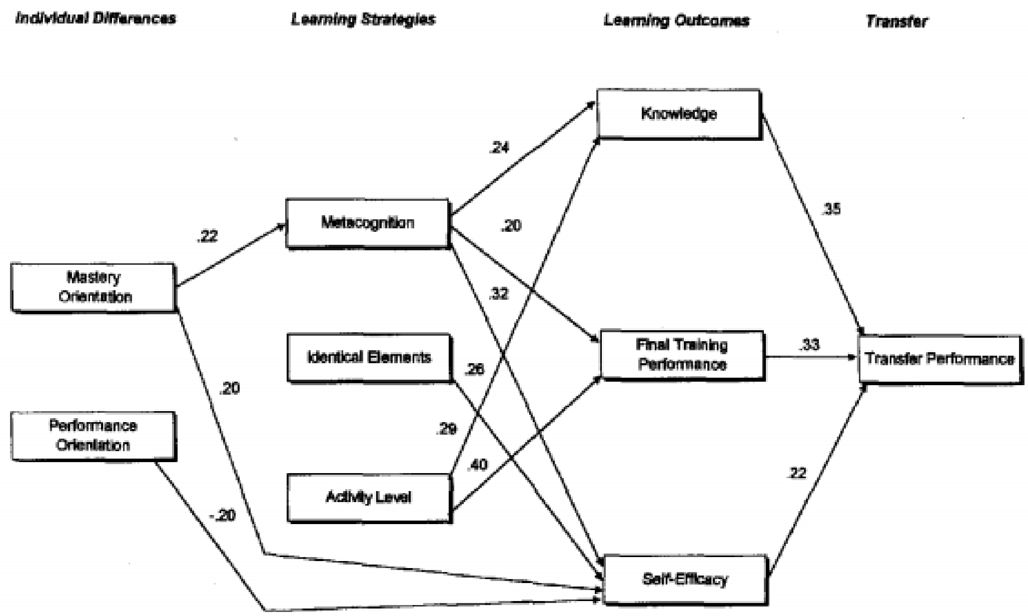


Figure 4. Modeling the effects of goal orientation on transfer. Reproduced from Ford et al., 1998.

The researchers employed a hierarchical regression technique with a predetermined order for family of variables based on their hypothesized strength of relationship with the dependent variable. This means inputting the variables from right to left as displayed in the model. This is a rudimentary latent causal modeling technique that exposes a researcher to misjudge effects if variables are entered in an incorrect order. The most telling part is revealed when the model is fit to predict transfer of learning.

In this model, knowledge, training performance, and self-efficacy—the learning outcomes family of variables—account for more than 51% of the variance in the transfer variable. Adding the rest of the variables in the model adds less than 2% of the variance explained. This doesn't necessarily mean that these subsequent variables have little effect on transfer, but rather that the specified order of the variables makes it likely that variables entered first will account for large percentages of the variance (because there is quite a bit of variance to explain) while subsequent variables will account for very little as most of their effects are suppressed by close correlations among variables (and by virtue of a lot less unique variance left to explain) giving the impression these variables don't matter as much (Keith, 2006). The researchers use these findings as evidence that self-efficacy is indeed a mediator variable.

An alternative explanation, however, emerges if we examine the zero-order correlations among variables—specifically between self-efficacy and mastery goal orientation. Self-efficacy is by far the highest variable correlated with mastery orientation ($r = .71$). This correlation makes it virtually certain that the two variables will continue to exhibit a strong relationship in a regression model regardless of the posited order and nature of their relationship. This diminishes the claim of a causal relationship between the two given the inability of the researchers to establish a temporal order for the relationship (neither was manipulated).

Further evidence raising questions about the nature of this relationship is provided by Usher and Pajares (2008) who conducted a systematic review of the self-efficacy literature in an effort to identify the sources or antecedents of self-efficacy. Their efforts were consistent with Bandura's theoretical conception that mastery experiences were, by far, the single biggest determinant of developing self-efficacy. Of the 28 studies reviewed, 27 found a significant relationship between mastery experience and self-efficacy (correlations ranged from $r=. 29$ to $r = .67$) (p. 772). Mastery experience, however, is not equivalent with a mastery-goal orientation. When a person experiences success performing a task, these mastery experiences act as feedback in letting a learner know they are capable of completing that task. Those experiences, thus, affect self-efficacy. Goal orientation, on the other hand, refers to a present belief about future abilities. While a learner's goal orientation is undoubtedly influenced by prior experiences, there is little evidence to suggest a learner's goal orientation shapes their beliefs about their capabilities to solve a task.

At most, the study establishes an indirect link between mastery-orientation and transfer, and a close relationship between mastery-orientation and self-efficacy. Both of these elements are incorporated in this study.

A more direct link between mastery goal orientation and transfer was established by Berevy-Mayer and Kaplan (2005). The researchers designed an experiment with 60 children ranging from 7-11 years old. They wanted to test the hypothesis that providing motivational prompts about mastery goals would result in better transfer of problem-solving strategies than prompting about performance goals. After conducting two experiments, the researchers had evidence of a direct link between mastery goals and transfer as well as evidence of a negative effect on transfer from the performance goals group. A logit regression analysis, which assigns odds and probabilities as parameter estimates, revealed learners in the mastery condition were much more likely to transfer than those in the control group. Subjects in the mastery condition (n=30) had 160% better odds of successfully exhibiting transfer versus those in the control group (n=30) (logit odds 3.6 vs. 1.99).

These findings were further replicated by Dupeyrat and Marine (2005) who sampled 76 French adults returning to school to earn the equivalent of a GED. The authors created a model of achievement—as measured by a composite average of grades on four different courses (including math). That model is depicted graphically in figure 5.

In the initial model, the authors hypothesized that self-theories of intelligences were the source of a learner's goal-orientation, which in turn predicted self-regulated behaviors that led to higher levels of achievement. Implicit theories of intelligence are marked by learners attributing success to pre-ordained abilities that cannot be changed (entity). Incremental theories of intelligence, on the other hand, have learners attributing success to experience and knowledge and thus imply an ability to manipulate it.

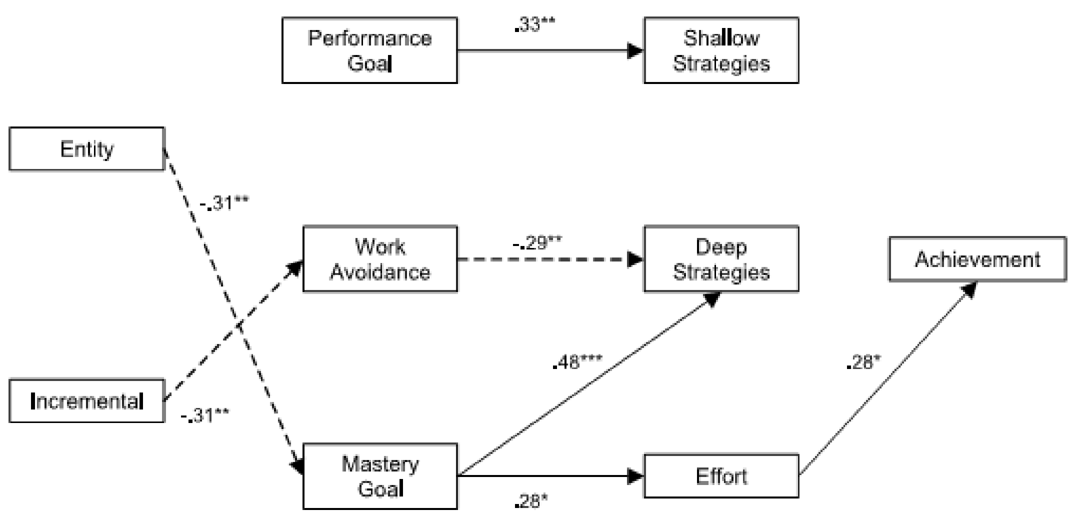


*Figure 5.*Mastery goal model of achievement proposed by Dupeyrat and Marine, 2005.

After conducting a path analysis, the researchers arrived at a final model (figure 5) indirectly linking mastery goals orientation to achievement. This relationship is mediated by effort, which is consistent with the theoretical explanations of the effects of goal-orientation on achievement (Grant & Dweck, 2003). Mastery goal orientation was also found to be a predictor of the use of deep self-regulatory strategies although no link between deep strategies and performance was found. These relationships, however, are established in the absence of a transfer measure. As deep strategies have been previously associated with transfer of learning (Mayer, 1998), it is reasonable to suggest a mastery goal-orientation might exert its influence on transfer through self-regulatory processes. That is precisely the argument made in this study. This argument is explored in more detail in the section describing evidence to support a mediating link between self-regulated learning and transfer.

Interest. Interest results from an interaction between a person and particular content (Hidi & Renninger, 2006). As a psychological state, interest manifests itself through attention to material and putting forth effort to engage in activities (Ainley, Hidi, & Berndorff, 2001). The interest literature identifies two main types of interest: individual and situational interest. *Individual interest* is an internal, personal disposition that remains constant throughout different tasks and situations. *Situational interest*, in contrast, is specific to a task and is a response to the features of a learning environment. It may or may not be sustained over time (Ainley et al., 2001; Hidi & Renninger, 2006; Krapp, Hidi, & Renninger, 1992; Schiefele, 1991).

Developing interest is considered to be a sequential four-step process beginning with the triggering of situational interest sparked by environmental features. This is supported and maintained externally through features of the environment. If this state is sustained for a long enough period of time, interest moves into maintained situational interest. This state results in focused attention and persistence. In order to maintain situational interest, a learner must engage in meaningful tasks or have personal involvement in the present learning context. Although this phase of interest development can be maintained through meaningful interactions, it is typically supported externally so learners are at risk of reverting to diminished interest (or no interest at all) if their interest is not maintained. Prolonged maintained situational interest leads to emerging individual interest.

This type of interest marks the beginning of an enduring personal disposition that leads learners to seek repeated engagement in these activities. External reinforcement is initially required to sustain individual interest so that it becomes well developed and relatively enduring. This phase is typically self-generated and is marked by a learner pursuing these interests on his or her own when given a choice. Well-developed individual interest is a desired state of psychological functioning as it has been linked to long-term creative endeavors, increased usage of deeper levels of strategies, and increased self-regulation (Hidi & Renninger, 2006). This theoretical hypothesis is supported by empirical evidence (Alexander & Murphy, 1998; Bates & Weist, 2004; Harp & Mayer, 1997; Ku & Sullivan, 2008).

In fact, a meta-analysis by Schiefele and his colleagues (1992) estimated interest accounted for as much as 10% of the variance in explaining performance across all subjects with a test of moderation suggesting the effect is consistent across all subject areas. The interest development model, along with empirical evidence, suggests individual interest is likely to affect overall levels of learning, self-regulation, and transfer. In addition, interest has theoretical congruence with an expectancy-value model of motivation. This makes interest a strong candidate for inclusion in the present model.

In comparison to goal orientation and self-efficacy, the mechanism by which interest affects transfer is not well understood. Mayer (1998) affirms: "unfortunately, researchers have not yet been able to clearly specify the mechanism by which interest affect what is learned, or even to clearly specify what interest is" (p. 58). Fortunately, Mayer's latter concern has been the subject of much research over the last few years with Hidi and Renninger's (2006) model of interest development as a major step in understanding the nature of interest and how it is developed. This has been continued by Linnenbrink et al. (2010) in efforts to provide construct validity evidence consistent with the interest model posited by previous interest researchers.

The interest literature that concerns mathematical performance and problem-solving performance has typically chosen to operationalize interest by personalizing instruction as to increase interest, and in turn test a possible relationship with improved performance. This is a somewhat problematic conception as the theoretical model of interest development specifies a sequential, prolonged process to achieve well-developed personal interest. These interventions are likely to only trigger situational interest, and are not sufficient to support the development of more enduring individual interest. As such, experimental manipulation of interest establishes a link between situational interest and performance, but lacks the ability to establish the same link to personal interest. This leaves us in the sensitive position of having to use correlational studies to establish a possible causal link between personal interest and transfer. This is less than ideal but given the nascent and rapidly developing nature of our understanding of the interest construct, it is the only sensible choice.

Fortunately, repeated studies converge on the same finding. Interest is indirectly linked to mathematical and problem-solving performance when instruction is personalized to trigger interest (Bates & Weist, 2004; Harp & Mayer, 1997; Ku & Sullivan, 2008). The next study reviewed is the exception to this rule choosing to establish a link to performance through correlational means.

Alexander and Murphy (1999) conducted a study with 329 undergraduate students in an educational psychology course. They sought to develop a profile of competency in analogical reasoning (a synonym for transfer) on a problem-solving task. Using cluster analysis, the authors were able to isolate variables that were most prevalent for those with the most success solving the given task. Learners were assessed on a variety of measures (domain knowledge, task performance, and strategy use) once before instruction took place and then again 15 weeks later after participating in instruction.

Before instruction took place, the "learning oriented" cluster emerged as a cluster characterized by an average level of domain knowledge and a high level of personal interest. This group scored highest in the analogical reasoning task closely followed by the "strong-knowledge" cluster composed of those learners with the highest amount of domain knowledge. Low interest, low domain knowledge subjects were placed in the "low-profile" cluster. They performed worse along all measures of performance and strategy use. After instruction took place, the subjects were assessed. Once again, the "learning-oriented" group emerged as the top-performing group in the analogical task. They were also a close second to a newly formed cluster—the "effortful-processor" cluster in strategy use. This group was characterized by low levels of domain knowledge and very high levels of interest and strategic effort. On the analogical reasoning task, his group performed only slightly worse (M = 43.28) than the strong knowledge group (M = 45.46) and the top performing learning oriented group (M = 45.49). These very similar results along the performance task for the three profiles suggest learners are able to compensate for a lack of domain knowledge by having high interest. Those with strong knowledge, despite having low interest, still perform at relatively comparable levels, but it seems interest allows learners with lower levels of domain knowledge to use strategies and exert efforts to equalize performance. As the authors summarize about the "learning-oriented" cluster:

> They used fewer strategies than did students in the Effortful-Processor group yet they documented significantly more strategies than the other two clusters nonetheless. They also tended to rely heavily on deep processing over surface-level strategies in their studying (p. 442).

And about the "effortful processors" cluster:

> Perhaps these effortful processors learned to compensate for their limited domain knowledge by working more effortfully and more strategically. It is also possible that this group of students is simply less skilled at taking declarative knowledge measures, such as the domain knowledge task in this study (p. 442).

This study makes a convincing argument that a strong correlation is present between transfer of learning and interest. Before examining the presence of a mediating mechanism between motivation and transfer, the attention now turns to the other major predictor of transfer—prior knowledge.

Prior Knowledge

Since the 1980s, the focus on understanding the mechanisms of expertise has become one of psychology's major focuses (Farrington-Darby & Wilson, 2006). In their seminal paper on expertise and problem-solving performance, Chi, Glaser, and Rees (1982) conclude:

> As a result of prior experience in various knowledge domains relevant to school, the representations required for solving school problems are more enriched and contribute to the ease and efficiency with which learning problems are solved (p. 71).

They were not the first to point out the effect of prior knowledge on problem-solving performance and transfer. In a comprehensive review of the transfer literature, Baldwin and Ford (1988) pointed to earlier studies assessing the role of prior knowledge on transfer (Downs, 1970; Gordon, 1955; Gordon & Cohen, 1973; Gordon & Kleinman, 1976). As a theoretical consideration, the early cognitive models of information processing (i.e. Miller, 1956) posited learning as an activity dependent on the integration of newly learned materials with prior knowledge.

The focus on prior knowledge carried over to subsequent, more specific theories of transfer. Under analogical encoding, for example, Gick and Holyoak (1980) proposed that transfer occurs as learners are able to respond to a problem by matching features of the problem to previously encoded sets of matching solutions. By matching the features of a problem, learners arrive at a solution they can use to solve the new problem. This is a mechanism entirely dependent on previously stored and encoded knowledge. A similar manipulation of prior knowledge occurs in two more widely used mechanisms of transfer—knowledge compilation and constrain violation (Nokes, 2009).

To ascertain the relative impact of prior knowledge on transfer one can look at virtually any study of transfer, which by default include a measure of prior knowledge. For example, Wong, Lawson, and Keeves (2002) set out test the effects of self-explanation training on performance with 43 9th grade students enrolled in a math class. They conducted an experimental study to test whether a less-directed approach to self-explanation training was more effective than a guided approach.

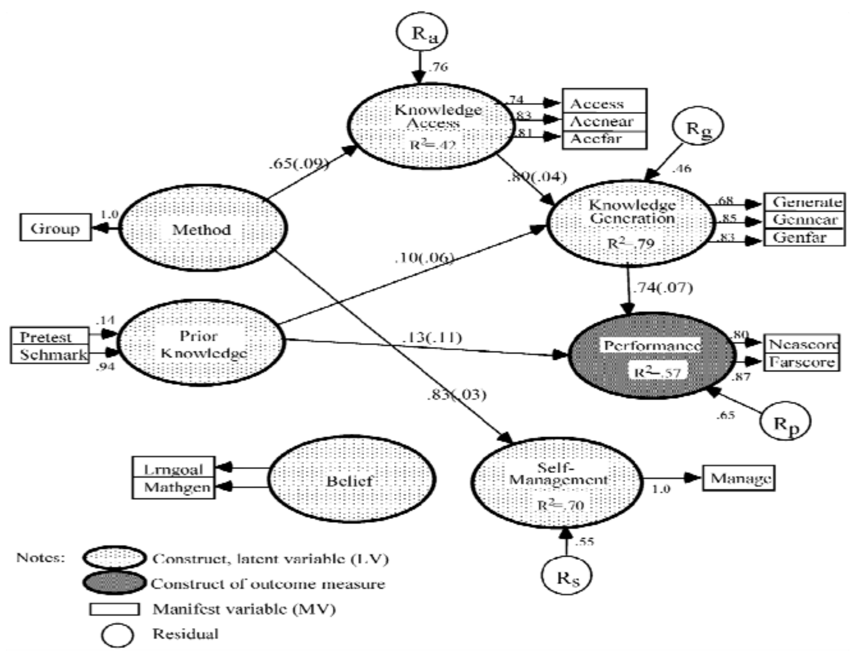


Figure 6. A validated model of transfer. Reproduced From Wong, Lawson, and Keeves, 2002.

But rather than focusing on finding main or interactive effects for the self-explanation treatment, the authors sought to model both the impact and role of self-explanation on performance, as measured by a transfer task. Figure 6 depicts the best-fit model determined by the researchers. Initially, the theoretical model was fully specified, which meant that it assumed direct and indirect relationships between all variables. An exploratory path analysis was then used to weed out significant relationships, which led the researchers to arrive at the final model that's presented here. This model established a relatively modest relationship between prior knowledge and performance (standardized path coefficient = 0.13) and an equally modest indirect relationship mediated by knowledge generation—a measure of the number of strategies learners employed during the problem-solving task.

These modest findings are in sharp contrast to other studies that have found prior domain knowledge to be the single greatest predictor of transfer (Ericsson & Smith, 1991; Hatano & Oura, 2003). Alexander and Murphy (1999) have developed a model of domain learning (MDL) that suggests a learner's ability to transfer moves them through a process of domain knowledge mastery beginning with acclimation with the material, proficiency using that material, and proficiency/expertise (p. 565). Their line of research (see for example, Alexander & Judy, 1988; Alexander, Kulikowich, & Jetton, 1995; Murphy & Alexander, 2002) has zeroed on characteristics of proficient, expert problem solvers:

> For the few who achieve proficiency, there is a tremendous breadth and depth of subject-matter knowledge. Another hallmark of proficiency is knowledge creation. In essence, proficient individuals contribute new knowledge to their field, transforming that domain in some fashion. Also, experts have a powerful and abiding interest in the domain and identify strongly with the community of practice. In addition, because these experts are pushing the boundaries of their domain and are engaged in problem formulation, they show an increased employment of general cognitive and metacognitive strategies over competent learners (Alexander & Murphy, 1999, p. 566).

The significant mediating relationship among prior knowledge, knowledge generation, and transfer that Wong and his colleagues (2002) found seems to be spelled out here and explains the lack of a larger direct effect linking prior knowledge to transfer in their study. Further, Alexander's and Murphy's findings cover many of the variables included in the present model, and highlight not only the role of prior knowledge, but posit an intersection of these variables to create optimal conditions for transfer. They identify interest, suggesting the role of motivational variables, and cognitive and metacognitive strategies as essential pieces of problem-solving expertise. Lastly, they identify the role of prior knowledge in the form of strategic knowledge about cognitive and metacognitive strategies.

Dochy, Moerkerke, and Martens (1996) define the nature of prior knowledge as fluid, flexible, organizable, and available in multiple forms. This leads to a distinction about domain knowledge—knowledge about subject matter content— and strategic knowledge—knowledge about *how* to use available content knowledge. Both Alexander and Judy (1988) and Dochy and Alexander (1995) have clarified this distinction settling on a dichotomous model of prior knowledge that contains both domain and strategic knowledge.

There is ample evidence across a variety of domains linking both types of prior knowledge to transfer in both correlational and experimental studies (Ben-David & Zohar, 2009; Brand-Gruwel & Stadtler, 2010; Chang, 2010; Hailikari, Nevgi, & Lindblom-Ylanne, 2007; Kilpatrick, Swafford, & Findell, 2001; Lee & Chen, 2009; Rittle-Johnson, Star, & Durkin, 2008; Schwartz, Bransford, & Sears, 2005; Star & Rittle-Johnson, 2007). These are in addition to findings of Dochy, Moerkerke, and Martens (2006), who found significant positive direct and indirect effects in 118 out of 129 studies including prior knowledge as a predictor of performance As it was done in chapter 1, the most recent studies lending support to both a direct and indirect effect of prior knowledge on transfer are showcased in table 6.

As with motivation, the relationship between prior knowledge and transfer seems to be mediated by at least one variable. Based on the literature, this study posits that mechanism to be self-regulated learning. While the process of another variable—namely knowledge generation—was also touched upon, it is argued that modeling the granular cognitive architecture processes that lead to transfer is beyond the scope of a study focused on modeling global motivational mechanisms.

Table 6. Summary of Recent Research Linking Prior Knowledge to Transfer.

Authors	**Research design**	**Knowledge type**	**Domain**
Star & Rittle-Johnson, 2007	Experimental	Strategic	Math
Rittle-Johnson, Star, & Durkin, 2008	Experimental	Domain	Math
Lee & Chen, 2009	Experimental	Domain	Math
Chang, 2010	Correlational	Domain	Science
Brand-Gruwel & Stadtler, 2010	Correlational	Both	Information seeking /web
Ben-David & Zohar, 2009	Experimental	Strategic	Scientific inquiry
Kilpatrick, Swafford & Findell, 2001	Lit Review	Both	Math
Schwartz et al., 2006	Experimental	Both	Data analysis
Hailikari, Nevgi, & Lindblom-Ylanne, 2007	Experimental	Both	Math

The next section carves out the argument that self-regulation is an appropriate mediator for these global processes and provides evidence linking effort and deep processing to prior knowledge and motivation thus establishing a link among motivation, prior knowledge, self-regulated learning, and transfer.

Self-Regulated Learning

Self-regulated learning (SRL) encompasses "proactive processes that students use to acquire academic skill, such as setting goals, selecting and deploying strategies, and self-monitoring one's effectiveness" (Zimmerman, 2008, p. 166). Further reading reveals evidence linking self-regulation and prior knowledge. In her research agenda linking self-regulation and prior knowledge, Boekaerts (1992, 1996, 1997) showed highly self-regulated learners relied on four particular aspects of prior knowledge: Domain specific knowledge and skills, cognitive strategies, metacognitive knowledge, and metamotivational knowledge and skills (Boekaerts, 1996, p. 101). Winne (2001) arrived at a similar conclusion using an "information processing approach" to self-regulation. Under this model, the process of self-regulation is made up of four distinct phases. Under the first phase, a learner constructs his or her own view of a task of problem. In order to do so, they must rely on experiences and prior knowledge retrieved from long-term memory. Studies using the information processing approach have been successful in finding a link between prior knowledge and self-regulation (Azevedo, Cromley, and Seibert, 2002; Azevedo & Cromley, 2004; Moos & Azevedo, 2008).

In a fairly recent study, Moos and Azevedo (2009) sought to extend the scope of their work and to test the possible mediation effects of monitoring processes on the relationship between prior knowledge, self-efficacy, and learning outcomes. Using think-aloud protocols, and mental model artifacts collected from twenty-one subjects, the researchers ran a set of regression analyses meant to test their mediation hypotheses. They found significant evidence of monitoring processes mediating the relationship between self-efficacy, prior knowledge, and learning outcomes.

Unfortunately, the authors employed separate regression analysis to test mediation effects from each variable. This has the important shortcoming of modeling each effect in isolation with the presence of the other variables instead of modeling the partial effects of each variable. As such, parameter estimates and tests of significance are highly unreliable, especially given the well-document close relationship between prior knowledge and self-efficacy (Bandura & Wood, 1989; Hoffman & Spatariu, 2008; Pajares & Miller, 1994; Usher & Pajares, 2008). Greene et al. (2010) addressed part of these deficiencies by using Structural Equation Modeling (SEM) to test a similar relationship between self-theories of intelligence, prior knowledge, and performance. They found evidence of a moderating relationship suggesting the effect of prior knowledge on performance was different depending on the level of self-regulation.

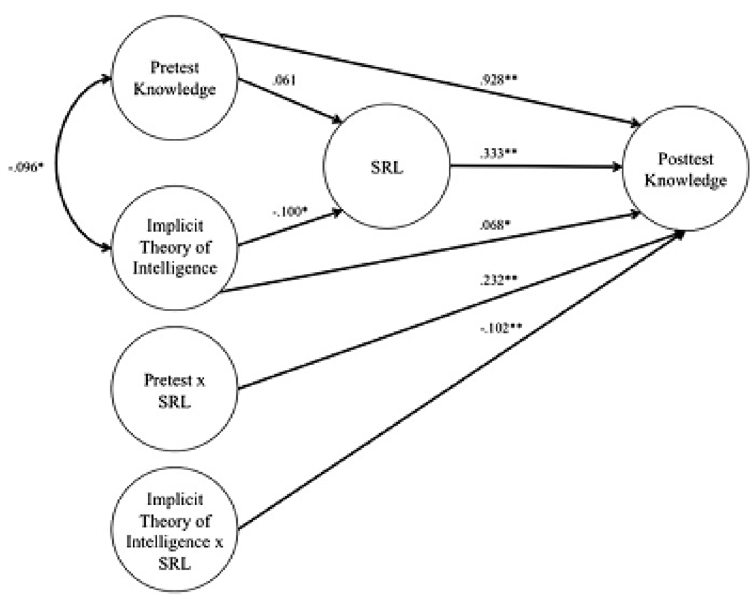


Figure 7. SRL and prior knowledge SEM Model. Reproduced From Greene et al., 2010.

While their study employed rigorous analytical techniques, it lacks theoretical congruence. The model, shown in figure 7, fails to include many of the antecedents of self-regulation that are related to performance such as those highlighted in this study—interest, goal-orientation, and self-efficacy. These motivational forces have been consistently shown to affect performance, and have been posited to affect self-regulation as well.

In the next section, it will be shown that there is ample evidence to suggest the motivation positively influences self-regulated learning. That, along with the evidence presented in the previous sections, showcases a model that presents a much more viable alternative to explaining the main motivational predictors, and mediating mechanisms affecting transfer of learning.

Self-Regulation and Motivation. The evidence establishing a link between self-regulated learning and motivation typically takes the form of experimental studies that manipulate environmental and design features to increase self-regulated behaviors. Through these manipulations, researchers hypothesize an increase in self-regulation that promotes transfer. There is evidence, for example, that suggests the use of conceptual scaffolding improves learning and positively affects the mental models that promote transfer (Azevedo & Cromley, 2004; Azevedo et al., 2005; Moos & Azevedo, 2008).

Figure 8. Phases of Self-Regulated Learning. Reproduced from Zimmerman, 2008.

In mathematical problem solving, a frequent line of inquiry centers on instructing learners to use self-regulated strategies. These have shown similar success (Fuchs et al., 2003; Perels, Gurtler, & Schmitz; 2005; Pape & Wang, 2003). There have also been efforts to correlate real-world performance with levels of self-regulation (Enos, Kehrhahn, & Bell, 2003; Kehr et al., 1999), which have resulted in similarly positive results. These studies pose an inherent question about how increased self-regulation leads to improved odds of transfer. To answer that question, it is important to describe the developmental phases of self-regulation. Figure 8 portrays this cyclical process.

Although cyclical, the development of self-regulated behaviors begin in a forethought phase that has learners engaging in key self-regulatory processes such as goal setting, and relying on self-beliefs to motivate themselves to self-regulate (Zimmerman, 2008, p. 178). These beliefs, along with planning strategies, carry the learner towards a performance phase where control and monitoring behaviors are used to assess problems, and design and carry out solutions. This is followed by a self-reflection phase where learners are able to assess current states, areas of improvement/decline, and appraise their capabilities in light of the recent experience. This is, for example, where mastery feedback would occur to improve self-efficacy, or a key area where a learner might move from having sustained situational interest to emerging personal interest. These steps are fairly consistent with the mechanisms specified in the current model and provide further support for the identification of self-regulation as the key process between motivation and transfer. Furthermore, they support the intertwined view of self-regulation as a process encompassing both cognitive and motivational components (Boekaerts, 1996).

On the cognitive front, prior knowledge (both domain and strategic) drives a learner to represent and accurately select appropriate cognitive strategies (Boakaerts, 1996, 1997, 2005; Boekaerts & Corno, 2005; Winne, 2005; Zimmerman, 1995). These cognitive self-regulatory strategies “refer to the cognitive processes and behavior that are especially geared toward accomplishing self-set (or adopted) goals, and toward regulating one’s activities in order to accomplish these goals” (Boakaerts, 1996, p. 107). These encompass domain-specific knowledge and skills, cognitive strategies, and cognitive self-regulatory strategies (often referred to as metacognitive skills). The motivational side of self-regulation is marked by a process where the goals set by learners in the cognitive side are “instigated and sustained” (Schunk & Zimmerman, 1994, p. 304).

Motivational regulation is concerned with “other aspects of behavior such as inclination, sensitivity, choice, level and time of involvement, and effort expenditure” (Boekaerts, 1996, p. 107). Zimmerman’s model merges both aspects of functioning and clearly separates the cognitive aspects (task analysis, self-control, and self-observation) from the motivational aspects (self-motivation beliefs, self-reaction, and self-judgment).

Pintrich (2004) used this model to develop an assessment framework for self-regulated learning derived from the distinctions between cognitive and motivational areas of functioning. For that reason, Pintrich's framework is used in this study. This is the same framework used to develop the instrument that will measure self-regulation in this study. Chapter 3 provides more details about instrumentation.

Having described the theoretical components of self-regulation, which lends support to argument that it is a key mechanism in promoting transfer of learning, it is now time to turn to the empirical evidence establishing a link between self-regulation and the other components outlined in the model.

Self-Efficacy and Self-Regulation. An individual's judgment about their ability to accomplish a task or solve a problem profoundly influences their ability to do so. Under social cognitive theory, Bandura (1993) asked us to change our conception of ability from "…a fixed attribute residing in one's behavioral repertoire" to "a generative capability in which cognitive, social, motivational, and behavioral skills must be organized and effectively orchestrated to serve numerous purposes" (p. 118). Once again, we see an intermediary focus on executive controls that help learners make sense of the resources they have available to them. Efficacy beliefs allow learners to make judgments "against the immediate and distal results of their actions, and to remember which factors they had tested and how they had worked. It requires a strong sense of efficacy to remain task oriented in the face of pressing situational demands and failures that have social repercussions" (Bandura, 1993, p. 120).

Bandura's own line of organizational research confirms the impact of self-efficacy on performance and transfer through self-regulatory mechanisms (p. 123, see also Jourden, Bandura, & Banfield, 1991, and Bandura & Jourden, 1991). This work has been replicated in different domains (Bandura & Wood, 1989; Pintrich & De Groot 1990; Zimmerman, Bandura, & Martinez-Pons, 1992).

Bandura and Wood (1989) extended their research on complex decision-making by conducting an experiment where they had subjects manage a simulated organization. A total of 24 subjects participated in the study. Participants were graduate students enrolled in a management graduate course. This complex performance task can be considered, by its nature, a far transfer task. Subjects were assigned to one of two experimental conditions. In one condition, learners were given instructions and feedback indicating the source of decision making either rested on an innate ability or in acquirable skills. The researchers then modeled the causal order of the measured variables using path analysis (see figure 9).

The repetition of variables is meant to indicate the repeated measures taken as well as the cyclical nature of the effect of self-efficacy on performance where mastery feedback after successful performance leads to improved self-efficacy. The model found evidence for both a direct and indirect effect of self-efficacy on performance. The indirect link went through analytic strategies, which can be considered a subset of self-regulatory cognitive strategies. Interestingly, the model also found evidence of the cyclical nature of self-efficacy as performance eventually predicted the second wave of self-efficacy validating the hypothesis that success on a task increases self-efficacy causing subsequent improvements in performance. Also of interest, is the finding that self-efficacy acted as a mediating mechanism for prior performance (a control variable that captured various aspects of past performance) but did not mediate the effect of personal goals, as it had been posited in the some of the studies cited under mastery goals. The study further validates the meditational link of self-regulation between self-efficacy and performance.

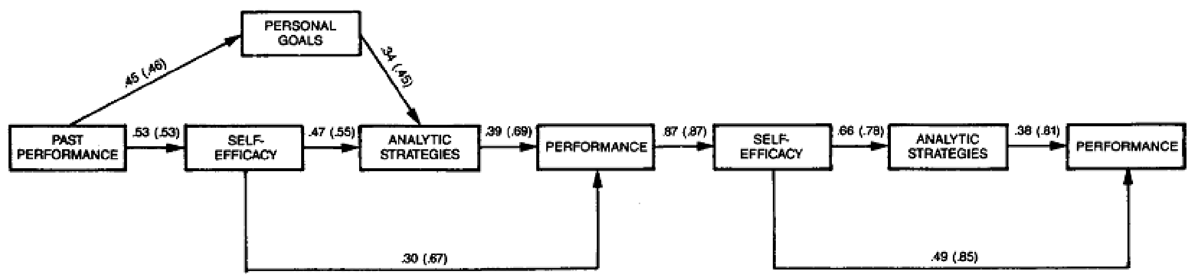


Figure 9. Model of complex decision making and transfer. Reproduced from Bandura and Wood (1989).

These findings were replicated in an academic environment with middle school students in a science environment. Pintrich and DeGroot (1990) conducted a survey (using the MSLQ instrument, which is partly used in this study) to model motivation's effect on performance using a model of motivation similar to the one used in this study and operationalized through three variables—intrinsic value, self-efficacy, and test anxiety, along with variables of self-regulated learning (strategy use and self-regulation). They surveyed 173 7th grade students. Various sets of analysis suggested cognitive strategy and self-regulation as having a suppressor effect (as the performance measures had negative partial correlations when these variables were included). The final model settled on self-efficacy and self-regulation as significant predictors of performance. Once again, the findings support the hypothesis that self-regulation mediates the relationship between self-efficacy and performance.

These results, however, are tempered by the relative weaknesses of simple multiple regression as a technique to model causal relationships. One obvious problem is the use of multiple variables to indicate a single construct (self-regulation strategies and cognitive strategies representing self-regulated behaviors). The high correlation between these variables (r

= .83) affects the parameter estimates as multicollinearity helps produce large standard errors that impact appropriate estimation of parameters and can severely disturb the nature of the relationships among predictor variables and the outcome variable (Keith, 2006). A more suitable approach is that provided by SEM where highly correlated variables can be used as indicator variables of a single construct, especially given theoretical and empirical justification to do so. This is one of the ways in which the current study improves upon the existing literature.

Similar results were reported by Zimmerman and Bandura (1994). Using a path analysis technique, the researchers once again found evidence for direct and indirect effects of self-efficacy on performance. This time, the variable mediating the relationship was found to be the goal setting component of self-regulation.

The theoretical and empirical evidence establishes both a direct and indirect link between self-regulation and performance with self-regulation consistently showing up as a mediator variable. A similar relationship has been found concerning goal orientation, self-regulation, and transfer.

Mastery Goal Orientation and Self-Regulation. The relationship between mastery goals, self-regulation, and transfer has not been systematically explored. There is, however, individual evidence that establishes a relationship between a mastery goal orientation and self-regulation. In turn, we have already reviewed the evidence suggesting a link between both mastery orientation and transfer, and self-regulation and transfer. As such, it appears reasonable to infer the presence of self-regulation as a mediator variable.

Mastery goals are known to affect the amount of effort and persistence learners put towards a task. In addition, there is evidence suggesting that learners who employ a mastery-goal orientation tend to make use of more self-regulatory strategies. This has been studied in depth in undergraduate students (Ames & Archer, 1988; Elliot et al., 1999; Elliot & McGregor, 2001; Greene & Miller, 1996; Schraw et al., 1995). The reasoning behind this link is much like the reasoning made for self-efficacy as a predictor of self-regulation. A mastery goal orientation leads to effort and persistence and this requires self-regulatory processes to motivate, monitor, and execute these tasks. This is where the cognitive and motivational components of self-regulation play their role.

An example highlighting this relationship was provided by Wolters (2004). The researcher surveyed 525 junior high school students from several math classes, and asked subjects to self-report on a variety of aspects including mastery orientation and mastery structure (the perceived emphasis on mastery goals from the classroom as a whole). Through a series of hierarchical regression models, the research sought to establish the effects of different orientations on self-regulation and performance while controlling for known predictors. The results are shown in table 7.

Table 7. Hierarchical Regression Results Reproduced from Wolters (2004).

	Cognitive strategies[a]			Metacognitive strategies[b]			Course grade[c]		
Variable	B	*SE* B	β	B	*SE* B	β	B	*SE* B	β
Step 1									
Prior standardized achievement	.01	.01	.04	.02	.01	.08	.10	.01	.47*
Gender	−.26	.10	−.11	−.28	.09	−.13*	−.16	.08	−.08
Step 2									
Prior standardized achievement	.00	.01	.01	.01	.01	.06	.10	.01	.46*
Gender	−.18	.09	−.08	−.21	.09	−.10*	−.13	.08	−.07
Mastery structure	.48	.05	.41*	.40	.04	.38*	.13	.04	.14*
Performance-approach structure	.10	.04	.11*	.10	.03	.12*	.01	.03	.02
Step 3									
Prior standardized achievement	.00	.01	−.01	.01	.01	.02	.08	.01	.35*
Gender	−.19	.09	−.08	−.26	.08	−.11*	−.34	.07	−.17*
Mastery structure	.25	.05	.22*	.17	.04	.16*	−.01	.04	−.01
Performance-approach structure	.06	.04	.06	.07	.03	.09	.00	.03	−.01
Mastery orientation	.44	.05	.47*	.42	.04	.47*	.05	.04	.07
Performance-approach orientation	.02	.03	.03	.06	.04	.03	.08	.02	.12*
Performance-avoidance orientation	.02	.04	.03	−.02	.03	−.01	.03	.03	−.01
Self-efficacy	−.09	.05	−.09	−.07	.05	−.06	.33	.04	.40*

Note. $N = 525$.
[a] $R^2 = .01, p = .04$ for Step 1; $R^2\ \Delta = .18, p < .01$ for Step 2; $R^2\ \Delta = .14, p < .01$ for Step 3.
[b] $R^2 = .02, p < .01$ for Step 1; $R^2\ \Delta = .16, p < .01$ for Step 2; $R^2\ \Delta = .16, p < .01$ for Step 3.
[c] $R^2 = .22, p < .01$ for Step 1; $R^2\ \Delta = .02, p < .01$ for Step 2; $R^2\ \Delta = .18, p < .01$ for Step 3.
* $p < .01$.

Beginning in step 2, we can see that goal orientation and efficacy variables account for 14% of the variance on cognitive strategies, 16% of the variance on metacognitive strategies, and 18% of the variance on course grade above the variance explained by the control variables. The control variables explained very little of the variance with regards to the self-regulatory strategies included (1% and 2% respectively), but explained quite a bit of the variance on course grade (22%). This is most likely due to the effect of prior standardized achievement, a measure of prior knowledge, on course grades.

This the same explanation provided by Wolters (p. 244). The contribution of a mastery orientation can be attributed as the single highest indicator of metacognitive and cognitive strategies use as exhibited by the strength of its standardized regression coefficient ($\beta = .47$ in both instances). While study design and analysis did not seek to analyze a mediating relationship between goal orientation and performance (as measured by grade), the study does provide support for a strong link between mastery orientation and self-regulation, even in the presence of other goal orientation variables and previously known predictors of performance. The same study, however, found no significant relationship between mastery orientation and course grade providing somewhat contradicting evidence about the link between mastery orientation and problem-solving performance.

There are two possible explanations. First, course grade does not capture the mathematical problem-solving efficiencies of learning. While it is a proxy variable for mathematical performance, it does not necessarily imply mastery of mathematical concepts—especially in the case of a standardized test that is most often associated with measures of recall and procedural knowledge. Secondly, as it has been argued in previous studies reviewed in this chapter, multicollinearity could be an issue distorting parameter estimates. In this case, high correlations between mastery orientation and self-efficacy ($r = .66$) point to a possible parameter distortion that can obscure the nature of the relationship, especially given the relatively small effect of goal-orientation when compared to the contribution of other variables. This suggests a need to employ—both in terms of design and analysis—more sophisticated methods as well as more careful specification of causal relationships to more accurately estimate the relative contributions of each of these variables on performance. These lessons, as well as the lessons derived from other studies, drive many of the methodological and analytical choices made in the present study. A similar pattern of significant findings, amidst questionable design and analytical choices, can be found in the relationship between interest and self-regulation.

Interest and Self-Regulation. Interest is considered an affective state triggered by particular features of the environment. Even the activation of personal interest is a response to a particular stimuli, be it a task, or situation. Ainley (2006) describes the process after interest is activated: "Triggering interest activates a system that generates positive feelings, focuses attention on the object that has triggered interest, and in the absence of strong competing motives will prompt cognitive activity" (p. 402). Sansone and Smith (2000) have shown that interest can lead individuals to regulate their behaviors to perform tasks they do not want to do over time (see also Sansone et al., 1992).

This has been a topic of some debate. Hidi (1990) has systematically analyzed the literature that suggested interest text and materials were easier to process and thus actually reduced processing levels and strategy use. Citing the work of Anderson and his colleagues as a classic example (Anderson, 1982; Reynolds & Anderson, 1982; Reynolds, Standiford, &

Anderson, 1979), Hidi shows that these lines of inquiry have concluded interesting materials are better recalled. She explains that this is likely due to “extra attention selectively allocated to them (the interesting materials) in proportion to their importance” (p. 560). This selective allocation is likely describing self-regulatory processes that influence learning.

Other researchers have arrived at similar results. Ainley and her colleagues (2002), for example, set out to model some of the mediating mechanisms between interest and learning using a study that exposed subjects to four different types of explanatory texts. They measured both individual and topical interest and were able to ascertain a mediating relationship between individual interest, affect, persistence, and learning. Results from the scientific text condition are presented in figure 10. Persistence, in this case, is used to indicate the frequency of deep level processing strategies associated with self-regulated learning. As the authors put it: “Hence, persistence as used in this study was an index of students’ engagement with the texts” (p. 558).

In fact, four different models generated by the authors (one per different text condition) all agreed that individual interest influenced affect, which influenced persistence, and ultimately led to improved learning. This is consistent with the theoretical basis of interest that posits interest influences learning by affecting the amount of effort and the learner’s persistence in completing a task (Hidi & Renninger, 2006). These samples highlight both the presence of a mediating mechanism between personal interest and learning, and the suitability of self-regulation as such mechanism.

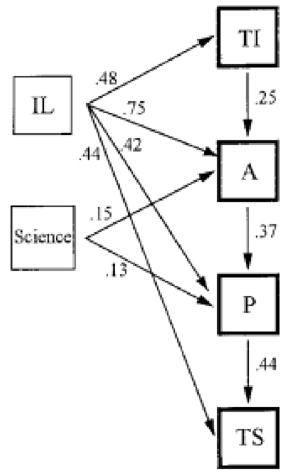


Figure 10. Path Diagram adapted From Ainley et al. (2002). Diagram shows mediating variables between interest and learning (IL = individual interest, TI = Topic Interest, A = affect, P = persistence, TS = test score, Science = prior domain knowledge).

Unlike the goal-orientation and self-efficacy literature, attempts to model the mediating mechanisms in the interest literature have been relatively rarer. This is likely due to the nascent understanding of the interest antecedents as well as to the relatively new theoretical advances that have spelled out the process by which interest is developed. The current study uses the most recent theoretical development in interest theory and attempts to model self-regulation as a mediational mechanism. The role of self-efficacy, mastery goal-orientation, and interest on transfer and self-regulation clearly established leads to an effort to simultaneously model the causal direction and order of these relationships in an effort to bridge the gap between motivation and transfer.

Summary

Much has been suggested in this chapter with regards to the relationship between motivation, prior knowledge, and transfer. A comprehensive review of the literature has shown a link between motivation and transfer. At a micro level, the operationalization of motivation as a three-variable construct has been justified along with evidence to link each of the three indicator variables to self-regulation and transfer. The current study has been established the presence of a variable that mediates the relationship between motivation, prior knowledge, and transfer. It has settled upon self-regulated learning, which manifests itself in the efficient use of strategies that help learners set goals, focus attention, and monitor their current knowledge structure, as a suitable candidate to fill that role.

Furthermore, the literature review has highlighted the lack of studies modeling these variables together as a system of variables. In those cases where an attempt has been made, study design flaws and the usage of substandard analytical techniques have hindered these efforts.

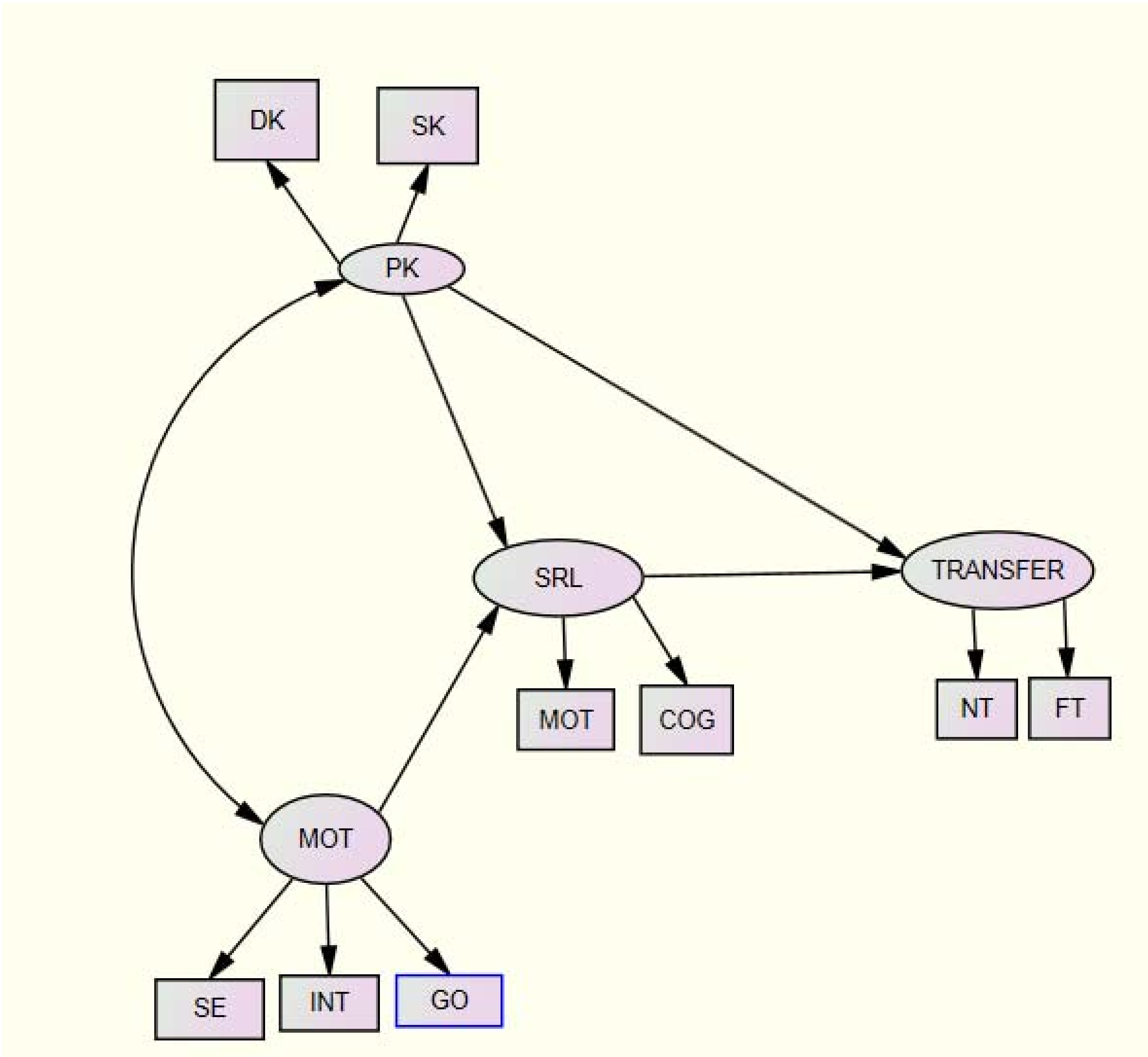


Figure 11. Graphical representation of the transfer model developed for this study**.** PK = Prior Knowledge, DK=Domain Knowledge, SK=Strategic Knowledge, MOT=Motivation, SE= Self-Efficacy, INT=Interest, GO=Goal-Orientation, SRL=Self-Regulated Learning, MOT = Motivational SRL, COG= Cognitive SRL, NT = Near Transfer, FT = Far Transfer.

This study departs from all those studies while using their findings as the empirical basis to construct a socio-cognitive model of transfer. This transfer model posits that prior knowledge directly affects transfer while indirectly, along with motivation, exerting its impact upon transfer through increased self-regulation. These relationships are once again displayed graphically in figure 11. The important details about study design, analytical technique, as well as other methodological choices and their rationale, are included in the next chapter.

CHAPTER 3: METHODOLOGY

Introduction

This study tests a model that describes the causal mechanisms by which motivation and prior knowledge work to promote transfer of learning. As it has been posited in prior chapters, motivation and prior knowledge exert their influence on transfer through increased self-regulation.

The main goal of this study is to validate the proposed model in the context of a mathematical task. Within this main goal, three major sub-goals are included. First, this study seeks to validate the direction of the relationships among the specified variables. This includes validating a measurement model consistent with theoretical specifications as well as providing support for a mediating relationship among prior knowledge, motivation, self-regulation, and transfer of learning. A second sub-goal is to identify the magnitude (effect sizes) of the relationships among the outlined variables and transfer of learning. This includes identifying direct, indirect, and total effects.

Third, this study seeks to systematically compare a series of competing models to identify the model that best adheres to the sampled data. To accomplish these goals, the study employs a structural equation modeling (SEM) technique. SEM is a technique from the family of General Linear Models that includes regression analysis, path analysis, and other similar techniques that are well suited to test systems of linear relationships among variables (Keith, 2006; Kline, 2010).

The technique makes use of latent variables (LVs) to specify multiple indicators for a single construct. This allows us to separate the model into a measurement model where each construct consists of multiple indicators. This provides a stronger, less error-ridden representation of the construct. The structural model then describes the relationships among the latent constructs specifying magnitude and significance using the validated measurement model. This modeling approach is preferred over single indicator analysis (i.e. path analysis) as measurement error is likely to be reduced by combining multiple indicators to form a single construct (Kline, 2010).

A more detailed explanation of these concepts, including the advantages over other analytical techniques is provided at the end of this chapter. The rest of the chapter includes information about research design, sampling techniques, and data sources. It also includes detailed information about data collection procedures that will be used to maintain the integrity of the study. Before covering these aspects, the study research questions are outlined again.

Research Questions

- R1: Does prior knowledge significantly increase transfer performance? What is the magnitude of the relationship?
- R2: Does self-regulation significantly increase transfer performance? What is the magnitude of the relationship?
- R3: Does self-regulation significantly mediate the relationship between prior knowledge and motivation? What is the magnitude of the relationship?
- R4: Does self-regulation significantly mediate the relationship between prior knowledge and transfer of learning? What is the magnitude of the relationship?
- R5: Does the specified model reasonably fit the data according to fit standards (x^2, CFI, RMSEA, AIC, etc.).
- R6: Which of the specified models (M1, M2, M3, M4, M5) best fit the data?
- R7: What modifications, if any, are proposed to improve the model's data fit?

Additional research questions need to be addressed to account for changes in the administration procedures that led to having two distinct samples. Chapter 4 details these changes.

- R8: Is the proposed measurement model consistent across the two samples of subjects?
- R9: Is the proposed structural model consistent across the two samples of subjects?

Research Design

The proposed study employs a survey design that uses primarily a correlational, descriptive, and explanatory approach. In this case, the term survey is used to denote a study design approach rather than a data collection procedure. This definition is consistent with methodological definitions of an empirical investigation that attempts to provide a quantitative or qualitative description of a process common to a population by studying a sample of that population (Babbie, 1990; Creswell, 2003). This study employs a cross-sectional design with the purpose of correlating measures of prior knowledge, motivation, and self-regulated learning with transfer of learning. A number of considerations have gone into selecting this type of research design. They include:

- Social science methodologists (Babbie, 1990; 2008; Creswell, 2003; Krathwohl, 1998) agree that correlational survey designs are a viable method for causal modeling.
- SEM methodologists (Kline, 2010; MacCallum & Austin, 2000; Schumaker & Lomax, 2004) point out survey design as the preferred method of causal modeling using SEM over experimental and other observational designs. They do not imply this is an optimal method but rather that in terms of frequency of used, it is the most common method employed by researchers in the social sciences.
- And while it has been established in prior chapters that formal quantitative modeling of the processes by which transfer of learning takes place has been largely neglected in the

educational research and psychology field, there is precedence for the use of the survey as a research design to explore motivational, cognitive, and other processes of transfer. This is especially true in studies employing the basic forms of regression techniques, which often rely on surveying as its choice of research design. Regression analysis provides the foundation for the more advanced techniques of path analysis and SEM and it is found throughout the literature in an attempt to employ basic modeling of single motivational variables and performance.

Since the purpose of this study is to provide a more comprehensive modeling approach, the relevant focus here is on studies employing the more advanced techniques of path analysis and SEM. A sample of the most relevant studies covering similar variables to the ones explored in this study is summarized on table 8. These studies were covered in detail in chapter 2 but are once again summarized here to provide evidence that the approach chosen for this study is consistent with the literature on the subject. These considerations along with the feasibility a survey design provides in obtaining large-enough sample sizes, collecting data from heterogeneous sources, and flexibility in administering instruments, summarize the decision to employ a survey methodology.

Data were collected through a series of instruments to be completed in an online environment. The instruments measuring prior knowledge and transfer of learning were administered in paper-and-pencil as this is the typical form often used for mathematical tasks and it allows the subjects to use paper to record their process and perform calculations without the difficulty of learning a complex new tool. More information about the instruments employed in the study is provided in the next section.

Table 8. Advanced Modeling Studies Employing Survey Research Designs.

Study	Constructs modeled	Research design &analytical technique
Pajares & Miller, 1994	Self-Efficacy, Self-Concept, and Mathematical Performance.	Survey Design / Path Analysis
Gonzalez-Pienda et al., 2002	Academic Aptitudes, Causal Attribution, Self-Concept, and Academic Achievement.	Survey Design / SEM
Marsh et al., 1997	Academic Self-Concept and Academic Achievement.	Survey Design / SEM
Ainley, Hidi, & Berndorff, 2002	Interest, Prior Knowledge, and Performance.	Survey Design / SEM
Dupeyrat & Marine, 2005	Goal Orientation, Cognitive Engagement, Achievement.	Survey Design / Path Analysis
Egan et al., 2004	Learning culture, Job satisfaction, and Motivation to Transfer.	Survey Design / SEM
Noe, 2000	Personality, Self-Efficacy, Cognitive Ability, Motivation, Learning Outcomes, Transfer, and Performance.	Survey Design / Path Analysis
Yamkovenko & Holton, 2010	Learning dispositions, goal orientation, intent to transfer	Survey Design / SEM

Data Collection Instruments

The creation of instruments to generate data is based on a number of considerations. Babbie (1990, 2007) describes three possible approaches to creating data collection instrumentation. The choices involve using original instruments as created, adapting instruments from existing ones, or creating instruments from scratch. There are inherent advantages and disadvantages associated with each approach. Creating new instruments, for example, allows researchers to specify items and scales directly matching variables of interest. As a downside, new instruments must be piloted and validated prior to use. This study primarily uses existing instruments, either using them in their original form or adapting them to fit within the current domain of interest. Only in cases where no instruments exist, or where the literature asserts that it is more appropriate to create task-specific instruments, are instruments created from scratch.

The advantage of using these existing instruments is that they have known psychometric properties, which allow us to have a better idea of the appropriateness of their use in the context of similar studies. In addition, existing instruments standardize research in these areas by replicating work using similar instruments. The downside is that the instruments might not fit exactly within the context of the present study, but it can be argued that adapting these instruments to fit within the content area and selecting instruments consistent with the theoretical frameworks employed in the study, address these issues.

The approach taken in this section is to look at each indicator variable separately and describe the items measuring such variables. Psychometric properties, when available, are provided. For those instruments created from scratch, justification and a description of the instrument creating procedures are provided.

Motivation Instrument. The motivation instrument measures three indicator variables: goal orientation, interest, and self-efficacy. Over the years, motivation has been operationalized in a multitude of ways depending on theoretical framework and research preferences. The selection of these instruments is based on theoretical congruence, validated empirical results, and frequency of use in research linking the constructs.

To measure *goal orientation*, six items from Elliot's and Church's (1997) goal orientation scale were selected. These items use a seven-point likert scale. This instrument was selected for a number of reasons. First, the scale was first developed and validated for use with undergraduate university students taking a psychology class. This is a close match to the population of interest in this study. Second, the authors operationalized the goal orientation construct as a hierarchical construct made up of three factors and then selected particular items from the *mastery* goals scale. This is the same theoretical construct outlined in chapter 1 and is consistent with instruments used in other empirical work linking goal orientation to self-regulation and transfer. Third, the study was piloted and validated providing evidence of strong psychometric properties. A factor analysis confirmed the hypothesized latent structure. Additionally, evidence for predictive validity was obtained by regressing the variable on achievement. Internal consistency for the items as measured by Cronbach's Alpha was strong (α = .89).

To measure *interest*, 10 items from a recently validated instrument are used (Linnenbrink-Garcia et al., 2010). These 10 items use a 5-point likert scale. Selection of these items is based once again on considerations of theoretical congruence and the availability of validated results. These items were designed to tap into "both the feeling and value students associated with math" (Linnenbrink-Garcia et al., 2010, p. 659). Internal consistency for this scale was strong (α= .90). Predictive validity validation showed a moderate correlation (r = .22) with final course grades.

To measure *self-efficacy*, a scale consisting of 8 items using a 10-point likert scale was developed specifically for this study. A number of studies have already developed self-efficacy scales. However, on the guidance of self-efficacy research, it was deemed more appropriate to develop these items from scratch. Bandura (2006) affirms:

> There is no all-purpose measure of perceived self-efficacy. The "one-measure-fits-all" approach usually has limited explanatory and predictive value because most of the items in an all-purpose measure may have little or no relevance to the selected domain of functioning. Moreover, in an effort to serve all purposes, items in a global measure are usually cast in a general, decontextualized form leaving much ambiguity about exactly what is being measured and the level of task and situational demands that must be managed. Scales of perceived self-efficacy must be tailored to the particular domains of functioning that are the object of interest (p. 307).

The development of a self-efficacy scale for this study seeks to contextualize the instrument in the domain and type of performance that is demanded of learners to solve the transfer task. It relies on Bandura's (2006) guidelines for developing effective self-efficacy measurements. No validation studies exist given the instrument has been developed from scratch. Psychometric properties are currently unavailable but will be reported with regards to this study.

To summarize, three separate scales consisting of twenty-four items measure the motivation latent. These items are consistent with the socio-cognitive motivational model outlined by Pintrich (1999) and described in chapter 1 and 2.

Prior Knowledge Instrument. Prior knowledge is operationalized in this study as a latent variable made up two indicator variables capturing prior knowledge of strategies and prior knowledge of content.

To measure *prior content knowledge,* a four-item performance task was developed. Creation of the instrument began with a cognitive task analysis (Jonassen, Tessmer, & Hannum, 1999) of the transfer task. When used as part of an instructional needs assessment, a task analysis reveals foundational knowledge that needs to be mastered as part of the learning experience. As such it is an appropriate technique to uncover the individual foundational knowledge blocks learners must possess in order to successfully complete a task. The following foundational skills were found to be necessary for successfully completing the transfer task:

1. Basic computational skills with whole numbers and decimals (adding, subtracting, multiplying, dividing).
2. Calculating and using percentages.
3. Finding numerical patterns.
4. Creating table of values/lists of values based on an equation.

5. Representing situations in multiple formats (table of values, graphs, equations).
6. Translating situations from words to equations.
7. Solving multi-step equations
8. Knowledge of exponential growth and decay
9. Ability to read a word problem and derive a solution.

An instrument was developed to cover these major areas. Rather than presenting each skill separately, the skills were embedded within simple word problems. This, in itself, was a performance measure to ensure learners were able to translate information from a word problem into mathematically meaningful formats (foundational skill #9 outlined above) and that they could make a plan to derive a solution. The procedure to validate this instrument is outlined after describing the *prior strategic knowledge* instruments.

To measure *prior strategic knowledge*, a 14-item instrument has been developed. These 14 items are a mixture of likert-scale type items, yes/no items, and open response items. The development of this instrument was necessitated to match the content area and task. Polya's problem-solving framework was used as guidance to create the instrument (Polya & Conway, 2004). Polya's problem-solving process is the most widely used and taught framework in mathematics since it was first published in 1942 (Schoenfeld, 1992). The four stages: 1) Understanding the problem, 2) Devising a plan, 3) Carrying out the plan, and 4) Looking back the solution, were used as guidance to develop a set of items concerned with the use of these strategies. Guidance from instruments used in the literature for other subject areas was further used to develop an instrument consistent with instruments used in prior empirical work. These include the MSQL critical thinking scale (Pintrich et al., 1991), D'Zurilla and Nezu's Social

Problem Solving Inventory (SPSI) rational thinking scale (1982), and an instrument by Antonietti, Ignazi, and Perego (2000) used to measure the use of strategies in computational problem-solving. Psychometric properties of the instrument for the current study will be described in the next chapter.

Given the development of a new instrument, validation is necessary to ensure construct and content validity. Haynes, Richard, and Kubany (1995) argue that content validity provides evidence for construct validity as it provides us with information about the degree to which elements in the assessment are relevant and represented of the targeted construct (p. 3). Furthermore, the authors remind us that validity is a conditional property of an instrument and as such, it must evaluated within the context of a particular study, its content area, and its population of interest. This is a particularly relevant point to this study, and this construct, as it depends heavily on the transfer task that learners are being asked to solve rather than a generic domain of knowledge. A four-step process to provide evidence of content validity is outlined by the authors. That process is followed here:

1. Carefully define domain and faces of the construct.
2. Subject all elements of an assessment to content validation.
3. Use population and expert sampling.
4. Use multiple judges of content validity.

Development of this instrument followed the process closely. First, to define the domain of the construct, a literature review of the strategic prior knowledge construct was conducted. Upon settling on a operationalized definition and theoretical background (outlined in chapter 1 and 2) that suggested closely looking at the structure of the task requiring prior knowledge, a cognitive task analysis was performed to discover the foundational knowledge structures of the task. The next three steps can be encompassed within the process of expert and subject validation that took place. This follows the suggestions and techniques outlined by Haynes and his colleagues.

A panel of five experts in mathematics education reviewed all items of the instrument as suggested. These experts were all secondary mathematics teachers who hold—at the very least—a master's degree in math education or mathematics. Each member of the panel has five or more years of experience teaching mathematics at the secondary level. The panel was asked to review the instrument holistically in the context of the transfer task as to uncover any inconsistencies or deficiencies in content coverage. Furthermore, they were asked to review each item (consisting of a problem) for wording, coverage, and feasibility based on the given transfer task. The panel was also been asked to rate relevance, specificity, representativeness, and clarity for this instrument on a five-point scale.

Lastly, the panel was asked to provide any qualitative feedback (suggestions for addition or removal of items, etc…) that they felt would improve the instrument. Based on the feedback from this panel, slight changes were made to the wording of some of the questions. No other substantive changes were suggested by the panel. Following the changes, the instrument was piloted with a small sample of potential subjects (N = 10). These subjects were graduate and undergraduate students. They were asked to provide holistic and qualitative feedback, and also to rate the instrument along the dimensions of relevance, specificity, representativeness, and clarity. While these students had no substantive suggestions to improve the instrument, they did make recommendations for the order of the administration of the entire set of instruments used in the study. These suggestions were consistent across the participants and thus were implemented into the administration of the study.

The validation procedure employed here is consistent with established practices in the psychological literature for these types of assessment. Strong adherence to these practices provides evidence of construct validity for the prior knowledge construct.

Self-Regulated Learning Instrument. To measure self-regulated learning, the Critical Thinking ($\alpha = .80$) and Metacognitive Self-Regulation ($\alpha = .79$) scales from the Motivated Strategies for Learning Questionnaire (MSLQ) are used (Pintrich et al., 1993). These scales consist of 17 items measured on a 7-point likert scale. This instrument is chosen to measure self-regulation as it directly encompasses the two self-regulation dimensions outlined in the theoretical portion of the model.

On the motivational front, the critical thinking scale “refers to the degree to which students report applying previous knowledge to new situations in order to solve problems, reach decisions, or make critical evaluations with respect to standards of excellence” (Pintrich et al., 1991, p. 22). These items encompass the motivational area of psychological function calling for efficacy judgments. The metacognitive self-regulation scale covers the cognitive area of psychological functioning outlined as the second component of self-regulated learning. This scale covers the general cognitive processes. These refer to “… the awareness, knowledge, and control of cognition…the three general processes that make up metacognitive self-regulatory activities: planning, monitoring, and regulating” (Pintrich et al, 1991, p.23).

Overall, the MSLQ is an 81 item self-report inventory developed to measure college students’ motivational and learning strategies orientations (Pintrich et al., 1991). The instrument has been used widely in motivational research over the years. A recent count covering a five-year span from 2000 to 2005 had the instrument used in over 50 empirical studies (Duncan & McKeachie, 2005). Initial validation took 3 years using a sample of over 1000 college students from a multitude of academic backgrounds (Pintrich et al., 1993). The instrument developers used factor analysis to establish evidence of dimensionality and provide evidence of construct validity. They also provided evidence of predictive validity with educational achievement. Internal consistency measures on the scales used in the current study ranged from $\alpha = .52$ (help seeking) to $\alpha=.80$ (critical thinking). The authors point out that establishing traditional reliability measures in the instrument is difficult as the instrument attempts to tap into constructs heavily dependent on context, which affect stability and variability in the instrument (Duncan & McKeachie, 2005). The factor structure has been further validated in other studies in the context of different populations (Hamilton & Akhter, 2009; Wilson, 2006), and even different languages (Huang, 2008; Lee, Zhang, & Yin, 2010).

The MSLQ is a practical, flexible, and suitable instrument to measure self-regulated learning. It is appropriate for the current study as it has been widely used on prior empirical work and is directly connected to the theoretical basis used in the study. It is important to point out that Pintrich (2004) considers the MSLQ a close, but incomplete, way to measure the dimensions outlined in this theoretical framework. Theoretical advancements since the development of instrument more than twenty years ago necessitate an updated instrument. This warning by Pintrich is heeded as a limitation, but currently no updated instruments have been developed to directly match Pintrich's framework. As such, the MSLQ instrument represents the most feasible—albeit imperfect—way to effectively measure self-regulated learning.

Transfer of Learning Task. It has been a long established tradition in the empirical literature to measure transfer of learning on a performance task. From the earliest transfer studies (Thorndike & Woodworth, 1901) to modern approaches (Nokes, 2009), this has been the approach employed. It makes sense, given the nature of the transfer phenomena as one based on performance. This study continues that tradition. As transfer of learning is context-dependent (Lobato, 2006), there are no standardized instruments used to measure it. Studies typically settle upon a domain of knowledge where they wish to explore transfer and a select a novel task requiring subjects to draw upon prior knowledge or to extend on a topic they have been exposed to during an intervention. That is the same approach followed in this study.

First, this study investigates transfer of learning in the domain of math. Specifically, this is done in the context of algebraic reasoning involving linear and exponential relationships. The selection of this domain and specific topic is based on particular interest in modeling motivational processes in the context of such topic, the researcher's content expertise, and considerations for the selected research design. Given the nature of the transfer task, and the population of interest, there was a need to select a domain that was accessible to a majority of subjects.

The National Council of Teachers of Mathematics (NCTM) is a global organization that provides guidance to educational entities in setting math curricula and selecting competencies that drive instruction. NCTM standards are used, in addition to state standards, to drive textbook and activity creations for mathematics instruction in the United States and many other countries in the world. Their algebra standards consist of a broad framework encouraging learners to 1. Understand patterns; 2. Represent and analyze mathematical situations using algebraic symbols; 3. Use mathematical models to represent and understand quantitative relationships; and 4. Analyze change in various contexts (NCTM, 2010). The transfer tasks developed for this study have been operationalized to cover those four competencies under the logic that college students are likely to have been exposed to mathematics curriculum covering these competencies in the span of their formal education. This is important as subjects participating in the study are solving the task in a context outside of an academic class or setting. The transfer task, thus, needs to be a task consisting of foundational components learners have experienced in the past. This is the best way to maximize the chance learners will be able to at least attempt to solve the posed problem.

To measure *near transfer,* three open-ended problems were selected. These problems are drawn from the New York State Integrated Math Regents examination administered during January and June, 2009. They are part of the algebra strand and map onto the NCTM standards previously described. These problems—as well as the rubrics for scoring them—have been extensively analyzed, calibrated, and scaled using advanced testing techniques (Pearson, 2008a, 2008b). Although no appropriate psychometric statistics are provided at the individual item level, the parcel of items containing the items used in this instrument had better than average reliability ($\alpha = .80$). Such validation established evidence for construct validity using item-response analysis and content validation by test creators, educators, and expert panels. The test was repeatedly field-tested and validated with diverse populations. The rubric calls for a maximum of 7 points to be assigned based on the given answers.

To measure far transfer, an extensive task was adapted from the NCTM lesson-plan repository. Once again, the problem was chosen to closely match the algebra standards/strands that were selected within the math domain. This instrument contains five overall items centered on a singular problem. The scoring rubric calls for a range of scores between 0 and 14. Given the nature of the task, no validation studies have been conducted on it and no psychometric properties have been collected. To the researcher's knowledge, the task has never been used in empirical research before.

Table 9. Summary of Instruments and Sources of Validation.

Construct / Variable	Instrument	Sources of Validation
Motivation		
Goal Orientation	Six items adapted from Elliot and Church, 1997.	Elliot & Church, 1997, 1999; Elliot, McGregor, & Gable, 2001.
Interest	Eight items adapted from Linnenbrink-Garcia et al., 2010.	Linnenbrink-Garcia et al., 2010.
Self-Efficacy	Eight newly developed items modeled after Pajares and Miller, 2004, and Noe, 2000.	Bandura's (2006) guidelines.
Prior Knowledge		
Content Knowledge	Four item performance task based on cognitive task analysis of transfer task.	Expert panel validation.
Strategic Knowledge	Fourteen-item instrument developed using Polya's problem-solving framework as guidance.	Expert panel validation.
Self-Regulation		
Motivational	Motivated Strategies for Learning Questionnaire (MSLQ) Critical Thinking Scale (5 items) (Pintrich et al., 1991).	Pintrich et al., 1993; Duncan & McKeachie, 2005; Used in over 50 research studies since its creation.
Cognitive	MSLQ Metacognitive Self-Regulation Scale (12 items) (Pintrich et al., 1991).	Pintrich et al., 1993; Duncan & McKeachie, 2005; Used in over 50 research studies since its creation.
Transfer		
Near Transfer	Three open-ended performance tasks taken from the NY state integrated math regents exam.	Pearson (2008a, 2008b);expert panel validation.
Far Transfer	Performance task with five sub-items derived from NCTM lesson plan.	Expert panel validation.

Although every effort was made to obtain a task that had been previously used, the domain of knowledge selected and the nature of the task made this an impossible endeavor. To measure transfer in this context, a task was required that allowed subjects to expand knowledge of basic concepts and procedures to a completely new situation. This necessitated development of the instrument from scratch. Steps, however, must be taken to ensure proper coverage of the domain was achieved. In this case, the same procedure employed to validate the prior knowledge instrument was used to provide evidence of content validity for this instrument. The same panel of content experts reviewed the task to ensure it sufficiently and appropriate covered the domain and specific topic selected. The panel of experts suggested minor changes to the language employed in the instrument but did not propose significant changes to the instrument.

To summarize, near and far transfer are measured through a performance task consisting of eight total items. These scores will range from 0-7 in the near transfer instrument and 0-14 in the far transfer instrument. Table 9 provides a complete summary of the instruments used in this study.

Population of Interest and Sample

The target population for this study was the student population at Syracuse University for the 2009-10 and 2010-2011 academic years. This population consists of approximately 20,336 undergraduate students and 5,682 graduate and law students (Syracuse University Office of Institutional Research & Assessment, 2010). The sampling frame for this population included all members of the Syracuse University Facebook and Twitter social networking sites, and individual students targeted through flyers posted in all academic campus buildings, class announcements, and departmental e-mail announcements.

These various ways to access participants likely overlap and thus it is very likely not all members of the student populations were reached. It is expected, however, that the multiple advertisement avenues made it more likely to have a heterogeneous sample rather than a sample clustered around particular departments, schools, or ability traits within the university. The advertisements (Appendix A) invited potential subjects to participate in the study. Potential participants were directed to attend a session where they were to complete a set of surveys followed by a transfer task. In exchange for their time, participants were entered into a raffle to win an iPad tablet (entered separately). Multiple sessions were held with the purpose of reaching a sample size adequate for the proposed study.

A number of authors have provided ways to estimate appropriate sample sizes for studies employing a structural equation model approach (Kline, 2010; Schumacker & Lomax, 2004). Kline (2010) discusses the issue of "large enough" sample size in SEM. The determination of sample size is based on a number of considerations, but an approach described by Kline and supported elsewhere in the literature (Bentler & Chou, 1987; Costello & Osborne, 2005; Mueller, 1996; Schumacker & Lomax, 2004) is to consider the number of parameters to be estimated and to try to maintain at least a 10:1, or optimally a 20:1 ratio of subjects to parameters estimated. In the case of this study, nine parameters are in need of estimation. As such, a minimum sample size of 90 subjects was determined to be sufficiently large. Attempts to obtain a larger sample size to get closer to the 20:1 optimal ratio of subjects to parameters were made.

Unfortunately, despite repeated advertisement campaigns, volunteers were scarce and even reaching the minimum sample size was a challenge that required an eight month extension to the data collection timeframe.

No exclusion criteria were applied to select the sample. Any student enrolled at Syracuse University either as a graduate or an undergraduate student was invited to participate. There were no restrictions about prior mathematical knowledge or current mathematical expertise as variability along those dimensions was desired. As subjects self-selected into the study, the sampling technique employed can be considered non-probability. Babbie (1990) refers to this sampling technique as "reliance on available subjects" (p. 183).

A non-probability sample indicates that members of the population of interest do not all share the same probability of being selected into the study (Babbie, 1990; Creswell, 2009; Krathwohl, 1998). This might seem counter-intuitive given there exists no exclusion criteria and any subject can choose to opt-in, but the point is that that with self-selection subjects themselves choose whether to participate in the study using criteria unknown to the researcher. Therefore, a random sample cannot be guaranteed or expected.

This raises a long-standing concern in the social sciences about whether subjects who self-select into a study accurately reflect the traits of interest of the entire population. This has been specially a concern in psychology studies that employ undergraduate courses to conduct research (Rosenthal & Rosnow, 2009). In such cases, it has been shown that those who volunteer to participate in study have certain traits that can bias the sample. Heckman (1979, 1985, 1990) showed that samples chosen without random sampling procedures could not be trusted to accurately replicate its population of interest, as the distribution of the sample did not accurately match that of the population.

This can have far reaching implications in the analysis of data. Changed population distribution parameters can bias statistical tests of significance. They also make it very difficult to generalize back to the larger population. Given the severe limitations of non-probability sampling, it might be suggested that a random approach is required even at the expense of sample size. For the purposes of this study, however, a case can be made that even though some limitations will still apply, the use of self-selected subjects in a non-random sampling technique is not likely to affect the distributions along variables of importance. Rosenthal and Rosnow (2009) reviewed extensive findings in the psychology literature regarding typical characteristics of human volunteer subjects.

Based on the available evidence, they settled on twelve characteristics that warrant some level of confidence when working with volunteer subjects. These characteristics are summarized in table 10 along with the authors' judgment regarding the level of confidence that should be attributed to each based on the available evidence.

Table 10. Volunteer Traits Adapted from Rosenthal and Rosnow (2009), p. 77-78.

Statements about volunteers warranting most confidence	**Statements about volunteers warranting some confidence**
1. Better educated	7. More sociable
2. Higher occupational status	8. More arousal-seeking
2a. But often from lower status background	9. More unconventional
3. In higher need of approval	10. Most often firstborn
4. Score higher on tests of intelligence	11. Younger
5. Less authoritarian	12. Female when task is standard
6. Better adjusted	12a. Male when task is threatening

It is not difficult to see that many of these traits could have a severe impact on a host of studies—whether in psychology or education. It is, however, difficult to make a case for any of these factors playing a role in influencing transfer of learning or severely impacting any of the other variables in the model. One concern is whether any of these traits could be reasonably expected to be a common cause or antecedent of any of the variables included in the model. With the exception of number 4 (score higher on tests of intelligence), this does not appear to be a reasonable inference. Given the concerns raised by this sampling technique, however, a number of steps were taken to maximize the likelihood that the sample chosen closely matched the population of interest.

First, the consideration that volunteers often score higher on tests of intelligence can bias the measures of prior knowledge and transfer and thus severely influence the ability of the analysis to generalize to learners with lower prior knowledge. This issue can be addressed by targeting subjects across campus from a variety of disciplines and backgrounds. As it has been shown in the literature review, prior knowledge (in terms of both content and strategies) is by far the most influential predictor of transfer.

This is a somewhat easier task in a university environment where subjects have already further self-selected into choices of academic majors and disciplines. Getting subjects from different disciplines seems, by far, the most efficient way to ensure the sample is as heterogeneous as the population. As such, subjects from a wide variety of disciplines were targeted by making class electronic announcements via department email lists and posting flyers and advertisements in all academic buildings throughout campus.

Second, It is likely that interest in the transfer task played a major role in whether a subject chose to participate in the study or not. To avoid a potential sample bias, the study and task description provided in the recruitment materials made only vague references to the completion of a performance task but it made no mention of the content covered or the specific nature of the task. Subjects were only exposed to this information upon agreeing to the study and attending the data collection session.

Even with these procedures in place, the limitations of a non-random sampling technique are acknowledged. Namely, the inability to generalize to populations beyond those specified is a major concern in this study. The measures taken to address sampling issues, however, present a strong case that the drawn sample will accurately represent the population of interest. This is, of course, a preliminary assertion that is further evaluated in the next chapter as the properties of data are described.

Subject Recruitment. Recruitment of subjects began early during spring semester in the 2010-2011 academic year. A series of flyers, e-mail announcements, and other advertisements were made through publicly available social networking sites, social lists, and physical postings placed in posting boards throughout the academic campus buildings that allow such advertisements. In exchange for their time, participants were offered a chance to win an iPad tablet device. The procedure for subject recruitment was as follows:

First, the flyers and advertisements directed participants to sign-up for the study through e-mail, phone, a web link, or in person. Participants were given the choice to sign up for a particular section that suited their availability. Additional sessions were scheduled to accommodate volunteers that had time and availability constraints.

Subjects were contacted after sign up and given a location and instructions for the attending the appropriate session. A subject ID was generated for each participant. This ID was included in all data collection instruments and used throughout the study to track the subject responses. No identifying information was associated with the ID thus making it impossible to determine the identity of the subject.

A total of 10 sessions were conducted. Sessions took approximately 90 minutes. Upon arriving subjects were asked to complete a consent form and received verbal instructions about the study. Learners were asked to complete the instruments in the following order:

a. Prior domain knowledge instrument.

b. Near and far transfer performance tasks.

c. Prior strategic knowledge instrument.

d. Motivation instrument.

e. Self-regulation instrument.

Upon completion, subjects were given an opportunity to enter into a raffle to win an iPad tablet device.

Data Collection

Data collection began in early spring semester after IRB approval was obtained (appendix E). A number of preparatory tasks were completed in preparation for data collection activities. These tasks included: 1) Assembling and preparing data-collection instruments; 2) Administering the instruments; and 3) Storing data.

Assembling and Preparing Data-Collection Instruments. A number of instruments have been highlighted as containing appropriate sub-scales to measure the constructs and indicators specified in the model. Two separate instruments were assembled based on those sub-scales and instrumentation. The first instrument contained items measuring prior content knowledge, near transfer, and far transfer. This instrument was followed by items measuring prior strategic knowledge, motivational indicators, and finished with the set of items used to measure self-regulated learning.

Instrument Administration. Participants that volunteered for the study were invited to attend a session in the IDD&E multimedia lab located in room 302 in the School of Education. This room is a computer lab consisting of individual workstations. Subjects were seated at a workstation with a computer where they first completed the prior knowledge, near transfer, and far transfer paper instrument. Upon completing these instruments, participants proceeded to complete the online surveys containing the strategic knowledge, motivation, and self-regulation items. Subjects were allowed to use any resources they deem appropriate as the nature of the problem permits it. They were given unlimited time to complete the task, although no participants exceeded ninety minutes.

A number of authors (Babbie, 1990, 2008; Creswell, 2009; Fraenkel & Wallen, 1993; Krathwohl, 1998) have pointed to the importance of consistent data collection procedures when collecting data. This is, of course, essential in experimental studies where manipulation across subjects of a particular group must be identical. In survey studies, this is also a critical consideration as the lack of consistency protocols may mean unintentional manipulation of the conditions for some subjects but not for others thus introducing bias into the study. This study followed a set of protocols during data collection in order to minimize the chance of this happening. The instructions provided to the subjects upon entering the lab were identical for all subjects. These are included in Appendix B. The researcher read these individually to all subjects. In those instances where graduate assistants other than the researcher administered the task, they were trained to use the study protocols and were given instructions about answering questions regarding the task.

Storing Data. The survey was hosted in the Survey Monkey website (http://www.surveymonkey.com). This survey administration service allows subjects to submit surveys and stores the raw data making it only accessible to the survey administrator that has the password. The service features redundant data storage and frequent backups to ensure data integrity. In addition, monthly copies of the raw data were stored in the researcher's computer. This computer is backed up daily to an online service and monthly to an external hard drive. For the paper instruments, data were score and stored in an Excel spreadsheet after all problem-sets were completed. All data were stored in the researcher's computer. All instruments were identified by a unique ID assigned to each participant. No personal or identifying information linking the ID to a participant's identity was collected.

Analytical Methods. The data collected fits within a theoretical model that has been specified and defined in chapters 1 and 2. This model is presented again in figure 11 for the convenience of the reader. To analyze the collected data and validate the outlined model, a structural equation modeling (SEM) analytical technique is employed. SEM is by no means a new technique with many tracing its roots to Sewell Wright's early path analysis in genetics (1918), Haavelmo's early econometrics models (1944), and continued in sociology by the work of Duncan, Simon, and Blalock in the 1960s (Matsueda, 2000).

The social sciences have seen an explosion of studies using SEM. By their estimation, MacCallum and Austin (2000) found over 500 examples of published applications of SEM in 16 psychology journals over a span of four years. This number is likely to have increased over the last few years as advances in factor analysis, SEM methodologies, and software capable of performing SEM analysis have become more straightforward and inclusive of different types of variables and measurement types (Kline, 2010).

Despite this increase popularity, SEM techniques are still relatively rare in comparison to quantitative studies employing regression or ANOVA approaches. It is important for the reader to have a common understanding of the technique used in the study. As such, the next few paragraphs attempt to present some background about the underlying logic of structural equation modeling. SEM is an extension of the linear regression families derived from the general linear model. This family of techniques includes simple and multiple regression techniques, ANOVA techniques, as well as more advanced techniques such as path analysis, discriminant analysis, and other similar techniques.

The main differentiating feature between SEM and other analytical techniques is its reliance on latent variables (LVs). A latent variable represents a hypothetical construct that can't be directly measured and instead must be represented through a series of indicator variables that together encompass the dimensions of the LV. These hypothetical constructs are common occurrences in psychology and education.

Take as example intelligence. We cannot directly measure a person's intelligence but we can approximate it through a series of indicators such as IQ, task performance, and a number of other variables. In SEM, these indicators are joined to create a latent variable encompassing the dimensions of the construct. In multiple regression or similar techniques, a variable like intelligence would be treated as consisting of a single measure or a composite of multiple measures (MacCallum & Austin, 2000).

This is important as a single measure implies perfect measurement accuracy, but as we know, perfection in measurement is an impossible achievement (Bollen & Lennox, 1991). Thus, the best we can do is to attempt to model the measurement error along with hypothesized relationships. We can accomplish this by obtaining multiple 'samples' of a measure and then attempting to analyze the strength and consistency of that measure.

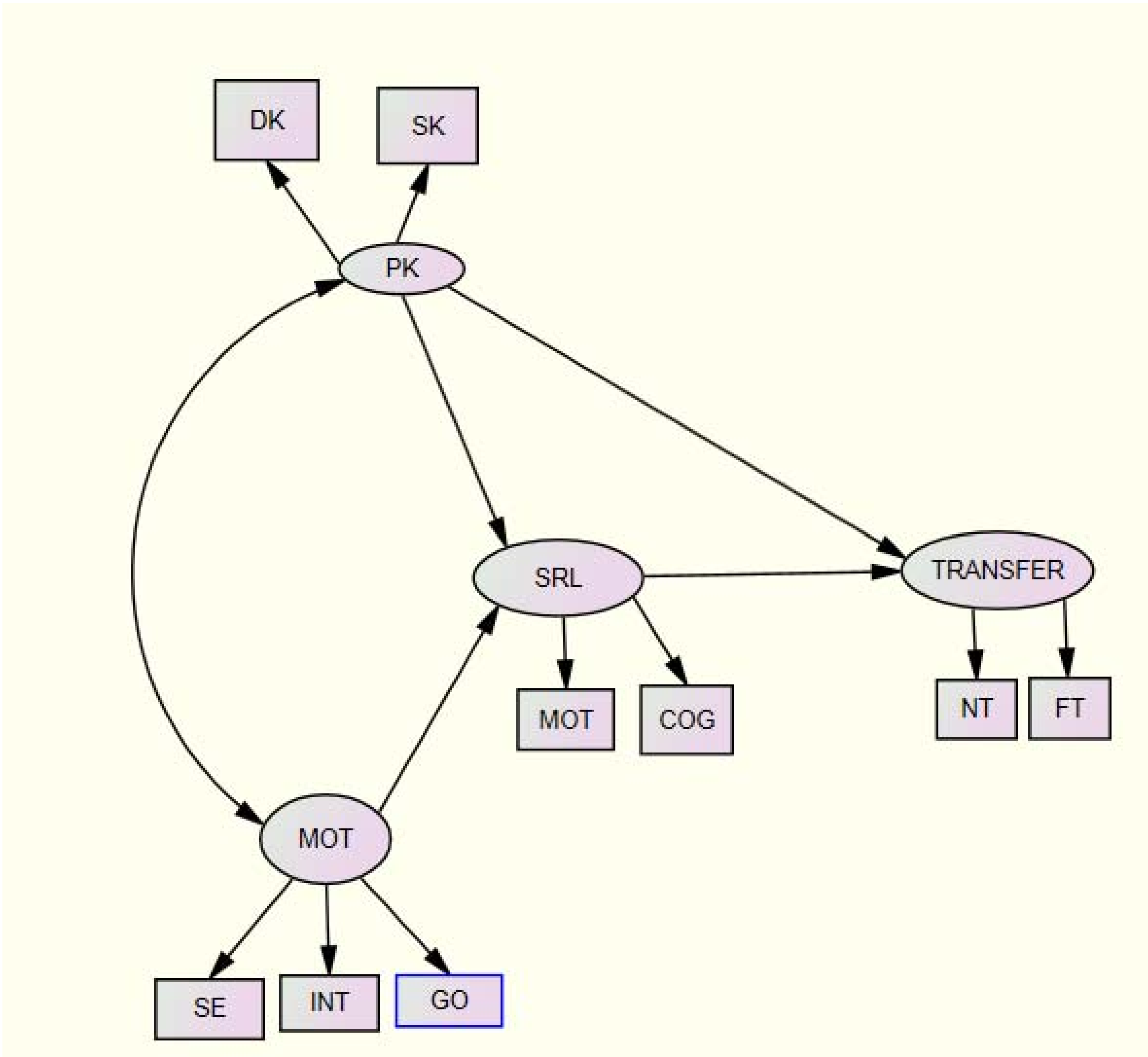


Figure 11. Theoretical model of transfer and motivation proposed for validation in this study.PK = Prior Knowledge, DK=Domain Knowledge, SK=Strategic Knowledge, MOT=Motivation, SE= Self-Efficacy, INT=Interest, GO=Goal-Orientation, SRL=Self-Regulated Learning, MOT = Motivational SRL, COG= Cognitive SRL, NT = Near Transfer, FT = Far Transfer.

In the case of SEM, this is done through factor analysis. This is our measurement model. We can then complement the measurement model, and more importantly consider the extent of estimated measurement error, to fit a structural model that spells out the direction and path of causal relationships. This allows us to model hypothesized causal structures while also accounting for measurement error and the latent structure of a construct.

This double-sided approach has a definitive advantage over more primitive regression and linear modeling techniques. As it has already been mentioned, measurement error is accounted for in the measurement model thus our analysis produces more accurate standard errors, and thus more accurate estimated parameters. Secondly, the factor analysis validation that is required to conduct an SEM allows gathering of evidence about construct and content validity. The validation of an underlying construct's factor structure can detect mispecified constructs with insufficient coverage or mistaken factor structures (Tomarken & Wallen, 2005). Third, multiple indicators are preferable to a single indicator as this decreases the likelihood of influencing outliers and narrow definitions. Lastly, the use of latent constructs reflects the reality of psychological traits that are inaccessible directly but can be modeled or represented through a careful combination of indicator variables. For these reasons, and for the feasibility and prior efforts to validate theoretical models using SEM (MacCallum & Austin, 2000), this technique has been chosen as the most effective and methodologically rigorous available to validate the proposed model.

To validate the proposed SEM model, a set of considerations must be taken into account. This study follows Kline's (2010) recommendations. The following six steps will be followed to validate the model.

1. Specify the model.
2. Operationalize constructs.
3. Estimate the model.
4. Evaluate model fit (If poor, skip to step 5).
    a. Interpret parameter estimates.
5. Consider equivalent or near-equivalent models.
    a. Respecify the model (If necessary).
6. Report the results.

Model Specification is the basis of any SEM study. This step begins by taking a set of formal hypotheses and turning them into a formal model to be validated. This requires using all available theory, empirical research, and available information to select variables and hypothesize a set of relationships among these variables (Schumacker & Lomax, 2004). This is a critical step as mispecified models can severely bias parameter estimates and thus distort the nature of the real-world relationships that are being modeled (Schumaker & Lomax, 2004, p. 58). Thus, it is essential that any model be grounded on solid theoretical and empirical grounds. Chapter 1 and chapter 2 in this study detail efforts to thoroughly and systematically create a model based on our most current knowledge of motivation and transfer.

Part of this step requires us to evaluate model specifications by identifying the model. This means assessing whether the theoretical model specified can be mathematically estimated. The underlying foundation of SEM is a set of mathematical equations that must be solved to arrive at estimated parameters. As with any system of equations, there must be enough information (i.e. number of simultaneous equations) to solve the number of unknown variables presented. This allows for three distinct possibilities: 1) the model can be just identified; 2) The model can be under identified; and 3) The model can be over identified. The example equations below can be used to better illustrate this point.

$$x + y = 14$$

$$y + z = 6$$

This set of equations requires us to estimate three separate parameters (x, y, z). But in this case, not enough information is provided to facilitate that estimation. There are multiple values that can possibly satisfy the equations ($x = 10$, $y = 4$, $z = 2$; $x = 8$, $y = 6$, $z = 0$, etc…). This is an example of what an *under-specified* model implies. There is simply not enough information to conduct a unique estimation of desired parameters. Parameters can be calculated but they won't be unique. That is not very useful. Suppose now, however, that we added an additional equation to this system as followed:

$$x + y = 14$$

$$y + z = 6$$

$$\mathbf{x + z = 12}$$

The addition of a new relationship allows us to calculate unique estimates for the estimated parameters. Solving these equations, we obtain: x = 10, y = 4, z = 2. In this case, we have just enough information to estimate these parameters. This is the case of *just-estimated* model. Lastly, if in addition to the equation, we were given x = 10 or provided with another equation using the same variables, we would say the model is over-identified. That is, we have more information than it is necessary to estimate the desired parameters. In the case of an SEM model, the available information is in the form of correlations and covariances among the variables in the model. This information is used to solve the complex underlying equations driving the model (Bollen, 1989). An SEM requires us to have, at the very least, a just identified model.

The next step is to *operationalize constructs*. An earlier part of this chapter was dedicated to describing the instruments used to measure each construct. That was the final part of construct specification. In Chapters 1 and 2, the logic and evidence for the selection and grouping of variables under each construct was covered. Typically, little guidance is provided on selecting indicators for constructs other than to use sound theoretical and empirical evidence for this selection.

Little, Lindenberger, and Nesselroad (1999); however, take this discussion further by developing a heuristic model that relies primarily on two dimensions to consider when selecting indicators. The first dimension is the centroid distance, which refers to the correlation between constructs. If constructs are closely correlated, it is likely that indicators will overlap between constructs and make the true correlations between construct more difficult to recover. The authors suggest that a confirmatory approach with constructs defined *a priori* and validated through confirmatory factor analysis can effectively address this issue and uncover true correlations. This is the approach taken in this study.

The second dimension is the number of indicators to include under each construct. Classical test theory indicates that the more indicators selected the better coverage of the construct to be achieved (Crocker & Algina, 1986). This however, must be balanced with issues of practicality and parsimony. A number of authors have suggested a rule of thumb where each construct must be represented by at least three indicators (Bollen, 1989; Kline, 2005; O'Brien, 1994; Schumaker & Lomax, 2005). That guidance is followed in this study as supported by theory and empirical work. In the cases where only two indicators are used (as in prior knowledge and transfer of learning), those indicators themselves are made up of a combination of multiple items and combined to create better coverage of the indicator.

A final issue with regards to construct and indicator selection is the depth at which indicators are selected and constructs are modeled (Bagozzi & Edwards, 1998). In the case of this study, many of the indicators selected can themselves be considered latent constructs that can be represented by a factor structure of multiple indicators. Goal orientation, for example, has often been operationalized as a three-factor latent construct (Elliot & Church, 2006; Vandewalle, 1997). A researcher has a choice to represent indicators at the most relevant level to answer the research questions posed in the study. However, consistency must be ensured so that indicators are represented at the same level throughout. The choice has been made in this study to model constructs and indicators at the most global level. This choice is driven by the research questions informing the study, and by the empirical and theoretical evidence that specifies relationships occurring among indicators at the scale levels where the indicators are defined.

Model Estimation follows. This step involves determining the value of unknown parameters and disturbances (error terms) associated with the latent variables in the model. To estimate the model, SPSS and AMOS were used. Successful model estimation also validates prior model identification as it indicates whether or not enough information was available for the software to estimate all required parameters.

After a model is estimated, it is necessary to evaluate the model to ensure it consistently fits the study data. For the overall model, this is done via a chi-square (χ^2) test and variety of fit-indices. This is typically followed by a more detailed assessment of fit comparing differences between the observed and generated covariance matrices (Anderson & Gerbing, 1988; Kline, 2005).

The testing of model fit is followed by interpretation of the estimated parameters in light of the research questions and stated hypothesis. The final step in estimating the model is comparing the model to any available alternative models. MacCallum and Austin (2000) warn that even when model fit is achieved there is a danger of confirmation bias. That is, the fact that data adequately fit a single model does not mean alternate, competing models fit data just as well or even better. To remedy this, Anderson and Gerbing (1988) suggest a two-step approach. The first step is to estimate a series of five nested models. Next, the researcher obtains a likelihood ratio chi-square value for each model. Strength of model fit can then be assessed by comparing chi-square differences and using fit indexes to determine best-fitting models. In this study, the five models generated are:

M1: A *saturated* structural model (Anderson & Gerbing, 1988, p. 418) in which all paths are estimated. This model posits that all constructs are directly related to other constructs.

M2: A *null* structural sub model in which all paths of the model are set to 0. This model posits that no relationships exist among the constructs.

M3: A *substantive model of interest.* This is the model specified in figure 1 and formally defined in chapters 1 and 2.

M4: A model representing the most likely alternative to M3. This model posits a direct relationship between motivation and transfer in addition to all other relationships specified in M3.

M5: A model representing the most likely alternative to M4. This model posits only indirect relationships to transfer of learning with prior knowledge being only indirectly related to transfer.

These five models form the basis for model testing in the study. Comparison of these alternative models addresses issues of bias confirmation and provides strong evidence of model validation following established SEM procedures.

The final step is to report the results. Procedures for reporting results consistent with the SEM literature will be followed. Information reported will include:

1. Descriptive statistics (Mean, SD, variances, zero-order correlations, frequency distribution, etc.).
2. Data diagnostics information (Tests of normality, kurtosis, skewness, collinearility, etc.).

For the specific model specified, the following will be reported:

3. Factors loadings for the measurement model
4. Correlations among latent variables for the structural model
5. Goodness of fit indices (χ^2, CFI, RMSEA, AIC, etc…) for the structural model
6. Path coefficients, including significance, for all structural models tested

The procedures outlined above describe the analytical procedures to be followed in this study.

Summary

The purpose of this study is to outline a model that describes the causal mechanisms by which motivation and prior knowledge work to promote transfer of learning. As it has been posited in prior chapters, motivation and prior knowledge exert their influence on transfer through increased self-regulation. The main goal of this study is to validate the proposed model using SEM techniques. The selection of SEM to validate this model has been made on the basis of the appropriateness of the technique for this type of studies, its increased use in the social sciences, and its superior methodological advantage over less advanced techniques such as regression and analysis of variance.

These first three chapters have established a sound theoretical framework from which a testable model has been derived. A set of testable hypotheses, covered early in the chapter by outlining research questions, has been generated. This study has made the argument that the conspicuously lacking absence of systematic inquiry into the motivation mechanisms that influence transfer is a severe limitation of the transfer and motivation literature.

Chapter 1 clearly defined that problem and offered a solution based on theoretical and empirical work. Chapter 2 provided a systematic and comprehensive review of the current state of the literature providing evidence for the hypothesized relationships while also showing points of departure where the present study seeks to improve on prior empirical work. In this chapter, a detailed outline of the design consideration, data collection and analytical procedures has taken place. The logical chain of reasoning that follows within, and through, each chapter provides a credible and rational argument to conduct the proposed study. The next chapters discuss the findings of the study and the implications for future research.

CHAPTER 4: RESULTS

The first three chapters established a theoretical and empirical base that led to a testable model of transfer. This model accounted for the motivational mechanisms previously omitted and proposed a methodological and analytical approach well suited to answer the set of research questions posed. The next two chapters conclude this dissertation by reporting the results of the study, summarizing what was learned, and providing insight into future work that may extend, and improve, the limited scope of the current study.

Procedure

A total of 99 subjects are included in this analysis. Data were collected over a span of ten months beginning in March 2011 and concluding in January 2012. Participants were part of two separate data collection efforts. During the first batch of data collection, which occurred from March 2011 to May 2011, a total of 44 subjects completed the problem set and survey instruments that were part of the study. These subjects were recruited through the posting of fliers around the campus, e-mail solicitations sent through department e-mail lists, and advertisements made during classes and various on-campus events as described in chapter 3.

The second data collection batch occurred from October 2011 to January 2012. After consulting with the dissertation committee, it was decided that in order to increase the number of possible subjects participating in the study, it would be wise to convert all instruments to the online format and to allow participants to be part of the study from anywhere they could access an online survey; although the population universe remained the same, Syracuse University students. The researcher petitioned the IRB board for an amendment to the data collection procedures. The approved amendment can be found in Appendix F. Subjects were once again targeted through fliers around campus, advertisements through departmental email lists, and social networking sites (Twitter and Facebook). Fifty-five subjects participated during this part of the data collection process. The entire process was automated through the Survey Monkey website with no intervention from the researcher and no direct contact with the subjects other than to provide clarification about the study.

Data Cleanup and Preparation

Following the recommendation of Kline (2010) a minimum acceptable sample size of 90 subjects was established. This was based on a rule of thumb in the SEM literature that suggests, at a minimum, a ratio of 10 subjects per indicator variable. An optimal ratio of 20 subjects per indicator was originally proposed. However, due to difficulties acquiring subjects that caused the data-collection stage to be extended for over six additional months, it was decided a sample size of 99 was adequate.

After the data collection window closed, data were downloaded from the Survey Monkey servers. Such data typically contain a number of extraneous fields not necessary for the analysis. These included IP addresses to identify the machine where the surveys were completed as well as unique record IDs to identify each set of surveys. These fields, along with any fields not included in the calculation of variables in the analysis were removed. An original file with raw data was preserved.

Descriptive Statistics

Means, standard deviations, and zero-order correlations for the indicators used in this study are presented in Table 11. Since normality is a major assumption of maximum likelihood estimation techniques used in SEM, exploratory analyses were performed to test normality in the included observed indicators.

Table 11. Means, Standard Deviations, and Zero-order Correlations among Observed Indicators

	Mean	STD	DK	SK	NT	FT	GO	INT	SE	MOTSRL	COGSRL
DK	14.52	2.72	1								
SK	40.25	6.98	.180	1							
NT	5.88	2.14	.423**	99	1						
FT	10.71	5.76	.535**	.267**	.644**	1					
GO	33.90	5.10	.100	.120	-.028	.183	1				
INT	37.41	10.37	.177	.287**	.121	.209*	.443**	1			
SE	604.65	132.52	.538**	.386**	.530**	.840**	.223*	.313**	1		
MOTSRL	60.36	9.33	.432**	.457**	.783**	.552**	.231*	.341**	.581**	1	
COGSRL	25.96	5.33	.255**	.552**	.635**	.469**	.075	.191	.423**	.779**	1

Note. *N=99.* The following abbreviations are used: DK = domain knowledge, SK= strategic knowledge, NT= near transfer, FT= far transfer, GO= goal orientation, INT= interest, SE= self-efficacy, MOTSRL = motivational SRL, COGSRL = cognitive SRL.

**** Correlation is significant at the .001 level. * Correlation is significant at the .005 level**

Figure 12 displays graphs for each indicator, overlaid with theoretical normal distributions. The graphs point to domain knowledge (DK) and near transfer (NT) as indicators with possible non-normal distribution. Skewness and Kurtosis values, displayed on table 12, confirm this diagnosis. Typically, when faced with a non-normal distribution, a researcher has the choice to transform the variable in an attempt to obtain a more normal distribution. In the case of domain knowledge, this might be problematic. The distribution of the variable actually shows a clustering of the responses around the higher levels of prior domain knowledge so kurtosis is not an issue, only skewness. Transforming the variable might actually obscure what is an important limitation of the variable—namely its supposed inability to differentiate between subjects with high and low levels of prior domain knowledge. Because of this, the choice was made to not transform the variable and instead deal with the consequence of univariate non-normality. Arbuckle (1997) suggests that non-severe departures from normality are often harmless if no definitive inferences about the population parameters are being made.

Table 12. Skewness and Kurtosis Statistics for Observed Variables.

	Skewness	Kurtosis
Domain Knowledge	-1.150	.634
Strategic Knowledge	.329	-.314
Near Transfer	-1.913	2.340
Far Transfer	-.302	-1.269
Goal Orientation	-.224	-.324
Interest	-.014	-.569
Self-Efficacy	-.244	-.857
Motivational SRL	-.593	.079
Cognitive SRL	-.867	.525

As for the near transfer indicator, symptoms of kurtosis and skewness can be detected. It appears that the shape of the distribution can be partially attributed to the limited range of the variable (0 to 7).

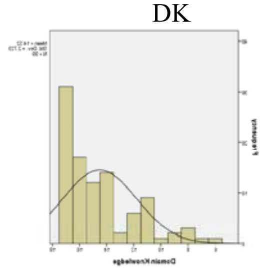
Table 13. Cronbach's Alpha Statistics for Included Scales.

Scale	**Cronbach's Alpha (α)**	**Number of Items**
Strategic Knowledge	.57	13
Goal Orientation	.69	6
Interest	.83	8
Self Efficacy	.76	8
Motivational SRL	.73	12
Cognitive SRL	.48	5
Domain Knowledge	.498	7
Near Transfer	.829	3
Far Transfer	.858	5

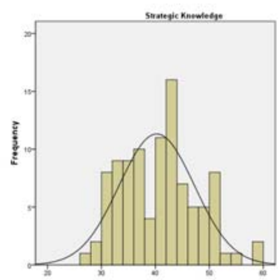
Figure 12. Frequency histograms with theoretical normal distributions for nine observed indicators.

Furthermore, the three items in the problem set that yield this score show a distinct pattern of response where subjects either successfully completed all three problems or were unable to successfully complete any problems at all. Given this pattern, the range of responses, and the theoretical range of the item, transforming the variable makes little sense. Given no other choice, this variable is treated as continuous although its practical range makes it more suitable to be treated as a categorical variable.

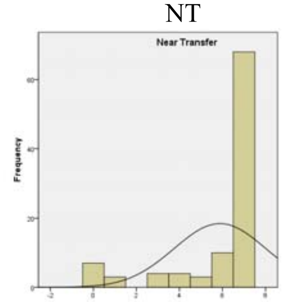
DK



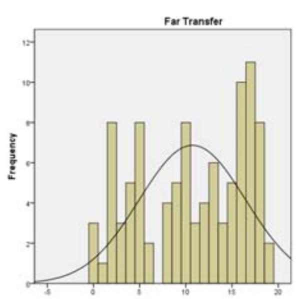
SK



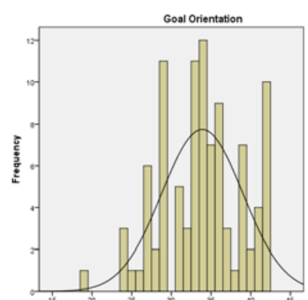
NT



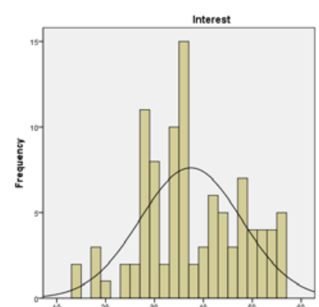
FT



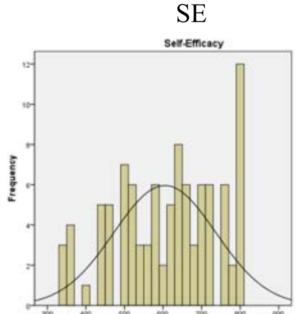
GO



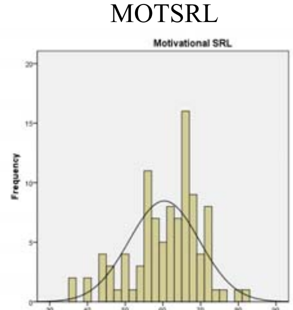
INT



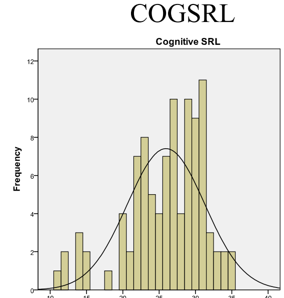
SE



MOTSRL



COGSRL



The Problem of Multiple Samples

As it was discussed in the procedures section, data were collected in two distinct samples. Although these samples were drawn from the same sampling universe (Syracuse University students), there is danger in assuming that these samples are perfectly drawn from the population and thus contain equivalent distribution of values. As this is a matter of empirical reality, steps were taken to ensure the equivalence of the samples. First, descriptive statistics were computed individually for each sample in order to compare across all observed variables.

Table 14. Means and standard deviations comparing two samples.

SAMPLE		DK	SK	NT	FT	GO	INT	SE	MOTSRL	COGSRL
Fall 2001	Mean	14.18	39.24	6.07	10.58	34.13	38.13	607.11	60.33	25.87
	ST DEV	2.80	6.52	1.96	5.73	5.62	10.78	129.56	8.85	5.18
Spring 2011	Mean	14.81	41.09	5.72	10.81	33.70	36.81	602.60	60.39	26.04
	ST DEV	2.66	7.29	2.29	5.83	4.67	10.07	136.12	9.78	5.51
Total	Mean	14.52	40.25	5.88	10.71	33.90	37.41	604.65	60.36	25.96
	ST DEV	2.72	6.98	2.14	5.75	5.10	10.37	132.52	9.33	5.33

As table 14 shows, the differences between the two samples are negligible. A more important test, however, is to see is correlations among observed variables differ by sample. This is a useful test as SEM analysis relies on covariances among indicators and latent variables, rather than means, to estimate path coefficients. Table 15 displays the zero-order correlations for the nine observed indicators, broken down by sample. A glance at the table reveals more complex differences. Rather than try to settle on a magnitude that is significant enough, the table highlights bivariate correlations that were significant under one sample but non-significant under another. As it can be seen, the relationships among the variables differ on several places. This indicates that there are differences between the samples and it raises the question of how significant those differences are.

Luckily, SEM provides a standard methodology for comparing measurement and structural differences when there are concerns about the homogeneity of multiple samples. As this analysis begins the testing of a set of hypotheses, the originally posed research questions are reviewed and discussed individually in the following sections. For the sake of methodological correctness, questions of multi-group equivalence and data fit are addressed first.

Table 15. Zero-order Correlations for Multiple Samples.

SAMPLE		DK	SK	NT	FT	GO	INT	SE	MOTSRL	COGSRL
Spring	DK	1								
2011	SK	.240	1							
	NT	.562**	.341*	1						
	FT	.600**	.366**	.679**	1					
	GO	.029	.148	-.068	.203	1				
	INT	.165	.410**	.105	.190	.487**	1			
	SE	.603**	.486**	.596**	.865**	.270*	.337*	1		
	MOTSRL	.506**	.513**	.843**	.616**	.283*	.331*	.662**	1	
	COGSRL	.344*	.582**	.697**	.545**	.135	.198	.532**	.811**	1
Fall 2011	DK	1								
	SK	.075	1							
	NT	.275	.148	1						
	FT	.463**	.131	.606**	1					
	GO	.180	.106	.009	.166	1				
	INT	.208	.161	.134	.236	.400**	1			
	SE	.473**	.257	.436**	.809**	.176	.285	1		
	MOTSRL	.347*	.384**	.698**	.467**	.178	.358*	.469**	1	
	COGSRL	.147	.516**	.554**	.370*	.014	.186	.277	.735**	1

Research Questions

R8: Is the proposed measurement model consistent across the two samples of subjects?

Multi-group SEM analysis (Dolan, 2000; Kline 2010; Marsh, 1994) provides a rigorous methodology to test for measurement invariance across samples. In plain terms, measurement invariance tests validate the hypothesis that factor loadings of indicators on particular latent variables do not significantly differ across groups (Muthen, 1994; Muthen & Asparouhov; 2011; Preacher, Zyphur, & Zhang, 2010).

A multi-group SEM of the hypothesized model was conducted using SPSS AMOS19. The first step in performing the analysis is to constrain the factor loadings to be equal across groups thus setting up a testable hypothesis. Table 16 displays the results of the various chi square tests performed to establish measurement invariance. The chi-square test labeled "measurement weights" indicates no significant differences exist on the factor loadings (weights) of the indicator variables across the two samples $\chi 2$ (5, *N=99) = 1.73, p > 05*.

Table 16. Tests of Measurement Invariance across Samples

Model	DF	Chi Square	P
Measurement weights	5	1.733	.885
Measurement intercepts	14	12.971	.529
Measurement residuals	27	28.723	.374

As recommended by Cheung and Rensvuld (1999) further tests were performed to establish "strong" measurement invariance across the samples. The chi square test labeled "measurement intercepts" tests whether the starting points for both groups (their means) are equivalent across the indicators. Once again, the results are not significant $\chi 2$ (14, *N=99) = 12.97, p >.05.*The chi-square test labeled "measurement residuals" tests the hypothesis that the error terms of the indicators on the latent variables are not significantly different across groups. Once again, the results show no significant differences $\chi2$ (27, *N=99) = 28.72, p >.05*.

Together, these tests show the measurement model is consistent across samples and suggests further testing to see if the case applies to the structural model as well.

R9: Is the proposed structural model consistent across the two samples of subjects? The same logic used to test the measurement model was extended to the structural model. Chi square tests result for this analysis are displayed on Table 17. The chi square test labeled "structural weights" constrains the path estimates in the model to be equivalent across the two samples. The test shows no significant differences between the two groups $\chi2$ (18, N=99) = 19.359, p > .05. The same test was applied to the covariances in the structural model (in this case a single covariance between the prior knowledge and motivation latent variables), and the results once again indicate no significant differences between the two samples $\chi2$ (1, N=99) = 1.088, p > .05.

Table 17. Comparison of Structural Weights and Covariances across Groups.

Model	DF	Chi Square	P
Structural weights	18	19.359	.370
Structural covariances	1	1.088	.297

Based on the results of the analysis, it is reasonable to conclude that no significant differences exist between the two samples on either the measurement or structural part of the model. Given this conclusion, it is a justifiable decision to combine the samples and treat them as a singular sample. This entire sample is used to answer the remaining research questions. Figure 13 displays the hypothetical model to be tested initially.

Before proceeding to answer substantive content questions, it is important to diagnose model fit in keeping with standard SEM practices (Kline, 2010). Therefore, research questions surrounding these issues are addressed first.

R5: Does the specified model reasonably fit the data according to fit standards (X2, CFI, RMSEA, AIC, etc.)? To answer questions of model fit, SEM methodologists rely mainly on two pieces of information. The first is the omnibus chi-square model test that compares whether the sample covariance matrix differs significantly from the population's (Barrett, 2007). The omnibus chi square test for the specified model shows significant differences $\chi 2$ (23, N=99) = 185.116, $p < .05$. This points to major sources of data misfit but closer investigation is required.

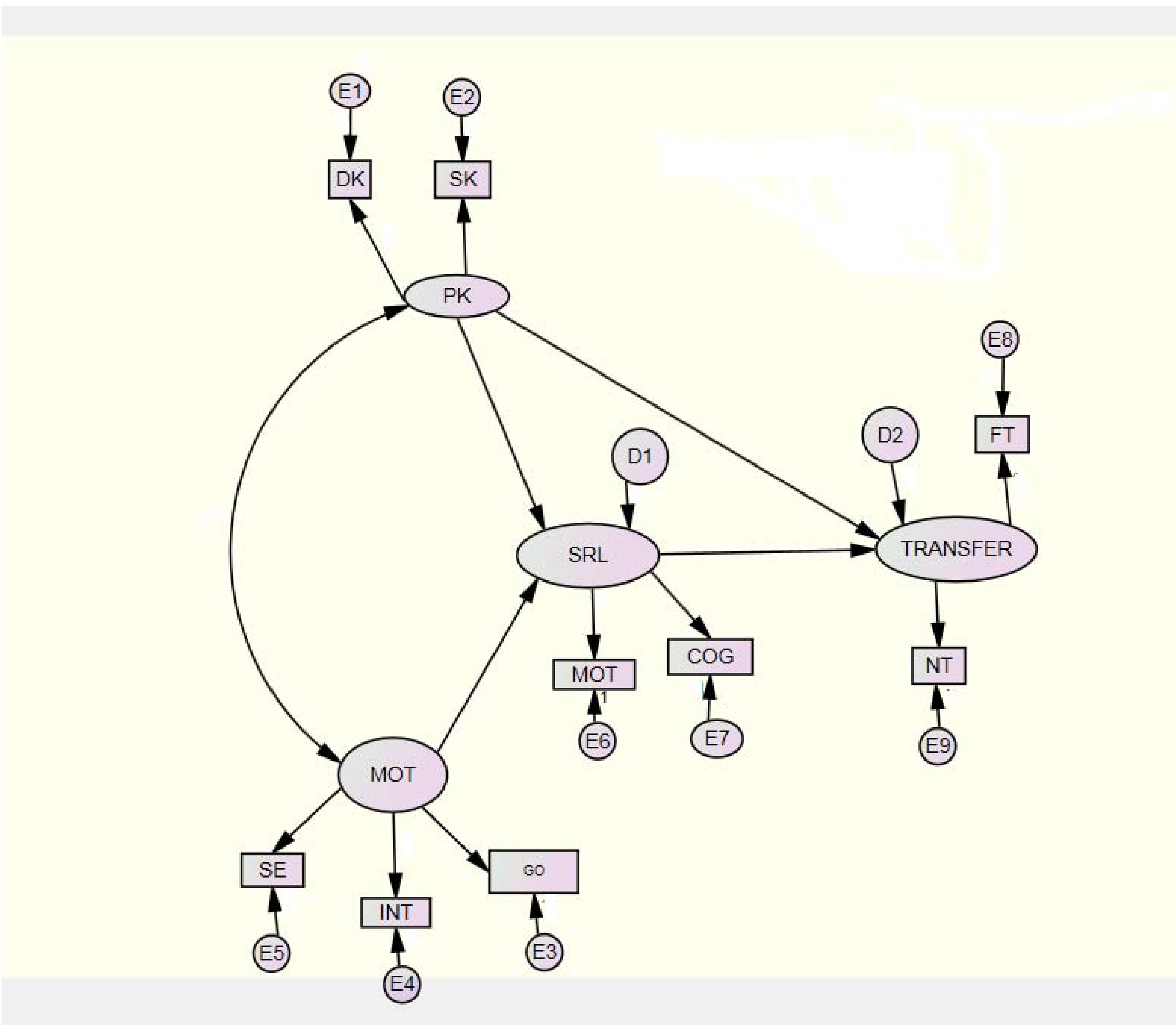


Figure 13. Theoretical SEM Model Validated in this Study.

Some researchers have pointed out chi-square tests are particular sensitive to sample-size, correlation sizes, and even small deviations from the data and are thus not always helpful for evaluating model fit (Bollen & Long, 1993; Marsh et al., 1988). In such cases, fit indices may provide more useful information. By nearly all standards of model fit, the hypothesized model is diagnosed to fit the data poorly. Table 18 lists these indices.

The results show severe deviations from the hypothesized model and the data collected. Of course, this is not particularly useful information as the indices fail to pinpoint exactly where the source of misfit is located. Such information can provide theoretically valuable information that may be useful in subsequent studies. The first step in obtaining this information is to explore whether reasonable alternate hypothesized models better fit the data.

Table 18 - Chi Square and fit indices for hypothesized SEM model.

Fit Index	Value for Current Model	Acceptable Threshold
Chi-Square	185.16, $P < .05$	Non-significant ($P > .05$) (Barrett, 2007; Kline 2010)
RMSEA	.27 (90% CI .23 to .31)	<= .08 indicates good fit (Browne & Cudeck, 1993)
TLI	.49	>=.90 (Schumacher & Lomax, 1996)
GFI	.76	>=.90 (Schumacher & Lomax, 1996)

R6: Which of the specified models (M1, M2, M3, M4, M5) best fit the data?

Alternative hypothesized models were previously described in chapter 3. To recap these models are as followed:

M1: A *saturated* structural model (Anderson & Gerbing, 1988, p. 418) in which all paths are estimated.

M2: A *null* structural sub model in which all paths of the model are set to 0.

M3: A *substantive model of interest.* The model formally defined in chapters two and three.

M4: An alternative model that posits a direct relationship between motivation and transfer.

M5: A model that posits only indirect relationships to transfer of learning with prior knowledge being only indirectly related to transfer.

By default, *M1 and M2* are used as baselines of fit to compare the substantive model of interest. So in practicality, a null model will fit the poorest as no relationships are posited among variables and indicators. The saturated model presents an exactly opposite scenario as it will fit the data perfectly by hypothesizing all possible relationships. A hypothesized model will fit somewhere in between. That leaves comparisons among M3, M4, and M5 as the only practical comparisons to be made.

The basis for comparing the models rests not only on comparing indices of absolute fit but also using additional relative fit indices (AIC, CFI) that provide a more structured basis for comparison among models (Bollen & Long, 1993; Tanaka, 1993). The results for models M3, M4, and M5 are listed on Table 18. Additional indices included are the comparative fit index (CFI) and Akaike's information criterion (AIC).

Table 19. Comparing Fit Indices across Models.

Model	Chi-Square /DF / P	RMSEA	TLI	GFI	CFI (higher is better)	AIC (lower is better)
M3	185.16	.27	.49	.758	.672	229.115
M4	162.88 / 22 / <.05	.256	.534	.781	.715	208.883
M5	190.23 / 24/ <.05	.266	.496	.748	.664	232.234

The fit indices provide a similar picture for all three models compared. They fit poorly given the data. M4, which posits a direct relationship between motivation and transfer, in addition to the other hypothesized relationships, fits best according to comparative indexes such as CFI and AIC. This is not surprising given one less degree of freedom needs to be calculated and thus the model is closest to the saturated model. The AIC index, however, which accounts for the number of parameters calculated, still shows M4 to be the best fitting model (for the AIC index, a lower value is better).

The evidence modestly suggests that among the models M4 is the best fitting model. This is, however, in light of overall poor fit. SEM researchers have cautioned interpreting results given a poor fitting model. Many have recommended that when encountering fit issues, the best approach is to investigate the source of misfit through multiple avenues. This should not, however, turn into a mathematical fishing expedition to lower or heighten a particular index. Rather, such information may provide substantive theoretical modifications that can be empirically validated against a different sample in future research (Barrett 2007; Hayduk, 2007; Kline, 2010; McIntosh, 2007; Mulaik, 2007). That groundwork is followed here in an attempt to better understand the sources of data misfit and to provide a set of suggestions that may inform future work.

Before the procedures employed to diagnose sources of misfit are discussed, however, full results are reported for the remaining research questions. It is important to remind the reader; however, that such results must be interpreted in light of the poor fitting models and so must be interpreted with severe caution. The chi-square test and fit indices for the model indicate that the hypothesized sets of relationships might not be accurate or stable despite the magnitude and direction of the calculated effects. Once again, caution is warranted in interpreting any of the following results as strongly validating any of the hypothesized relationships that were originally proposed. For reporting purposes, the originally hypothesized model—*M3*—is used.

For the reader wishing to review all the results in a more unified format, standardized direct, indirect, and total effects along with significance levels are displayed on table 20. The path diagram including standardized estimates is displayed on figure 14.

Table 20. Standardized Direct, Indirect, and Total effects.

	Direct		**Indirect**		**Total**	
	SRL	TRA	SRL	TRA	SRL	TRA
PK	-.03	.22*		-.02*	-.03*	.19
MOT	.75*	.00		.58*	.75*	.58*
SRL		.73*		.00		.78*

* p < .05 established through bootstrapping estimation

R1: Does prior knowledge significantly increase transfer performance? What is the magnitude of the relationship? As prior empirical evidence established, prior knowledge is considered one of the main predictors of transfer. The model hypothesized both a direct and indirect relationship between prior knowledge and transfer. The direct effects show a modest effect of prior knowledge on transfer ($\beta = .22$, $p <.05$) that is not statistically significant. For every standard deviation increase on prior knowledge, there is nearly a one fifth of standard deviation increase on transfer scores. This is a strong effect. Given that prior knowledge is likely to be normally distributed, we can assume that students who are two standard deviations above the mean on prior knowledge (the top 5% of the population) would see an increase of .44 standard deviations on a transfer score given average motivation. In such context, the magnitude of the effect is consistent with the literature demonstrating a stronger effect between prior knowledge and transfer.

R2: Does self-regulation significantly increase transfer performance? What is the magnitude of the relationship? In all models tested, SRL exerts a direct effect and acts the mechanism that mediates transfer. SRL shows a strong total effect ($\beta = .78$, $p > .05$) on transfer. This is by far the largest effect, which is not surprising given the role the central mediator role SRL is posited to play in the hypothesized model.

R3: Does self-regulation significantly mediate the relationship between prior knowledge and motivation? What is the magnitude of the relationship? Chapter one and two established the viability of motivation as an indirect predictor of transfer. It was shown that often motivational variables exerted their influence on transfer and other measures of problem-solving through a mediating variable. In this case it was posited that self-regulated learning (SRL) might play such a role. Model *M3,* the hypothesized model, shows a strong indirect effect between motivation and transfer ($\beta = .58$, $p > .05$).

A change of a standard deviation in the motivation score yields a .58 standard deviation increase in the transfer score. So we would expect a highly motivated student (two standard deviations above the mean) with average domain knowledge to have increases in self-regulation behaviors and in turn have a transfer score 1.16 standard deviations above the mean. This is a profoundly strong effect that suggests motivation compensates for lower levels of prior knowledge. While these might appear to be encouraging results to support the stated hypothesis, caution is warranted because of the model's poor data fit.

An alternate model, *M4,* performed marginally better in tests of comparative fit. Such model posited a direct relationship between motivation and transfer, along with a mediated relationship through SRL. Under this model, the total effect of motivation was even larger, (β=.75, .62 direct, .13 indirect). These results are shown to demonstrate that the estimates are unstable under the current circumstances. It is entirely possible than in an untested model (perhaps one including a third exogenous latent or a model with a different measurement structure) motivation’s influence could turn out to be much weak, or even non-significant.

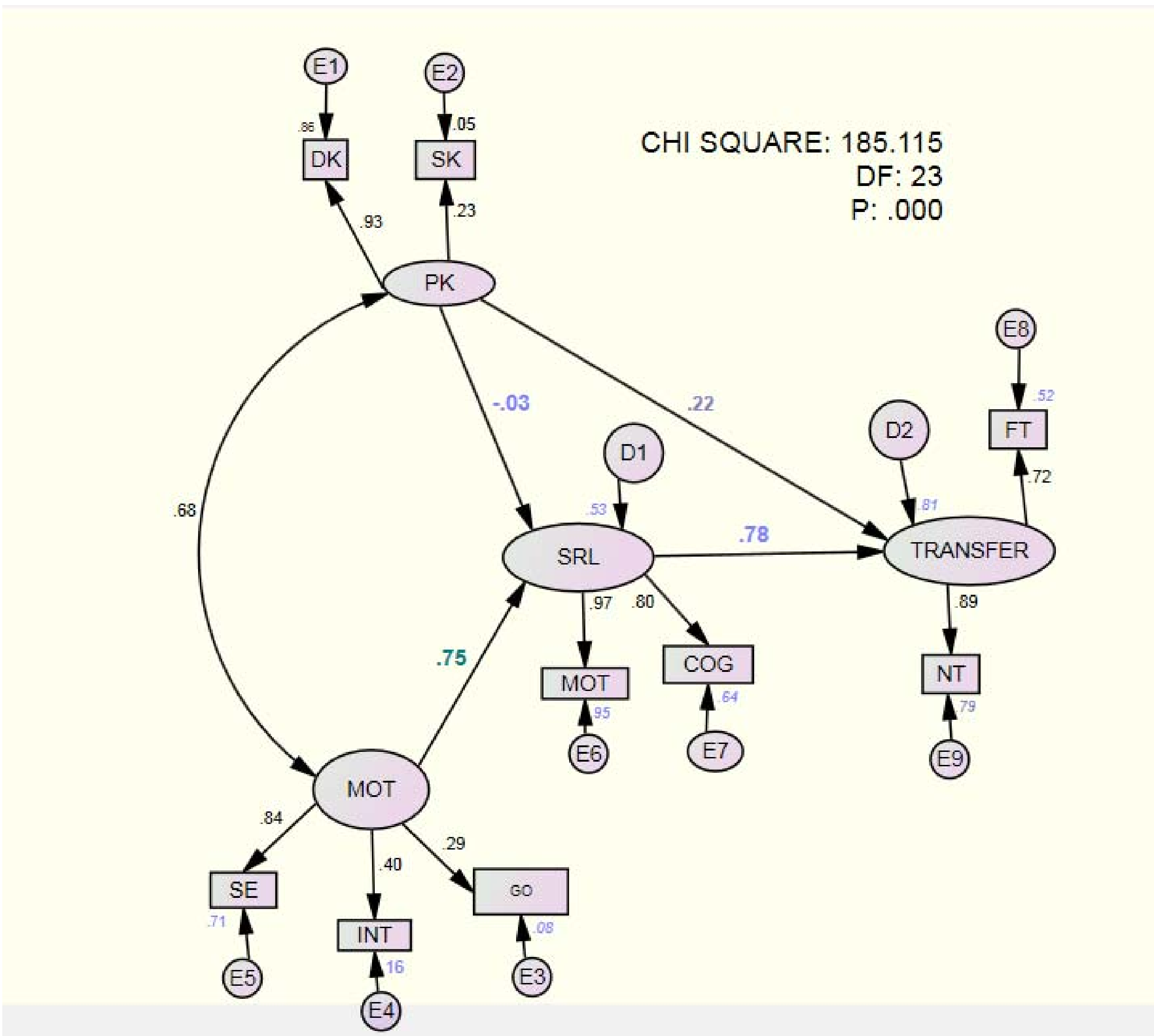


Figure 14. Standardized Estimates for Model M3. R^2 for endogenous variables are SRL = .53, Transfer = .81. PK = Prior Knowledge, DK=Domain Knowledge, SK=Strategic Knowledge, MOT=Motivation, SE= Self-Efficacy, INT=Interest, GO=Goal-Orientation, SRL=Self-Regulated Learning, MOT = Motivational SRL, COG= Cognitive SRL, NT = Near Transfer, FT = Far Transfer.

R4: Does self-regulation significantly mediate the relationship between prior knowledge and transfer of learning? What is the magnitude of the relationship? The final substantive question turns to the issue of mediation. There is an established tradition first articulated by Baron and Kenny (1986) to test for mediation in regression-based models. This same procedure can be extended to SEM. In conceptual terms, establishing mediation requires a four-step process. First, it must be established that the predictor (in this case prior knowledge) and the outcome variable are significantly correlated. Correlation between the predictor and the mediator must be established next. This must be followed by showing that the mediator affects the predictor variable. When these three conditions are established, one can proceed to establish complete mediation by showing that the effect of the predictor on the outcome variable completely suppresses the effect of the mediator variable on the outcome variable.

So if we can show that in the presence of prior knowledge, the effect of SRL on transfer is non-existent, we'll be able to establish full mediation. Figure 14 shows that this is not the case as SRL still has a direct effect on transfer. This is expected however, as full mediation is rare. Partial mediation is a much more common outcome. Establishing partial mediation means merely showing that the effect of SRL on transfer is diminished when prior knowledge is included as a predictor. This is equivalent to a significant indirect effect of prior knowledge on transfer. Statistical packages such as AMOS and SPSS, unfortunately, do not calculate standard errors and significance levels for indirect effects. One must turn to bootstrapping to estimate standard errors and confidence intervals that essentially perform a mediation test.

Bootstrapping is a statistical technique that allows the estimation of robust estimation. It is particularly useful in cases where no formulas to estimate a particular statistic are implemented as it is the case with the standard error of indirect effects in AMOS. Bootstrapping relies on drawing multiple samples from the data and using the deviations from each sample to estimate standard errors (Arbuckle, 2010). In this case, the bootstrapping procedure was set to draw 2000 samples.

The results indicate the indirect effect is not significant, $p > .05$, 90% CI [-.62, .23]. Under this particular model, SRL appears to have a direct effect on transfer but does not appear to mediate the relationship between prior knowledge and transfer as suggested by the literature.

The answers to these substantive questions are reported here for the sake of completeness but due to limitations of model fit, these estimates cannot be considered stable or reliable. In 2007, a special issue of the journal *Personality and Individual Differences* was dedicated to the subject of model fit in SEMs. There was significant disagreement among the various contributors about the absolute utility of the chi-square test vs. other fit indices. What was a clear conclusion however, was that in light of data misfit, the best course of action was to attempt to diagnose the underlying sources of misfit, to report that information, and to use that information to build better models (Hayduk et al., 2007; McIntosh, 2007; Mulaik, 2007). That is the course of action followed here.

Diagnosing Sources of Model Misfit (R7)

Before examining possible sources of misfit, it helps to understand the reasons why the chi-square test and fit indices would report poor fit. The omnibus chi-square test of model fit tests the hypothesis that the residual covariance matrix implied by the tested model is zero (Bollen, 1989; Kline, 2010). A significant chi-square test indicates error exists in the residual covariance matrix and thus point to less than perfect cohesion between the specified model and the theoretically derived covariance matrix. Mulaik (2007) finds the notion of perfect data fit tested by the hypothesis to be overly optimistic. Using this logic, he advocates the use of other fit indices as they're much more able to measure degrees of misfit rather than an absolute benchmark.

Of course when both the chi-square test and fit indices converge on poor fit, as it is the case here, the evidence stacks up pointing to clear issues with the model. Bollen (1987) and McIntosh (2007) point to several factors that play a role in poor fit. Multivariate normality is one such factor as highly skewed distributions affect the estimation of parameters and covariance and residual matrices that assume normal distributions. In this case, non-normality might be an issue, especially on the near transfer indicator. To test this assumption, the near transfer indicator was transformed using a logarithmic transformation (log (near transfer)). Despite the transformation, fit indices did not improve.

Table 21. Complete list of generated modification indices

Proposed Modification				M.I.	Par Change
1.	SK_SCORE	<---	MOT	7.648	.507
2.	SK_SCORE	<---	SRL	13.356	.283
3.	SK_SCORE	<---	TRANSFER	5.677	.417
4.	SK_SCORE	<---	INT_SCORE	5.942	.162
5.	SK_SCORE	<---	SE_SCORE	6.411	.013
6.	SK_SCORE	<---	COGSRL_SCORE	24.162	.634
7.	SK_SCORE	<---	MOTSRL_SCORE	12.564	.261
8.	INT_SCORE	<---	GO_SCORE	12.992	.691
9.	GO_SCORE	<---	INT_SCORE	11.666	.164
10.	GO_SCORE	<---	NT_SCORE	4.409	-.488
11.	SE_SCORE	<---	FT_SCORE	27.541	8.865
12.	COGSRL_SCORE	<---	SK_SCORE	9.913	.153
13.	MOTSRL_SCORE	<---	INT_SCORE	5.496	.105
14.	MOTSRL_SCORE	<---	GO_SCORE	6.463	.232
15.	MOTSRL_SCORE	<---	FT_SCORE	4.834	-.178
16.	NT_SCORE	<---	INT_SCORE	6.325	-.031
17.	NT_SCORE	<---	GO_SCORE	13.268	-.091
18.	FT_SCORE	<---	MOT	13.120	.412
19.	FT_SCORE	<---	PK	6.548	.460
20.	FT_SCORE	<---	SE_SCORE	30.906	.018
21.	FT_SCORE	<---	DK_SCORE	5.097	.353
22.	DK_SCORE	<---	SK_SCORE	4.253	-.065

Having partially ruled out multivariate normality as an issue, it is likely that misspecification errors exist. Diagnosing these issues can be tricky. Luckily, most SEM packages now provide modification indexes that simulate significant changes to the chi-square test if certain modifications are made to the model. For the sake of completeness, the entire set of modification indices is provided on table 21.

To orient the reader, the first column presents the proposed modification. In this case, the modifications are all related to paths and factor-indicator relationships. The second column (labeled M.I) indicates the magnitude of the change on the chi-square test that would result from making the change. The third column gives an indication of how a parameter might change based on the modification.

As an example, the first suggestion is to create a path between the motivation latent and the strategic knowledge indicator. This is akin to loading strategic knowledge as an indicator of motivation. This would drop the chi-square statistic by about 7.6 point thus theoretically improving fit. While modification indexes are useful, SEM researchers caution abusing them for the sake of improving fit. Modification indexes are theory-agnostic and concerned only with reducing the covariance matrix residuals in order to improve fit. As a result, any modification must be evaluated from a theoretical and logical point of view first.

With that approach in mind, we can examine the indices with the potential to influence the chi-square statistic most and determine whether they present a feasible modification to the model. The first two areas of focus are modification indexes 11 and 20. Both of these deal with the far transfer and self-efficacy indicators. Index 20, which would reduce the chi-square statistic by almost 31 points, suggests that far transfer should be established as a predictor of self-efficacy. This is not necessarily consistent with the transfer and self-efficacy literature but potentially makes sense from the perspective of transfer and self-efficacy having a recursive relationship where successful transfer increases self-efficacy and increased self-efficacy leads to successful transfer.

The more important suggestion however, is that of a different measurement model that might possibly include far transfer and self-efficacy as individual latent variables. This is much more unlikely to be the case, although given the limited range of the near transfer indicator; it might explain its incongruence with the far transfer indicator. The next two items of interest deal with the strategic knowledge indicator. Index 6 suggests that strategic knowledge should be a predictor of cognitive self-regulation. This is actually quite a reasonable hypothesis that was demonstrated to be viable in the literature review. Again; however, this requires a different measurement model. This is exactly the point of index 2, which suggests loading strategic knowledge under the motivational latent variable rather than prior knowledge latent. This is not a far-fetched modification given that self-regulated learning involves a strategic knowledge component covered under cognitive self-regulation.

There is overlap between these items in that they both tap into knowledge of certain cognitive strategies. Given the similarity, it is not surprising that strategic knowledge would also load well under the motivation latent. This once again showcases the tendency of the modification indices to point to alternative measurement models that will produce better data fit. Given this tendency and the existence of several alternative measurement models, it is likely that the source of misfit lies therein. This makes it imperative to explore the measurement model in more detail in an attempt to uncover possible misspecifications.

An exploratory factor analysis was conducted to look further into the measurement model. The Scree test (Cattell, 1966) was used to graphically determine the number of optimal factors underlying the data. The test yielded a three-factor model consistent with the theoretical model under validation. Next, a three-factor solution was generated. The solution was rotated using a Varimax rotation (Kaiser, 1958; Cureton, 1975). The purpose of the rotation is to simplify the factor structure and thus facilitate interpretation (Abdi, 2003; Cattell, 1978). Table 22 lists the rotated solution.

Table 22. Three-Factor Solution with Varimax Rotation.

	Component		
	1	2	3
SELF-EFFICACY	.797		
DOMAIN KNOWLEDGE	.760		
STRATEGIC KNOWLEDGE		.833	
COGNITIVE SRL	.424	.782	
MOTIVATIONAL SRL	.573	.669	
GOAL ORIENTATION			.861
INTEREST			.789

Note: Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Loadings below .40 are excluded.

According to this factor analysis, self-efficacy and domain knowledge load strongly on one factor. Strategic knowledge, cognitive SRL, and motivational SRL load strongly on another, and goal-orientation and interest load strongly on a third factor. Figure 15 shows this model graphically. Of course, there is no reason to suggest self-efficacy and domain knowledge share a dimension that makes them part of the same latent variable, but the factor analysis provides evidence of yet another measurement model. This is a concerning trend that raises doubts about the validity of the measurement model.

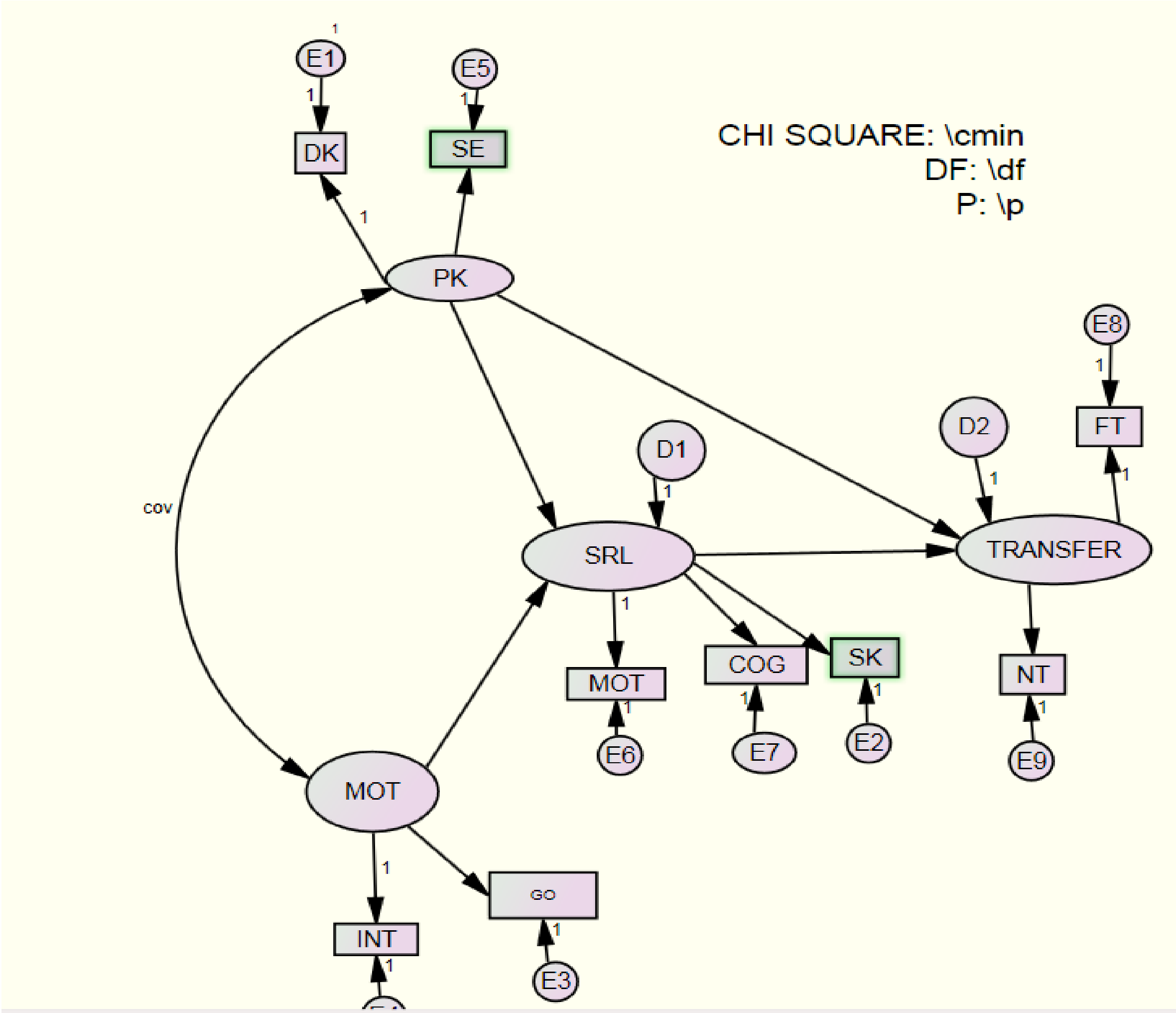


*Figure 15.*Alternative measurement model suggested by factor analysis.PK = Prior Knowledge, DK=Domain Knowledge, SK=Strategic Knowledge, MOT=Motivation, SE= Self-Efficacy, INT=Interest, GO=Goal-Orientation, SRL=Self-Regulated Learning, MOT = Motivational SRL, COG= Cognitive SRL, NT = Near Transfer, FT = Far Transfer.

But these findings are a step removed from showing that changing the measurement model guarantees fit improvements. In fact, as table 23 shows, when the model is ran as suggested by the exploratory factor analysis, the chi-square test is still significant and the other fit indices are fairly similar.

Table 23. Fit Indices for Alternative measurement model.

Model	Chi-Square /DF / P	RMSEA	TLI	GFI	CFI	AIC
ALTERNATIVE	170.55 / 23 / <.05	.26	.496	.80	.70	214.55

There are many other possible theory-agnostic combinations that could be attempted, and there are no guarantees that it would get us closer to deriving a model that is both theoretically valid and statistically robust. As it stands, discussions of data fit have shifted us from substantive questions that are the main focus of this study. While it is important to use the best and most rigorous tools available to answer these questions, there are diminishing returns in departing so far from theory and into a mathematical exercise of optimization. While these diagnostic techniques have been useful in helping identify possible areas of concern and sources of misspecification, it is time to get back to the literature and theory in order to summarize what was learned and to prescribe a course of action that will benefit future research efforts.

CHAPTER 5: DISCUSSION

A central and enduring goal of education has been to provide learners with the foundational and strategic knowledge to use what they have learned in different contexts and circumstances. Despite this focus, more than 100 years of research in educational psychology and education have failed to establish a set of consistently verifiable instructional strategies and practices to improve transfer across a multitude of disciplines. This dissertation has argued that a particular deficiency in the literature is a weak understanding of the causal mechanisms that lead to transfer. Moreover, it has been argued that the omission of motivation as a key variable in the process has missed an important aspect of the transfer process. Using this argument, a theoretical model of transfer containing various motivational variables was put forth. A structural equation modeling (SEM) analytical framework was proposed to validate the model as it provided a rigorous and appropriate analytical technique.

To summarize, the model posited an expectancy-value model of motivation with self-efficacy, interest, and goal-orientation as indicator variables. The motivation construct was thought to indirectly influence transfer through increased self-regulation activity. The model controlled for prior content and strategic knowledge, key predictors of transfer, according to prior theoretical and empirical findings. Findings from the study were presented in chapter 4 along with a general discussion of SEM methodological issues regarding data fit and model diagnostics. This chapter discusses the implications of these findings and concludes with a discussion of the implications for future research.

Review of Findings

Two major sets of questions were posed during this dissertation. The first set was comprised of substantive questions about the relationships among motivation, prior knowledge, self-regulation, and transfer of learning. The second set was methodological, by nature, and dealt with the degree to which the proposed model was a match for the data collected. These questions also proposed a set of alternative models that were used as a comparison basis. This was necessary to rule out the existence of reasonable alternative models that would better explain the transfer mechanism based on the sampled data.

Few modeling studies exist describing the mechanism by which transfer of learning occurs. And only a few cases that take this approach pay close attention to the motivational variables known to affect transfer. Wong, Lawson, and Keeves (2002), as an example, concentrated on belief and self-management (analogous to self-efficacy and self-regulation) in addition to cognitive mechanisms of transfer. Pajares and Miller (1994) looked at self-efficacy and self-concept as predictors of mathematical performance. Ford et al. (1998) explored goal-orientation tendencies as predictors of training performance when mediated by certain instructional interventions. This study builds on that work but insists that a larger set of motivational variables are responsible for promoting transfer. Furthermore, it proposes that these variables are dimensionally situated in such a manner than they can be encompassed by larger constructs such as motivation, prior knowledge, and self-regulated learning. More explicitly, that relationship is said to be an indirect one where motivation exerts its effect on transfer through self-regulation.

Testing these hypotheses in the context of a structural equation modeling (SEM) intertwines content and methodology in a unique manner. As it was discussed in the previous chapter, the parameter estimates necessary to answer these questions are directly influenced by the fit of the SEM model. Poor fit often implies unstable parameters with magnitude and significance in danger of becoming unreliable. As such, the discussion of these results is framed within these caveats.

Motivation, Self-Regulation, and Transfer of Learning. The path estimates show a moderate indirect relationship between motivation and transfer. A slightly stronger relationship was found between motivation and self-regulated learning. As it was discussed in the previous chapter, bootstrapped estimates provide one way to circumvent the unreliability of estimates exhibiting poor fit and allow for the estimation of confidence intervals and significance tests. Using this approach, it can be seen that both the relationship between motivation and self-regulation ($p < .05$, 95% CI [.36, 1.68]) and the indirect effect of motivation on transfer ($p < .05$, 95% CI [.28, 1.23] are statistically significant. Furthermore, the wide confidence intervals indicate large standard errors, which once again to point to less than stable parameter estimates. This can be taken as evidence that motivation—operationalized as a three-factor latent construct –significantly affects transfer.

This evidence is confounded by the fact that both goal-orientation and interest load weakly on the motivation factor. This suggests that perhaps self-efficacy forms a unique factor different from motivation. This is a reasonable conjecture as the literature reviewed often pointed to self-efficacy as an individual predictor of transfer—albeit in the absence of any latent modeling approaches. Moreover, the notion that this would affect the direct and indirect effects estimates is reasonable but speculative. There is no definitive evidence to suggest this is the case and attempts at modeling latent variables in this manner resulted in no improvement in fit or significant changes in the parameter estimates in question. If we set aside model fit, motivation is found to be a strong predictor of transfer. This effect is indirect and is exerted solely through self-regulation.

This suggests that as a learner' levels of motivation increase we can expect increased self-regulated behaviors such as more error checking, questioning materials, and focusing on critical parts of the problem being solved even for learners with average levels of prior knowledge. This in turn increases performance on transfer problems so motivation is effectively able to compensate for lower levels of prior knowledge.

Prior Knowledge, Self-Regulation, and Transfer. Motivation's effect on transfer and self-regulated learning appears to be moderate. Similarly, the literature has been consistent in showing prior knowledge as a strong predictor of transfer. That is a much more dubious conclusion to reach from this study. In this case, the bootstrapped estimates show non-significant effects between prior knowledge and transfer ($p > .05$, 95% CI [-.05, .48]). The size of the effect ranges from very small to moderate. Again, large standard errors yield rather large confidence intervals. The same can be said of the relationship between prior knowledge and self-regulated learning ($p > .05$, 95% CI [-.92, .45], which yields a rather large confidence interval. Once again, these findings are confounded by weak factor loadings, which in this case point to measurement issues in the strategic knowledge variable.

Measurement issues creep up again but the conclusion that prior knowledge—as operationalized—does not directly or indirectly influence transfer of learning is warranted by the analysis of this data sample. This is a puzzling finding given the overwhelming evidence suggesting otherwise. Rather than dismissing a well-established theoretical tradition, it makes sense to temper these findings within a larger discussion about the role of SEM and the meaning and implications of model fit information.

The Model Fit Question. The question of why model fit matters and why it tempers the findings previously discussed was addressed in detail in chapter 4. The implication of poor model fit is that it taints all other results. Bootstrapped estimates help alleviate this matter somewhat but when they produce very wide confidence intervals, they leave much open to interpretation and speculation. That is the heart of the issue and why every hypotheses test and discussion of parameter estimates has been followed closely by a discussion of data fit. The issue, however, remains somewhat abstract and mathematical and so it is useful to present a concrete example to showcase the points that have been made.

Figure 16 displays an alternative model derived through trial-and-error and the use of the modification indexes. This is, by far, the best fitting model (GFI = .92, RMSEA = .10, AIC = 92.01, CFI = .96) based on the fit indices and chi-square statistic. The model, purposely, keeps the same structural model (that is, the original relationships among latent variables are maintained) but changes the measurement model and adds correlations between error terms. Through these means, fit is improved significantly.

Theoretically, however, the model makes little sense. Correlating errors indicates there are systematic reasons to believe the error terms vary together such as is the case when answering a set of questions incorrectly leads to answering another set incorrectly as well. That's not the case with the items correlated here. The structural model makes little sense as well. Self-Efficacy is part of the transfer construct, and strategic knowledge and near transfer are parts of the self-regulation construct. Despite a lack of theory, this model produces more stable estimates.

Most importantly, the hypotheses tests established earlier have different answers under this model. Both prior knowledge and motivation have significant effects on transfer (both directly and indirectly) and they yield moderate estimates (total standardized effects of .58 and .16 for prior knowledge and motivation respectively). Furthermore, self-regulation is shown to be a significant mediator of transfer as hypothesized.

Of course, this model should only be used for illustrative purposes. Theory trumps mathematical optimization techniques in all cases. Using modification indices and a trial-and-error approach, one could modify the model *ad infinitum* to reach any desired level of data fit. But that's not the purpose of SEM.

As Anderson and Gerbing (1988) warn:

> We recognize that most often some respecification of the measurement model will be required. It must be stressed, however, that respecification decisions should not be based on statistical considerations alone but rather in conjunction with theory and content considerations. Consideration of theory and content both greatly reduces the number of alternate models to investigate and reduces the possibility of taking advantage of sampling error to attain goodness (p. 416).

Ultimately SEM is a theory testing tool. The absolute rejection or adoption of a finding must be considered in the context of prior empirical and theoretical work. And like all other empirical research, it must be replicated under alternative assumptions and conditions. The alternate model presented here merely adds to the evidence that the source of misfit lays most likely within the measurement model.

Whether it is a matter of items, scales or specified dimensions, the evidence clearly points to a flawed latent structure possibly lacking unidimensionality on various constructs. This must also raise questions about the nature of the relationships proposed. But the rejection of the model is not particular interesting, useful, or beneficial to the literature. Having reached this conclusion, the important contribution is in summarize the lessons learned while providing a set of prescriptive steps to improve, and further the state of transfer and motivation theory.

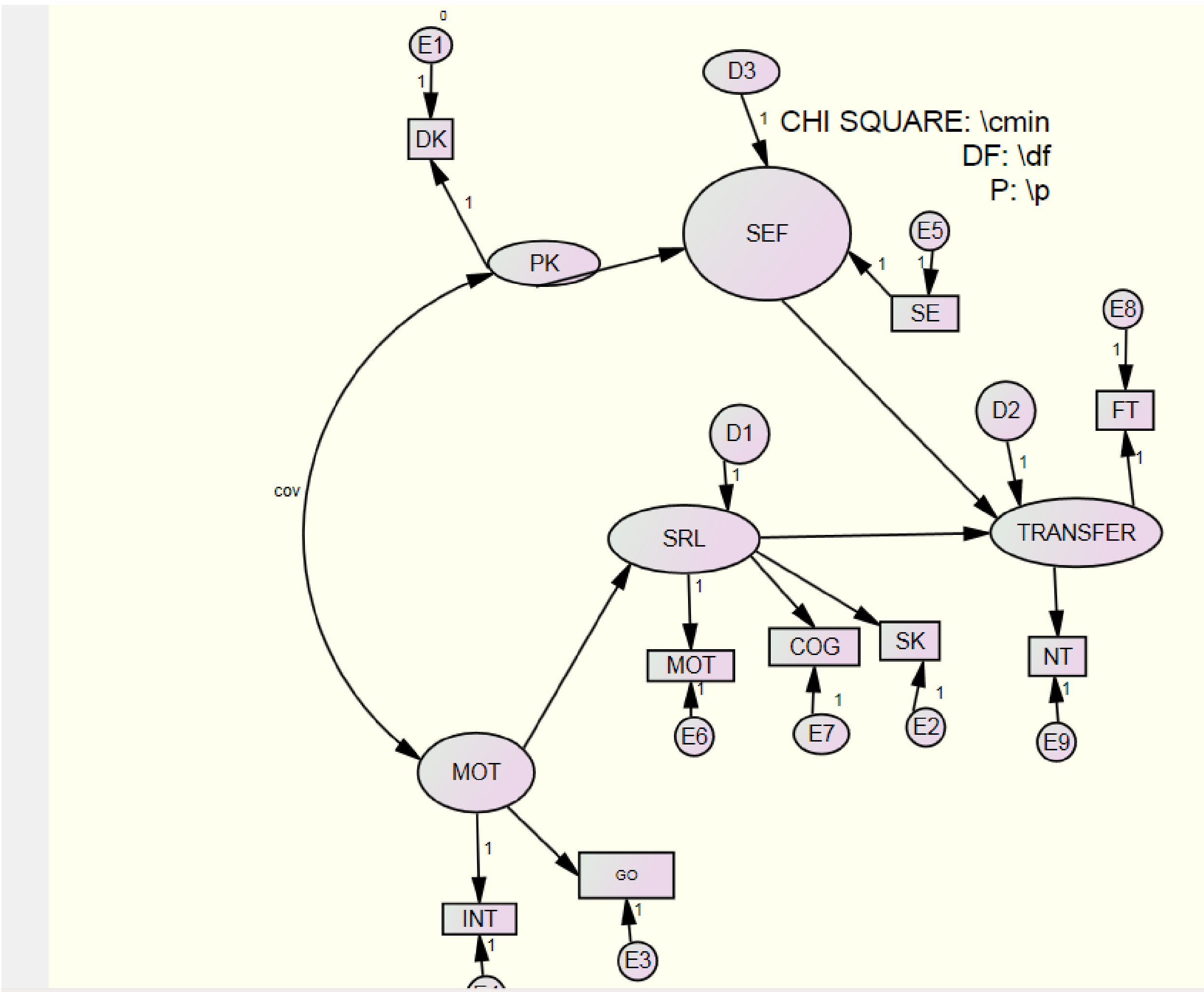


Figure 16. An example of an alternate model developed through trial-and-error and modification indices.PK = Prior Knowledge, DK=Domain Knowledge, SK=Strategic Knowledge, MOT=Motivation, SE= Self-Efficacy, INT=Interest, GO=Goal-Orientation, SRL=Self-Regulated Learning, MOT = Motivational SRL, COG= Cognitive SRL, NT = Near Transfer, FT = Far Transfer.

The Question of Statistical Power. A question left unexplored thus far is that of statistical power. A smaller sample size might turn out to be too homogeneous because the sampling frame does not capture the true variability of the population. Conversely, the sample could also turn out to be too heterogonous because extreme values in the population would affect smaller samples more severely. Saris, Satorra, and van der Veld (2010) showed that low power in SEM makes it more difficult to detect smaller differences thus potentially reducing data fit. In earlier discussions about power, rules of thumb have been suggested to determine power. One of those rules of thumb, namely a 1:10 ratio of indicators to subjects, was used in this study to establish sufficient statistical power.

Recently, SEM methodologists have suggested a more rigorous approach to establish power. This approach relies on simulated results based on effect sizes, number of indicators, and a number of other nuanced factors germane to the hypothesized model (Muthen & Muthen, 2002; Thoemmes, MacKinnon, & Reiser; 2010). There are a number of algorithms that can estimate retrospective power based on a given sample size. Preacher and Coffman (2006), for example, provide a calculator that is helpful in determining power based on desired fit indices values. In this study's case, the calculator suggests a sample size of 212 to achieve statistical power of .90 (meaning differences will be detected 90 out of 100 times) to detect acceptable fit index values in the RMSEA index. A sample size of 165 yields power of approximately .80. With the current sample size of 99, the power estimate is around .57. These numbers suggest a case of low statistical power. It has been shown in some cases, however, that a large sample size is not always necessary to obtain good statistical power (Browne et al., 2002). In fact, it has been shown in this study that merely manipulating error variances and the measurement model can product results where the RMSEA fit index falls to a barely acceptable level of .10.

Hayduk (2007) suggests that the ability to *reject* a particular model or theory can be taken as evidence of sufficient statistical power. Barrett (2007), on the other hand, suggests that we ignore any SEM results with a sample size smaller than 250. The answer likely lies somewhere in between these two extreme points of view. In this study, there is evidence to suggest low power through a number of tests and benchmarks. Without employing the most rigorous power estimation techniques, the probability of that being the case only increase. But as it is often the case, gold standards are not always employed. A majority of SEM studies report estimation of statistical power using benchmarks rather than the simulation approaches to compute appropriate power (Barrett, 2007; Muthen & Muthen, 2002). This is not meant to defend the use of inferior methodological choices but rather to illustrate that any research study is an exercise in trade-offs to balance rigor, content, and available resources.

In this study, the decisions made around statistical power were made in the context of available resources (time, budget) and available subjects. While all efforts were made to extend data collection until a large number of subjects were reached, such efforts proved difficult, in part due to the relatively extended time commitment without compensation that the study required. As such, when a reasonable number of subjects were recruited, data collection activities ceased. While this is not an ideal approach, it is the approach taken in this study given the scope of the dissertation.

As has been the pattern through most of this study, a call is made to exercise caution. A single study with ambiguous results is not sufficient to fully reject or embrace a theory. It is a piece of evidence to add to a larger dossier used to make educated determinations. Based on this study, the theoretical model proposed is rejected. More importantly, however, the present study presents a number of implications for future research efforts attempting to model the effects of motivation on transfer. These are discussed in the next section.

Implications and Discussion

It is somewhat unfortunate that the discussion of the results has taken a turn into detailed methodological issues over issues of substantive theory. This detour was necessary, however, as the quality and range of inferences to be made depends heavily on the rigor and accurateness of the methodology and the design of the research as a whole. But it is not particularly useful to reject a theoretical model and close the chapter. The real value lies in returning to the literature to provide well-grounded recommendations.

Research Design. An initial lesson and implication to be derived from this study centers around the overall research design. Originally, the study proposed contained provisions to investigate the transfer phenomena and its motivational processes in the context of an existing course. This proposal had the advantage of being able to use course assessments to measure both domain knowledge and transfer with minor modifications preserving the conditions under which transfer typically occurs.

By being related to the material in the class, these instruments would have high content validity while also mirroring the types of assessment that learners typically face. Rather than creating artificial tasks and instruments, the study would be situated in the context of a real academic scenario with more realistic variability across variables of interest.

Unfortunately, the logistics for a study of this type proved impossible. Efforts to recruit a class large enough to support such a study were unsuccessful. Concerns about instructional time being taken away from students eventually overwrote research benefits. This led to settling for a more artificial study and to the selection of an arbitrary topic that was thought to be accessible to the population of interest and of interest to the research.

While this choice was necessary, it posed difficulties in narrowing the scope of the subject and developing instruments that were valid—content wise—but also detailed and complex enough to be accessible to a large population while differentiating clearly between novices and experts. This also meant that subjects only spent a relative small of amount of time with the task. Generally, after spending thirty to forty-five minutes on a task, learners were asked about motivational traits that are often developed over time and prolonged exposure to a topic, such as is the case in an academic course. This might have led to less content-valid, insensitive measures that did not capture the true abilities and perceptions of the subjects sampled. Measuring these variables in the context of an academic class would have likely provided a more accurate picture and would have described the transfer process in its more natural setting.

Thus the first logical suggestion for future research is to observe the transfer mechanism under a more natural context. A more realistic setting would provide a closer and more accurate representation of the motivational and cognitive processes that are at play when learners transfer learning to a novel situation. Additionally, it would allow for the use of instruments that should already have content-coverage and construct validity in the domain of the course.

Omitted Variables and Parsimony. Moving beyond research design, a realistic possibility explaining the rejection of the model is that there is an omitted construct (or a set of constructs) that explain transfer. Statistically, this would explain the large error residuals that cause the chi-square test to be significant. Unexplained variance automatically becomes error variance in any linear model. Transfer researchers have suggested several possibilities for cognitive constructs separate from motivational constructs. Nokes (2009), for example, outlined three separate cognitive mechanisms by which varying levels of transfer may occur. Wong et al. (2002) outlined knowledge access and knowledge generations as mediating mechanisms of transfer. Butterfield and Nelson (1989) extended Piaget's conceptions of assimilation and accommodation from the learning mechanism to the transfer mechanism. It is difficult to argue that there is no overlap among the mechanisms outlining general learning and those outlining transfer. If one assumes transfer to be a specialized subset of learning then by definition a subset of the learning mechanisms (with perhaps some additions) define the transfer process. The omission of the cognitive constructs from this study was a conscious trade-off for parsimony as it was believed that the cognitive self-regulation dimension would account for a large part of the cognitive transfer mechanisms.

As it turns out, the cognitive mechanisms might encompass a dimension of their own and ought to be modeled individually and separately from the motivational mechanism. This would also suggest that some of these cognitive mechanisms may play mediator roles severely altering the relational and latent structure of the transfer model proposed. Without data to test these hypotheses, however, this is simply a proposal to test an alternative model of transfer that includes these cognitive mechanisms. These cognitive mechanisms should be included in future studies along with the motivational mechanisms posed here, to at the very least, rule out the possibility of omitted variables.

Deficient Existing Instruments. An elegant theory is simple and parsimonious despite its complexity. But when we drill down to the details, good theories are characterized by good measurement instruments. Every effort was made in this study to locate existing, validated instruments that captured the indicators being modeled. Despite these efforts, this was a complex task as previous examples of modeling multiple indicators measured by disjoint instruments were virtually non-existent. In this study, four separate existing instruments were deployed while transfer, domain knowledge, strategic knowledge, and self-efficacy instruments were developed from scratch. And while the existing instruments were previously validated with evidence pointing to high reliability and construct validity, it is important to point out these validation efforts took place in a homogenous measurement concerned with singular dimensions rather than an entire system of variables.

It would be one thing if there were a motivation instrument already encompassing self-efficacy, goal-orientation, and interest, but instead the challenge was to use three separate instruments, created by different researchers, to serve as indicators for a single latent construct. In retrospect, this may be the source of some of the issues captured by poor data fit. Table 24 compares the psychometrics properties of the instruments used with this sample to the values obtained in previous validations.

Table 24. Comparison of Internal Consistency Estimates.

Scale	**Cronbach's Alpha (α) from this sample**	**Cronbach's Alpha (α) in Previous Validations**
Goal Orientation	.69	.89
Interest	.83	.90
Motivational SRL	.73	.79
Cognitive SRL	.48	.80
Strategic Knowledge	.57	New instrument
Self Efficacy	.76	New instrument
Domain Knowledge	.50	New instrument
Near Transfer	.83	New instrument
Far Transfer	.86	New instrument

The cognitive self-regulation scale does not fare well in terms of internal consistency. This means that the individual items aren't well correlated with one another. Duncan & McKeachie (2005) warned about the instability of reliability coefficients when validating these scales due to the sensitivity to context. In their own validation study, which had 1000 subjects, they had reliability estimates as low as .50 so this might be a case where the context of the present study is not particularly suitable for this scale.

Recent developments in the measurement of self-regulated learning suggest that self-monitoring and self-control behaviors associated with self-regulated learning are dynamically allocated by individuals without definitive patterns. This suggests learners might be unable to accurately recall these behaviors retrospectively as they are typically asked to do in a survey. Greene et al. (2010) overcame this suggestion by using talk-aloud protocols to tap into self-regulated behaviors in real-time. Moos and Azevedo (2008) had proposed and employed a similar measurement strategy. Despite the added complexity and increased resources necessary to collect, code, and properly analyze talk-aloud data, it is recommended that this approach be employed in future studies departing from the well-established practice of using surveys to measure internal, and often subconscious, regulatory processes.

The Strategic Knowledge Instrument. A second implication that jumps out from closely reviewing the instruments employed is the poor internal consistency of the prior knowledge indicator scales. Both domain and content knowledge fall below the acceptable .75 value used as a standard of internal consistency. Upon further review, the conception of the strategic knowledge scale and items leaves a lot to be desired. The instrument measuring strategic knowledge consists of 13 items (see appendix H) asking about the use of particular strategies germane to the transfer task. It uses a 1-5 likert scale corresponding to these choices:

1 = I wasn't aware of this strategy.
2 = I knew about the strategy but chose not to use it for this problem.
3 = I tried to use the strategy but was unable to use it in this problem.
4 = I used the strategy.
5 = I used the strategy AND it helped me solve the problem.

Conceptually, it makes sense to measure strategic knowledge this way, but an issue arises because more points are awarded for using a strategy unsuccessfully as opposed to just being aware of a strategy and potentially being able to use it correctly.

It is not unreasonable to assume that high-performing learners would rely only on a single or a handful of strategies to solve the problems. The most elegant solution to the transfer task was to develop a generic algebraic solution that modeled the change in the fish population. Realistically, learners employing this strategy would have no need to use any other strategy and thus would score lower on the strategic knowledge component even if they were aware of all the other strategies listed. Lower performing subjects might have used multiple strategies, albeit with no success, but end up scoring much higher on the strategic knowledge component. This is not consistent with the hypothesized relationship between strategic knowledge, and transfer.

A secondary concern is that of retroactively recalling strategies used rather than doing so at the moment when the strategies are being applied. Based on these issues and given the prior recommendation, it is suggested that talk-aloud protocols be used in future studies. This method, along with an observation component that independently codes the use of strategies by subjects as it is happening, can be used to effectively assess the knowledge and use of specific content strategies. This approach was proposed long ago by Ericsson and Simon (1993, 1998) as a protocol to study expertise, and it has been followed and endorsed by a number of other researchers (Chi & Bassok, 1989; Ericsson & Simon, 1993; Higgins, 1997; Ke, 2008; Lovett, 1994; Pape& Wang, 2003).

The Domain Knowledge Limitations. The prior knowledge construct also relies on domain knowledge. The internal consistency estimate for domain knowledge shows the same inconsistency found in the strategic knowledge indicator. In the case of domain knowledge, the items were selected after a careful task analysis of the transfer items. Furthermore, they were revised after consultation with a panel of content experts. Despite these efforts, there appear to be a number of problems with the domain knowledge instrument. Figure 17 shows this insensitivity. Seventy-five percent of the responses for this variable are above 14 points (74 out of 99 responses) and 32% (31 of the 99 subjects) obtained the maximum score.

This seems problematic for a variable with a possible theoretical range between 0 and 18 and an assumed normal distribution. This indicates that either the sample of subjects is skewed towards high performers—suggesting a non-normal distribution that violates the assumptions of SEM—or that the instrument is unable to differentiate properly between high and low performers. Since scores on the far transfer task are much more normally distributed, it is reasonable to infer that the issue lies in sensitivity of the domain knowledge instrument rather than in the sample selecting only high performing subjects.

Given the population for the study as university students and given that the instrument was selected from a set of questions in the NY State Regents exams designed for 9^{th} and 10^{th} grade students, it seems the selected questions were not sufficiently challenging for the population being studied. This selection of items was made purposefully to provide items that were accessible to participants having varying levels of mathematical expertise. Clearly, however, these seemed to have issues differentiating between the true high performers and the average or lower than average participants sampled for the study.

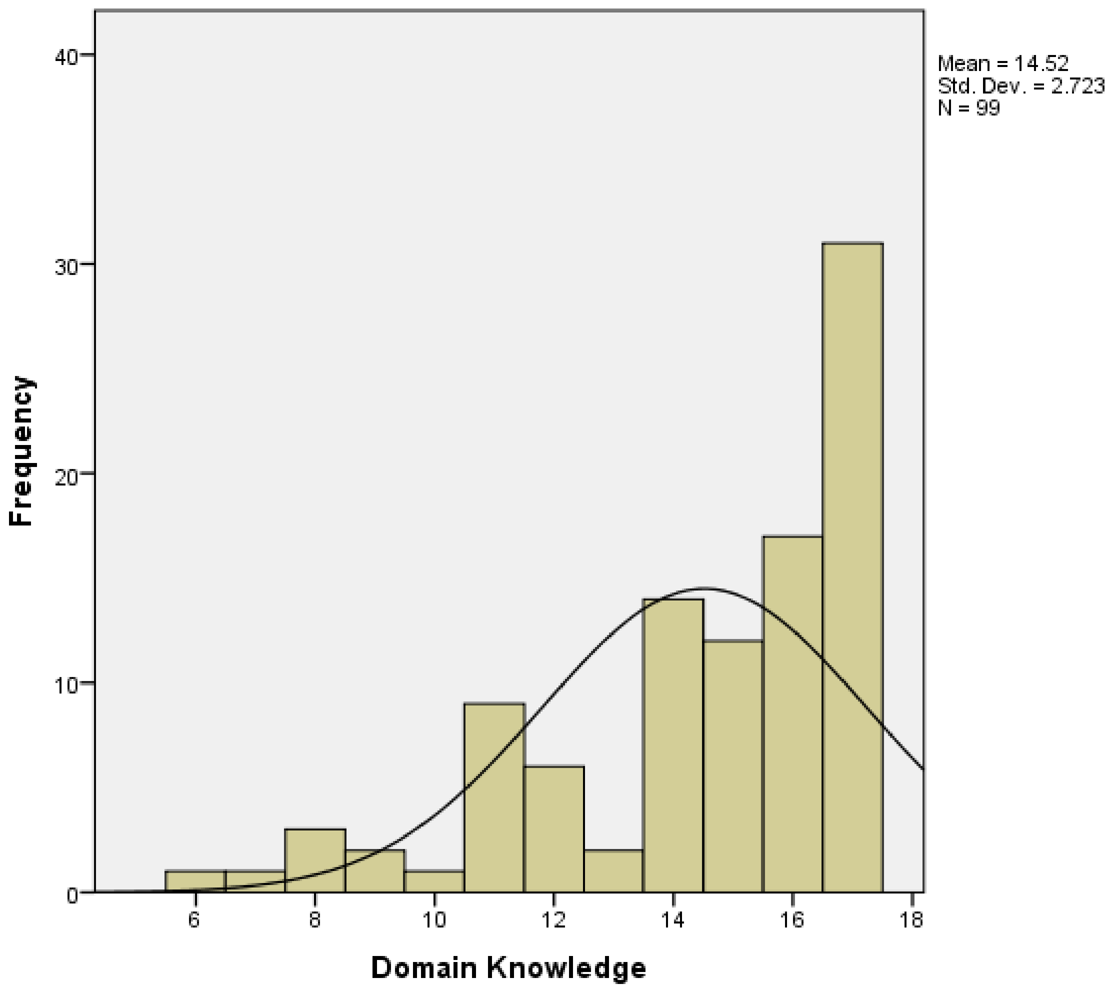


Figure 17. Domain knowledge frequency distribution.

Future research would benefit from the use of a different instrument to assess domain knowledge. Part of the challenge in identifying a strong domain knowledge instrument is the context-dependency of the instrument. Generic instruments do not work because they might not necessarily tap into the concepts and principles derived from the transfer task. But the clear lesson here is that care must be taken to balance the difficulty level of the content items used to differentiate between high and low-performing subjects. A suggestion when using subject-specific tasks for a population of university students is to tap into college entry and remediation exams designed specifically for college students. Also, using a larger set of items, and selecting more difficult items to help differentiate better at the highest levels, would help make the scale more sensitive of the levels of prior knowledge that are predictive of transfer. Ideally, such an instrument would be validated with a small sample first, tested for its ability to differentiate among varying levels of mathematical expertise through item analysis and item-response theory (IRT) analysis, and then modified for accessibility and maximum sensitivity.

Statistical Power. Along with this recommendation, the issue of statistical power should not be ignored and so it is recommended that future research using SEM as a theory-validation tool should employ a more throughout power analysis approach. This is facilitated by the effect-size ranges estimated by the current study, which can be used to create power simulations that give a rough estimation of the sample size needed to detect statistically significant differences. Overall, the recommendation is to follow the advice of Muthen and Muthen (2002) and Thoemmes and his colleagues (2010) to simulate the ability of a model to differentiate between good and bad fit given a range of acceptable values on a given index through simulations. This approach would be much more stringent in providing an acceptable sample size range.

Conclusion

Why does transfer matter? Why do we need to understand the processes that cause it? The study of transfer of learning has a rich history of theoretical and empirical work. Being a central question of psychological and education research, among other fields, transfer has occupied the minds and efforts of researchers for over a century. The centrality of transfer is evident when we consider the ultimate goals of education at all levels. President Obama highlighted this focus on a recent speech to a group of young students:

> You'll need the knowledge and problem-solving skills you learn in science and math to cure diseases like cancer and AIDS, and to develop new energy technologies and protect our environment. You'll need the insights and critical thinking skills you gain in history and social studies to fight poverty and homelessness, crime and discrimination, and make our nation more fair and more free. You'll need the creativity and ingenuity you develop in all your classes to build new companies that will create new jobs and boost our economy (Obama, 2009).

The president's vision represents the optimal case for transfer; the extension of foundational concepts and skills into meaningful problem-solving approaches that address issues of health, poverty, and social justice. Promoting this is, of course, not just a matter of developing theory or singular instructional interventions. Rather, it is a systematic effort to promote these developments across diverse programs and populations of learners. But these efforts are likely to begin with more effective approaches at the micro levels of instructional interventions. They are more likely to take place by promoting transfer across singular interventions and scaling up to more diverse groups and programs.

And at this level, substantive theory is needed to develop interventions that address underlying processes rather than symptomatic surface features. If we can show that increased interest and self-efficacy are the key to indirectly altering self-regulated behaviors, which in turn increase transfer performance then we would know that we must provide sound instructional strategies and design opportunities for students to engage their interest, build their confidence, and set proper goals for their learning. Of course, these are practices teachers and curriculum designers already follow based on instincts but learning scientists cannot follow instinct alone. A robust theory of transfer, validated under multiple setting would be the first step in providing guidance for instructional scientists to derive and test combinations of instructional strategies and tools to help curriculum designers and teachers create meaningful activities that support and promote successful transfer practices.

But that reality is still some steps away and much more work remains to be done. Future empirical work must use better and more sensitive instrumentation to measure the motivational and psychological processes that underline the executive mechanisms that help us take seemingly disjointed information and assemble it into meaningful and robust problem-solving approaches. That work also needs to model, in unison, cognitive and motivational mechanisms to answer questions about the intertwined nature of these mediating processes and the distinctive (or perhaps converging)processes that predict their positive effect on transfer.

Finally, the strength of this work should be based on observations derived in natural settings under circumstances that replicate the type of conditions that learners will be exposed to when they are called upon to transfer. This might mean observing how transfer and motivation are intertwined when engaging in a novel work task or how highly motivated students deploy limited prior knowledge to solve a problem in a course assessment. Despite the inconclusive answers, this study provides a starting point in asking questions that have not often been asked in previous inquiries of transfer. As with the beginning of any theoretical endeavor, mistakes may occur along the way and miscalculations might lead to faulty assumptions that will need to be rectified. This dissertation is full of those miscalculations, but such lessons should pave the way towards a more robust transfer theory. As with any theoretical endeavor, revision and validation are needed. The recommendations outlined here should make for strong and improved research efforts that will bring us closer to a viable theory of motivation and transfer.

Appendix A: Subject Recruitment Flyer

VOLUNTEERS WANTED FOR A RESEARCH STUDY

What's your motivation to transfer learning?

For my dissertation research, I need your help to answer the question of how things such as your goal orientation, interest, self-efficacy and prior knowledge influence your ability to transfer what you have learned in the past to a completely new problem.
To motivate YOU, I'm offering a chance to win an iPad. So why not help out a fellow student?

Who can participate in the study?

Any undergraduate or graduate student can participate. Students from all majors are welcome to participate.

What do I have to do?

- Complete a problem-solving task.
- Take a survey regarding some basic motivational traits.
- The whole thing should take no more than **90 minutes**, but we do encourage a relaxed problem-solving environment so you can take as long as you like.

What is in it for me?

- A chance to win a 1st generation iPad (Wifi, 16 GB).
- An opportunity to learn more about research, get to know a little more about your motivational tendencies, and help out a fellow student.

Risks?

There are no known medical or psychological risks associated with the study.

Okay, I'm in, how do I sign up?

E-mail: sutransfersresearch@gmail.com
Phone / Text : (315) 256-0149
Web: http://bit.ly/idstudy

E-mail: sutransfersresearch@gmail.com
PHONE / TEXT : (315) 256-0149
Web: http://bit.ly/idstudy

E-mail: sutransfersresearch@gmail.com
PHONE / TEXT : (315) 256-0149
Web: http://bit.ly/idstudy

E-mail: sutransfersresearch@gmail.com
PHONE / TEXT : (315) 256-0149
Web: http://bit.ly/idstudy

E-mail: sutransfersresearch@gmail.com
PHONE / TEXT : (315) 256-0149
Web: http://bit.ly/idstudy

E-mail: sutransfersresearch@gmail.com
PHONE / TEXT : (315) 256-0149
Web: http://bit.ly/idstudy

E-mail: sutransfersresearch@gmail.com
PHONE / TEXT : (315) 256-0149
Web: http://bit.ly/idstudy

E-mail: sutransfersresearch@gmail.com
PHONE / TEXT : (315) 256-0149
Web: http://bit.ly/idstudy

E-mail: sutransfersresearch@gmail.com
PHONE / TEXT : (315) 256-0149
Web: http://bit.ly/idstudy

E-mail: sutransfersresearch@gmail.com
PHONE / TEXT : (315) 256-0149
Web: http://bit.ly/idstudy

E-mail: sutransfersresearch@gmail.com
PHONE / TEXT : (315) 256-0149
Web: http://bit.ly/idstudy

Appendix B: Administration Protocol Script

SAY: Thank you so much for agreeing to participate in this study. Please have a seat.

At this point, the subject can be directed to an open workstation.

SAY: Today you'll be completing a few surveys on the computer and completing a problem-solving task on paper. You have as much time as you want to complete these instruments but we don't anticipate it will take more than 90 minutes. After you complete all the instruments, please help yourself to some pizza and refreshments next door. It is okay if you need to leave the room for any reason. Just please let me know if you intend to come back so that I can hold the workstation for you.

SAY: First, let me assign you an ID. This ID is not tied to your name or any personal information. It is just a way for us to keep track of all the surveys.

Assign the next available ID to the participant.

SAY: Great. You will need to enter that ID in all the instruments you complete today. The first thing you'll fill out is a consent form.

Present the paper consent form to participants and have them complete it before proceeding. If participant refuses to complete the form, thank them for their time and inform them their participation in the study is completed.

SAY: Thank you. Do you have any questions or concerns about the study?

Wait a few seconds. If there any questions about the study please direct the students to speak to the faculty supervisor or student researcher.

SAY: Thank you. First, you'll be completing a short math problem set on paper. This will be followed by three surveys on the computer. Please let me know when you finish all the surveys and I'll provide you with the last problem, a short mathematical task. Do you have any questions I can answer?

Answer any questions regarding the study. Please refrain from answering any questions directly related to the mathematical domain of the task or the nature of the task to be completed.

Administration Protocol Script: Continued

SAY: Great, when you complete everything, you're free to help yourself to pizza and refreshments next door. There is a short form by the exit and a box where you can enter your name and contact information for a chance to win an iPod touch. You can, of course, choose not to participate in the raffle. We'll be selecting two winners at random.

Wait a few seconds

SAY: If you don't have any questions or concerns, I will leave you to it. Thanks again and please get my attention if you need clarification on anything.

Please provide no clarification on any of the survey items or the mathematical task. Instead answer, "please read the question again and answer what you consider the best answer." If the question is about the task, ask the subject to read the task again and to express any confusion about the task on the problem set.

1. *Direct participants to first complete the "Prior Content Knowledge" paper instrument.*
2. *Once they have completed these instruments, direct participants to complete the three surveys online.*
3. *Once participants have completed the three surveys, direct them to complete the "Transfer" instrument on paper.*
4. *Collect all materials and scrap paper. Thank participants for participating and remind them they can sign up for a raffle and help themselves to pizza and refreshments.*

Appendix C: Request for Faculty Support to Advertise Study

SYRACUSE UNIVERSITY

INSTRUCTIONAL DESIGN, DEVELOPMENT AND EVALUATION

Dear <Instructor/Faculty Member>,

My name is John A. Gonzalez and I am a doctoral candidate in the Instructional Design, Development, and Evaluation program in the school of education**.** I have a small request, which I'm hoping won't take much of your time.

I am interested in learning more about how motivational processes influence a learner's ability to solve novel mathematical problems. My research consists of completing a set of surveys along with two short problem-solving tasks. The study is to take place in the Instructional Design, Development, and Evaluation multimedia lab located in Room 302 in the School of Education (Huntington Hall). It should take, in total, no longer than **90** minutes to complete all parts of the study.

In short, I was hoping you'd be kind enough to pass on this message to your students in hopes of enlisting their participation. As an incentive to participate, an iPad will be raffled off. Those wishing to participate can sign up directly at the following website (http://www.signupgenius.com/go/syracuse) or by e-mailing SUTransferResearch@gmail.com.

There are no known physical or psychological risks associated with participating in this study. IRB approval has been obtained (*IRB # 11-050*). If you have any questions about the research, please contact me – John A. Gonzalez (jagonz01@syr.edu, 315-560-7841) or my faculty supervisor - Dr. Tiffany A. Koszalka (takoszal@syr.edu, 315-443-5263). Alternatively, the Syracuse University Institutional Review Board can be reached at 315-443-3013.

Many thanks for your time and consideration of my request,

John

John A. Gonzalez
Jagonz01@syr.edu | 315.560.7841
Doctoral Candidate | Instructional Design, Development, and Evaluation
School of Education | Syracuse University

Appendix D: Informed Consent Form

MECHANISMS OF TRANSFER: MODELING MOTIVATIONAL AND SELF-REGULATORY PROCESSSES THAT PROMOTE TRANSFER OF LEARNING

My name is **John A. Gonzalez** and I am a **doctoral candidate** at **Syracuse University.** I am inviting you to participate in a research study. Involvement in the study is voluntary, so you may choose to participate or not. This sheet will explain the study to you and please feel free to ask questions about the research if you have any. I will be happy to explain anything in detail if you wish.

I am interested in learning more about how motivational processes influence your ability to use things you have learned in the past under new circumstances, especially in the context of math-related problems. You will be asked to complete a set of surveys along with two short problem-solving tasks related to algebraic equations. This will take approximately **90** minutes of your time. All information will be kept anonymous. I will assign an ID number to your responses but will have no way of tying them back to your identity. Information such as your name, or any other identifying information about you, will **NOT** be collected during this study.

The benefit of this research is that you will be helping us to understand how motivation affects people's ability to use previously learned materials in new problems. This information should help us develop better instructional materials and learning environments to maximize application of knowledge—in addition to improving our theoretical understanding of these mechanisms. There are no known benefits to you by taking part in this research.

There are no known physical or psychological risks associated with you taking part in this study. You might be uncomfortable if you have anxiety related to math or other types of problem-solving assessments. These risks will be minimized by providing a relaxed, non-judgmental environment. If you do not want to take part, you have the right to refuse to take part, without penalty. If you decide to take part and later no longer wish to continue, you have the right to withdraw from the study at any time, without penalty.

If you have any questions, concerns, complaints about the research, contact Dr. Tiffany A. Koszalka (faculty supervisor) at takoszal@syr.edu or 315-443-5263 or John A. Gonzalez (student researcher) at jagonz01@syr.edu or 315-560-7841. If you have any questions about your rights as a research participant, you have questions, concerns, or complaints that you wish to address to someone other than the investigator, if you cannot reach the investigator contact the Syracuse University Institutional Review Board at 315-443-3013.

All of my questions have been answered, I am over the age of 18 and I wish to participate in this research study. I have received a copy of this consent form.

Appendix D: Continued

______________________________ ____________________
Signature of participant Date

____
Printed name of participant

______________________________ ____________________
Signature of researcher Date

____
John A. Gonzalez

Appendix E: IRB Approval

SYRACUSE UNIVERSITY
Institutional Review Board
MEMORANDUM

TO: Tiffany Koszalka
DATE: February 28, 2011
SUBJECT: **Determination of Exemption from Regulations**
IRB #: 11-050
TITLE: *Mechanisms of Transfer: Modeling Motivational and Self-regulatory Processes that Promote Transfer of Learning*

The above referenced application, submitted for consideration as exempt from federal regulations as defined in 45 C.F.R. 46, has been evaluated by the Institutional Review Board (IRB) for the following:

1. determination that it falls within the one or more of the five exempt categories allowed by the organization;
2. determination that the research meets the organization's ethical standards.

It has been determined by the IRB this protocol qualifies for exemption and is assigned to category 2. This authorization will remain active for a period of five years from **February 25, 2011** until **February 24, 2016**.

CHANGES TO PROTOCOL: Proposed changes to this protocol during the period for which IRB authorization has already been given, cannot be initiated without additional IRB review. If there is a change in your research, you should notify the IRB immediately to determine whether your research protocol continues to qualify for exemption or if submission of an expedited or full board IRB protocol is required. Information about the University's human participants protection program can be found at: http://www.orip.syr.edu/humanresearch.php. Protocol changes are requested on an amendment application available on the IRB web site; please reference your IRB number and attach any documents that are being amended.

STUDY COMPLETION: The completion of a study must be reported to the IRB within 14 days.

Thank you for your cooperation in our shared efforts to assure that the rights and welfare of people participating in research are protected.

Kathleen King, Ph.D.
IRB Chair

Note to Faculty Advisor: This notice is only mailed to faculty. If a student is conducting this study, please forward this information to the student researcher.
DEPT: IDD&E, 335 Huntington Hall **STUDENT:** John Gonzalez

Office of Research Integrity and Protections
121 Bowne Hall Syracuse, New York 13244-1200
(Phone) 315.443.3013 • (Fax) 315.443.9889
orip@syr.edu • www.orip.syr.edu

Appendix F: IRB Modifications Approval

SYRACUSE UNIVERSITY
Institutional Review Board
MEMORANDUM

TO: **Tiffany Koszalka**
DATE: August 31, 2011
SUBJECT: **Amendment for Exempt Protocol**
AMENDMENT#: 1 – A) Other – Research Instrument Change (Paper to Online Format), B) Change in Consent (Written to Electronic)
IRB #: **11-050**
TITLE: *Mechanisms of Transfer: Modeling Motivational and Self-regulatory Processes that Promote Transfer of Learning*

Your current exempt protocol has been re-evaluated by the Institutional Review Board (IRB) with the inclusion of the above referenced amendment. Based on the information you have provided, this amendment is authorized and continues to be assigned to category 2. This protocol remains in effect from **February 25, 2011 to February 24, 2016**.

CHANGES TO PROTOCOL: Proposed changes to this protocol during the period for which IRB authorization has already been given, cannot be initiated without additional IRB review. If there is a change in your research, you should notify the IRB immediately to determine whether your research protocol continues to qualify for exemption or if submission of an expedited or full board IRB protocol is required. Information about the University's human participants protection program can be found at: http://orip.syr.edu/human-research/human-research-irb.html Protocol changes are requested on an amendment application available on the IRB web site; please reference your IRB number and attach any documents that are being amended.

STUDY COMPLETION: The completion of a study must be reported to the IRB within 14 days.

Thank you for your cooperation in our shared efforts to assure that the rights and welfare of people participating in research are protected.

Tracy J. Cromp

Tracy Cromp, M.S.W.
Director

Note to Faculty Advisor: This notice is only mailed to faculty. If a student is conducting this study, please forward this information to the student researcher.
DEPT: Instructional Design, Development & Evaluation, 330 Huntington Hall **STUDENT:** John Gonzalez

Office of Research Integrity and Protections
121 Bowne Hall Syracuse, New York 13244-1200
(Phone) 315.443.3013 • (Fax) 315.443.9889
orip@syr.edu • www.orip.syr.edu

Appendix G: Domain Knowledge Instrument

SECTION 1: PRIOR KNOWLEDGE

4 / 11 36%

Please answer all the questions below. Show as much work as possible, and please attempt the problem even if you're not sure how to complete it. You may use any resources available to you to solve these problems (computer, calculator, etc...).

It might be useful to perform all work in calculations on a separate piece of paper and include your explanation for how you solved the problem in the appropriate spaces.

***1. Amazon.com is holding a sale. All laptops are 15% off. A new Macbook Pro retails for $1099.**

How much would you pay after a 15% discount and 8% tax?

1a. Please explain the process you used to answer the previous question (or show any work that you wish to show here)

***2. Consider the table of values.**

A. Write the equation that corresponds to that table of values.

X	Y
-2	10
-1	7
0	4
1	1
2	-2

Please explain the process you used to answer the previous question (or show any work that you wish to show here)

Appendix G: Continued

***3a. Given the equation Y = 2x - 3, find the following:**

The value of Y, if X =-3

The value of Y, if X = 0

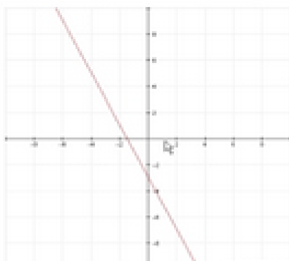
The value of X, if Y = 3

The value of X, if Y = 5

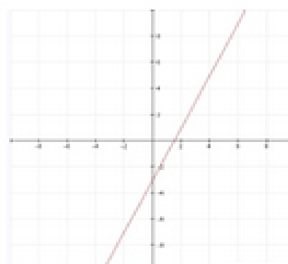
***3b. Which of the graphs below represent the equation Y = 2x - 3**

- A
- B
- C
- D

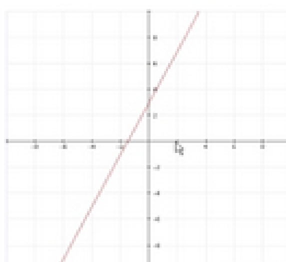
A



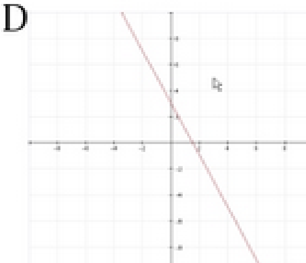
B



C



D



***3c. Using the graph and equation above to identify:**

The slope of the line

The Y-Intercept

The X-Intercept

3d. Please explain the process you used to answer the previous question (or show any work that you wish to show here)

Appendix H: Strategic Knowledge Instrument

3. STRATEGIC KNOWLEDGE

This section will help us better understand your use of problem-solving strategies.

The following questions reference the problem set you just completed. For your convenience, a printable copy of the problem set can be downloaded from here. Please reference that document when the problem set is referenced throughout this survey.

For the following items, please refer to the set of bass problem in section 3, page 8

"Due to pollution and other environmental factors, the bass population at Onondaga Lake has been declining. To help combat this reduction, each Spring volunteers add more fish to the lake. Here's what you need to know:"

Think back to the first time you saw the problem referenced above.
Select the most appropriate response to each of the statements.
Give ratings according to the following scale:
1 = I wasn't aware of this strategy.
2 = I knew about the strategy but chose not to use it for this problem.
3 = I tried to use the strategy but was unable to use it in this problem.
4 = I used the strategy.
5 = I used the strategy AND it helped me solve the problem.

	1	2	3	4	5
I read the problem multiple times until I understood it.	○	○	○	○	○
I drew a picture or multiple pictures to help me understand the problem.	○	○	○	○	○
I restated the problem in my own words.	○	○	○	○	○
I worked out my own examples to help me understand the problem.	○	○	○	○	○
I attempted to guess and check to solve the problem.	○	○	○	○	○
I made an organized list.	○	○	○	○	○
I drew a picture to help me decipher the pattern.	○	○	○	○	○
I used another strategy to look for a pattern.	○	○	○	○	○
I made a table.	○	○	○	○	○
I attempted to use variables to find the answer.	○	○	○	○	○
I tried to solve a simpler problem.	○	○	○	○	○
I experimented with different approaches.	○	○	○	○	○
I worked backwards.	○	○	○	○	○

Appendix I: Self-Efficacy Instrument

*** Please refer to sections 2 and 3 in the problem set you just solved. For each part of the problem, please rate how certain you are you can successfully solve it.**

RATE YOUR DEGREE OF CONFIDENCE BY RECORDING A NUMBER FROM 0 to 100 using the scale given below:

	0 (Cannot do at all)	10	20	30	40	50 (Moderately can do)	60	70	80	90	100 (Highly certain can do)
Problem 4. A bank is advertising...											
Problem 5A. Write an equation...											
Problem 5B. Using this equation...											
Problem 6A. What do you think will happen...											
Problem 6B. Why do you think this is a reasonable...											
Problem 6C. Test your conjecture											
Problem 6E. Does the bass population...											
Problem 6F. Given all the information...											

Appendix J: Goal Orientation Instrument

4. YOUR MOTIVATION

In this section, you'll answer some questions about certain motivational aspects as it relates to solving mathematical problems. Please select the option that most closely matches your feelings about the posed statement.

***Please think about math courses you're taking or have taken in the past. For each statement, select the choice that most closely matches your approach while taking math classes. Use the scale below to answer the questions.**

If you think the statement is very true of you, select 7; if a statement is not at all true of you, circle 1. If the statement is more or less true of you, find the number between 1 and 7 that best describes you.

	1 (Not at all true of me)	2	3	4	5	6	7 (Very true of me)
I want to learn as much as possible from my math courses.							
It is important for me to understand the content in my math courses as thoroughly as possible.							
I hope to have gained a broader and deeper knowledge of math when I am done with my math courses.							
I desire to completely master the material presented in my math courses.							
In my math courses, I prefer course materials that arouse my curiosity, even if it is difficult to learn.							
In my math courses, I prefer course materials that really challenges me so I can learn new things.							

Appendix K: Interest Instrument

***For the following questions, please think about the subject of math as a whole. For each statement, select the choice that most closely matches your feelings towards math. Remember there are no right or wrong answers, just answer as accurately as possible. Use the scale below to answer the questions.**

If you think the statement is very true of you, select 7; if a statement is not at all true of you, circle 1. If the statement is more or less true of you, find the number between 1 and 7 that best describes you.

	1 (Not at all true of me)	2	3	4	5	6	7 (Very true of me)
Math is practical for me to know.	○	○	○	○	○	○	○
Math helps me in my daily life outside of school.	○	○	○	○	○	○	○
It is important to me to be a person who reasons mathematically.	○	○	○	○	○	○	○
Thinking mathematically is an important part of who I am.	○	○	○	○	○	○	○
I enjoy the subject of math.	○	○	○	○	○	○	○
I like math.	○	○	○	○	○	○	○
I enjoy doing math.	○	○	○	○	○	○	○
Math is exciting to me.	○	○	○	○	○	○	○

Appendix L: Self-Regulation Instrument

5. SELF-REGULATED LEARNING

The following questions ask about your learning strategies, study skills, and problem solving approach in math class. Again, there are no right or wrong answers. Answer the questions about how you study in math class as accurately as possible. Use the same scale to answer the remaining questions. If you think the statement is very true of you, select 7; if you think a statement is not at all true of you, select 1. If you think the statement is more or less true of you, find the number between 1 and 7 that best describes you.

*** For each statement, please select the option that best matches your behavior. When answering these questions, please think of your experience in previous math classes.**

	1 (Not at all true of me)	2	3	4	5	6	7 (Very true of me)
A. I often find myself questioning things I hear or read to decide if I find them convincing.	○	○	○	○	○	○	○
B. When I'm presented with a theory, interpretation, or conclusion, I try to decide if there is good supporting evidence.	○	○	○	○	○	○	○
C. I treat course material as a starting point and try to develop my own ideas about it.	○	○	○	○	○	○	○
D. During class time I often miss important points because I'm thinking of other things.	○	○	○	○	○	○	○
E. When solving a math problem, I make up questions to help focus.	○	○	○	○	○	○	○
F. When I become confused about something in math class, I go back and try to figure it out.	○	○	○	○	○	○	○
G. If a math problem is difficult to understand or solve, I change my approach.	○	○	○	○	○	○	○
E. Before I study new math course material thoroughly, I often skim it to see how it is organized.	○	○	○	○	○	○	○
F. I ask myself questions to make sure I understand the material I have been studying in math class.	○	○	○	○	○	○	○
G. I try to change the way I study in order to fit math course requirements and the instructor's teaching style.	○	○	○	○	○	○	○
H. I often find that I after working through a set of math practice problems, I still don't know what they're about.	○	○	○	○	○	○	○
I. I try to think through a math topic and decide what I am supposed to learn from it rather than just reading it over when studying for this course.	○	○	○	○	○	○	○
J. When working on a math problem, I try to determine which concepts I don't understand well.	○	○	○	○	○	○	○
K. When working on a math problem, I set goals for myself in order to direct my activities in each study period.	○	○	○	○	○	○	○
L. If I get confused during math class, I make sure I sort it out afterwards.	○	○	○	○	○	○	○
M. Whenever I read or hear an assertion or conclusion in math class, I think about possible alternatives.	○	○	○	○	○	○	○
N. In math class, I try to plan around with ideas of my own related to what I am learning.	○	○	○	○	○	○	○

Appendix M: Near Transfer Instrument

SECTION 2: APPLICATIONS

Please answer all the questions below. You might find it difficult to show your work in these boxes so please use the box below each question to describe your process so that we can better understand how you solved the problem. Please attempt all the problems, even if you're not sure how to complete it. You may use any resources available to you to solve these problems (computer, calculator,etc...)

***4. A bank is advertising that new customers can open a savings account with an interest rate of 4% compounded annually. Robert invests $5,000 in an account at this rate.**

A. If he makes no additional deposits or withdrawals on his account, find the amount of money he will have, to the nearest cent, after 3 years.

***5. The table of values represents the number of hours a student worked and the amount of dollars the student earned.**

A. Write an equation that represents the number of dollars (D), earned in terms of the number of hours (H), worked.

Number of Hours (h)	Dollars Earned (d)
8	$50.00
15	$93.75
19	$118.75
30	$187.50

***5b. Using this equation, determine the number of dollars the student would earn for working 40 hours in a week.**

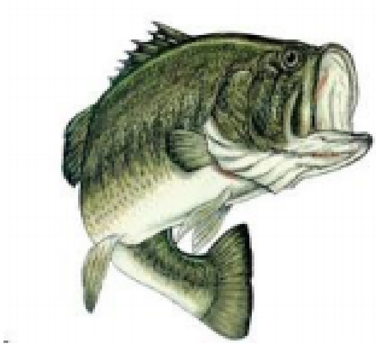
5c. Please explain the process you used to answer the previous question (or show any work that you wish to show here)

Appendix N: Far Transfer Instrument

SECTION 3: PUTTING IT ALL TOGETHER

This is the final problem-solving task. It is an extended problem that covers many different concepts. You might find it difficult to show your work in these boxes so please use the box below each question to describe your process so that we can better understand how you solved the problem. Please attempt all the problems, even if you're not sure how to complete it. You may use any resources available to you to solve these problems (computer, calculator,etc...)

6. Due to pollution and other environmental factors, the bass population at a local lake has been declining. To help combat this reduction, each Spring volunteers add more fish to to the lake. Here's what you need to know:



There are currently 3000 bass in the lake.

Due to fishing, natural death, and pollution, the population decreases by 20% each year.

At the end of each year, 200 bass are added to the lake.

For purposes of ecological equilibrium, scientists believe the bass population should never be below 1500 or above 3500.

*** 6A. What do you think will happen to the bass population?**

- ◯ It will grow without bound.
- ◯ It will level off.
- ◯ It will vary randomly.
- ◯ It will die out.

6B. Why do you think this is a reasonable conjecture?

*** 6C. Test your conjecture.**

How many bass are left after 10 years?

How many bass are left after 100 years?

Appendix N: Continued

*** 6D. How did you arrive at these answers?**

*** 6E. Does the bass population ever reach equilibrium, that is, does the replenishment rate ever match the decline rate so that the bass population stays the same?**
If so, in what year does this first happen?
How did you arrive at this answer?

*** 6F. Given all the information that you have, assuming you want to keep ecological equilibrium by maintaining the bass population between 1500 and 3500, and assuming the rate of decline remains constant for the foreseeable future, what would you suggest the volunteers do?**

- ◯ I. Keep replenishing the bass at the rate of 200 per year.
- ◯ II. Increase the number of bass added to the lake each year.
- ◯ III. Decrease the number of bass added to the lake each year.

If you would choose to increase or decrease the number of bass, what would you change the number to?

*** 6G. Please provide rationale for your choice.**

Appendix O: Prior Knowledge Grading Rubric

Problem 1	
Score	**Criteria**
3	The participant answers \$1088.88 OR An answer between \$1088 and \$1089 is obtained (to account for rounding error). It's NOT necessary that work be shown.
2	Appropriate work is shown, but one computational error is made.
1	Appropriate work is shown, but two or more computation errors are made. OR Appropriate work is shown, but one conceptual error is made.
0	A zero response is completely incorrect, irrelevant, or incoherent.

Problem 2	
Score	**Criteria**
4	The participant answers Y = -3x +4.
3	Appropriate work is shown, but one conceptual error is made resulting in an equation that does not match the table of values.
1	Appropriate work is shown, but two or more computation errors are made result in an equation that does not match the table of values. OR Appropriate work is shown, but one conceptual error is made resulting in an equation that does match the table of values.
0	A zero response is completely incorrect, irrelevant, or incoherent.

Problem 3A

Score	Criteria
2	The participant correctly completes the table with the values -9, -3, 3, and 4 respectively.
1	The table is partially completed with 1 or more incorrect responses.
0	A zero response is completely incorrect, irrelevant, or incoherent.
Problem 3B	
Score	**Criteria**
2	The participant correctly graphs the linear equation Y = 2x - 3
1	A partially correct graph is produced which contains one of the following mistakes: 1. The x-intercept is incorrectly specified and graphed. 2. The y-intercept is incorrectly specified and graphed. 3. The slope is incorrectly specified or graphed (either graphed as a negative slow or a different slope all together).
0	More than 1 of the errors outline above are present in the response OR The response completely incorrect, irrelevant, or incoherent.
Problem 3C	
Score	**Criteria**
3	All correct answers are specified (2, -3, and 1.5)
2	Two correct answers are specified.
1	One correct answer is specified.
0	No correct answers are specified

Maximum Possible Score: 14
Minimum Possible Score: 0

Appendix P: Near Transfer Grading Rubric

Problem 4	
Score	**Criteria**
3	A response of 5264.32 (or a similar number, accounting for rounding error) is provided.
2	Appropriate work is shown, but one computational error is Made.
1	Appropriate work is shown, but two or more computational errors are made.
0	A zero response is completely incorrect, irrelevant, or incoherent.

Problem 5A	
Score	**Criteria**
2	A response of $d = 6.25h$ or an equivalent equation is provided.
1	Appropriate work is shown, but one computational error is made. ***Or*** Appropriate work is shown, but one conceptual error is made. ***or***
0	A zero response is completely incorrect, irrelevant, or incoherent.
Problem 5B	
Score	**Criteria**
2	A response of*$250* is provided.
1	Appropriate work is shown, but one computational error is made. ***Or*** Appropriate work is shown, but one conceptual error is made.
0	A zero response is completely incorrect, irrelevant, or incoherent.

Maximum Possible Score: 7
Minimum Possible Score: 0

Appendix Q: Far Transfer Grading Rubric

Problem 6A	
Score	**Criteria**
2	A conjecture is stated an appropriate rational is provided to support the conjecture. Note that this doesn't necessarily need to be a correct conjecture but the supporting evidence provided must be based on reasonable logic.
1	The correct conjecture is provided (level off), but no rationale is provided.
0	A zero response is completely incorrect, irrelevant, or incoherent.
Problem 6B	
Score	**Criteria**
4	A response between 1214 and 1215 (to account for rounding) is provided.
3	Appropriate work is shown, but one computational error is made that results in an incorrect answer.
2	Appropriate work is shown, but one conceptual error is made that results in an incorrect answer.
1	Appropriate work is shown, but two or more computational errors are made that results in an incorrect answer. OR Appropriate work is shown, but two or more conceptual errors are made that results in an incorrect answer. OR Appropriate work is show, but at least one conceptual AND one computational error are made that result in an incorrect answer.
0	A zero response is completely incorrect, irrelevant, or incoherent.
Problem 6C	
Score	**Criteria**
4	A response of 1000 (within round error) is provided.
3	Appropriate work is shown, but one computational error is made that results in an incorrect answer.
2	Appropriate work is shown, but one conceptual error is made that results in an incorrect answer.

1	Appropriate work is shown, but two or more computational errors are made that results in an incorrect answer. OR Appropriate work is shown, but two or more conceptual errors are made that results in an incorrect answer. OR Appropriate work is show, but at least one conceptual AND one computational error are made that result in an incorrect answer.
0	A zero response is completely incorrect, irrelevant, or incoherent.
Problem 6D	
Score	**Criteria**
5	A response of yes is provided, and a year between 25 and 30 is given as the year when this first happens. AND The response includes reference to a generalized algebraic expression that participant derived to answer the question.
4	A response of yes is provided, and a year between 25 and 30 is given as the year when this first happens.
3	Appropriate work is shown, but one computational error is made that results in an incorrect answer.
2	Appropriate work is shown, but one conceptual error is made that results in an incorrect answer.
1	Appropriate work is shown, but two or more computational errors are made that results in an incorrect answer. OR Appropriate work is shown, but two or more conceptual errors are made that results in an incorrect answer. OR Appropriate work is shown, but at least one conceptual AND one computational error are made that result in an incorrect answer.
0	A zero response is completely incorrect, irrelevant, or incoherent.

Problem 6E	
Score	**Criteria**
4	Choice II is selected and a number is provided that keeps the population of bass between 1500 and 3500. Many answers are possible.
3	Choice II is selected and an incorrect number is provided although a clear rationale for providing that argument is given. This might be due to a computational problem.
2	Choice II is selected although an incorrect number is providing to maintain population. This error is due to a conceptual error. OR Choice II is selected and no rational is provided.
1	Either choice I and III are provided and an appropriate rationale is given to support the answer – although such rationale might contain conceptual or computation errors.
0	A zero response is completely incorrect, irrelevant, or incoherent.

MINIMUM POSSIBLE SCORE → 0

MAXIMUM POSSIBLE SCORE → 19

REFERENCES

Abdi, H. (2003). Factor rotations. In M. Lewis-Beck, A. Bryman, T. Futing (Eds): *Encyclopedia for research methods for the social sciences*, 978-982. Thousand Oaks (CA): Sage.

Adey, P., & Shayer, M. (1993). An exploration of long-term far-transfer effects following an extended intervention program in the high school science curriculum. *Cognition and Instruction, 11*(1), 1-29.

Ainley, M. (2006). Connecting with learning: Motivation, affect and cognition in interest processes. *Educational Psychology Review, 18*(4), 391-405.

Ainley, M., Hidi, S., & Berndorff, D. (2002). Interest, learning, and the psychological processes that mediate their relationship. *Journal of Educational Psychology, 94*(3), 545-561.

Ainley, M., Hidi, S., & Berndorff, D. (2002). Interest, learning, and the psychological processes that mediate their relationship. *Journal of Educational Psychology, 94*(3), 545-561.

Ainsworth, S. (2006). DeFT: A conceptual framework for considering learning with multiple representations. *Learning and Instruction, 16*(3), 183-198.

Ainsworth, S., & Loizou, A. (2003). The effects of self-explaining when learning with text or diagrams. *Cognitive Science, 27*(4), 669-681.

Alexander, P. A. (2003). The development of expertise: The journey from acclimation to proficiency. *Educational Researcher, 32*(8), 10-14.

Alexander, P. A., Jetton, T. L., & Kulikowich, J. M. (1995). Interrelationship of knowledge, interest, and recall: Assessing a model of domain learning. *Journal of Educational Psychology, 87*(4), 559-575.

Alexander, P. A., & Judy, J. E. (1988). The interaction of domain-specific and strategic knowledge in academic performance. *Review of Educational Research, 58*(4), 375-404.

Alexander, P. A., & Murphy, P. K. (1998). Profiling the differences in students' knowledge, interest, and strategic processing. *Journal of Educational Psychology, 90*, 435-447.

Alexander, P. A., & Murphy, P. K. (1999). Nurturing the seeds of transfer: A domain-specific perspective* 1. *International Journal of Educational Research, 31*(7), 561-576.

Ames, C., & Archer, J. (1988). Achievement goals in the classroom: Students' learning strategies and motivation processes. *Journal of Educational Psychology, 80*(3), 260-267.

Anand, P. G., & Ross, S. M. (1987). Using computer-assisted instruction to personalize arithmetic materials for elementary school children. *Journal of Educational Psychology, 79*(1), 72-78.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin, 103*(3), 411-423.

Antonietti, A., Ignazi, S., & Perego, P. (2000). Metacognitive knowledge about problem-solving methods. *British Journal of Educational Psychology, 70*(1), 1-16.

Arbuckle, J. L. (2010). IBM SPSS® AMOS™ 19 User's guide. Smallwaters Corporation, Chicago IL.

Azevedo, R., & Cromley, J. G. (2004). Does training on self-regulated learning facilitate students' learning with hypermedia? *Journal of Educational Psychology, 96*(3), 523-535.

Azevedo, R., Cromley, J. G., & Seibert, D. (2004). Does adaptive scaffolding facilitate students' ability to regulate their learning with hypermedia?* 1. *Contemporary Educational Psychology, 29*(3), 344-370.

Azevedo, R., Cromley, J. G., Winters, F. I., Moos, D. C., & Greene, J. A. (2005). Adaptive human scaffolding facilitates adolescents' self-regulated learning with hypermedia. *Instructional Science, 33*(5), 381-412.

Babbie, E. (1990). *Survey research methods.* Belmont, CA: Wadsworth.

Babbie, E. R. (2007). *The practice of social research.* Belmont, CA: Wadsworth.

Babbie, E. R. (2008). *The basics of social research* (4th Ed.). Belmont, CA: Thomson.

Bagozzi, R. P., & Edwards, J. R. (1998). A general approach for representing constructs in organizational research. *Organizational Research Methods, 1*(1), 45.

Baldwin, T. T., & Ford, J. K. (1988). Transfer of training: A review and directions for future research. *Personnel Psychology, 41*(1), 63-105.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory.* Englewood Cliffs, NJ: Prentice-Hall, Inc.

Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational Psychologist, 28*(2), 117-148.

Bandura, A. (1997). The nature and structure of self efficacy. *Self-efficacy: The exercise of control* (pp. 36-115). Worth Publishers.

Bandura, A. (2006). Guide for constructing self-efficacy scales. *Self-Efficacy Beliefs of Adolescents, 5*, 307-337.

Bandura, A., & Jourden, F. J. (1991). Self-regulatory mechanisms governing the impact of social comparison on complex decision making. *Journal of Personality and Social Psychology, 60*(6), 941-951.

Bandura, A., & Wood, R. (1989). Effect of perceived controllability and performance standards on self-regulation of complex decision making. *Journal of Personality and Social Psychology, 56*(5), 805-814.

Barnett, S. M., & Ceci, S. J. (2002). When and where do we apply what we learn? Taxonomy for far transfer. *Psychological Bulletin, 128*(4), 612-637.

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173-1182.

Barrett, P. (2007). Structural equation modeling: Adjudging model fit. *Personality and Individual Differences*, 42(5), 815-824

Bartlett, F. C. (1995). *Remembering: A study in experimental and social psychology*. New York: Cambridge University Press.

Bates, E. T., & Wiest, L. R. (2004). Impact of personalization of mathematical word problems on student performance. *The Mathematics Educator, 14*(2), 17-26.

Beach, K. (1999). Consequential transitions: A sociocultural expedition beyond transfer in education. *Review of Research in Education, 24*, 101-139.

Bentler, P. M., & Chou, C. P. (1987). Practical issues in structural equation modeling. *Sociological Methods and Research, 16*(1), 78-117.

Bereby-Meyer, Y., & Kaplan, A. (2005). Motivational influences on transfer of problem-solving strategies. *Contemporary Educational Psychology, 30*(1), 1-22.

Bereby-Meyer, Y., Moran, S., & Unger-Aviram, E. (2004). When performance goals deter performance: Transfer of skills in integrative negotiations. *Organizational Behavior and Human Decision Processes, 93*(2), 142-154.

Berry, D. (1983). Metacognitive experience and transfer of logical reasoning. *Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 35*, 39–49.

Bielaczyc, K., Pirolli, P. L., & Brown, A. L. (1995). Training in self-explanation and self-regulation strategies: Investigating the effects of knowledge acquisition activities on problem solving. *Ethics & Behavior, 13*(2), 221-252.

Boekaerts, M. (1992). The adaptable learning process: Initiating and maintaining behavioural change. *Applied Psychology, 41*(4), 377-397.

Boekaerts, M. (1996). Self-regulated learning at the junction of cognition and motivation. *European Psychologist, 1*(2), 100-112.

Boekaerts, M. (1997). Self-regulated learning: A new concept embraced by researchers, policy makers, educators, teachers, and students. *Learning and Instruction, 7*(2), 161-186.

Boekaerts, M., & Corno, L. (2005). Self-regulation in the classroom: A perspective on assessment and intervention. *Applied Psychology, 54*(2), 199-231.

Bollen, K. A. (1989). *Structural equations with latent variables*. NY: Wiley Online Library.

Bollen, K., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological Bulletin, 110*(2), 305-314.

Bollen, K. A., & Long, J. (1993). *Testing structural equation models.* Sage Publications, Inc.

Booth, W. C., Colomb, G. G., & Williams, J. M. (2003). *The craft of research*. Chicago, IL: University of Chicago Press.

Brand-Gruwel, S., & Stadtler, M. (2011). Solving information-based problems: Evaluating sources and information. *Learning and Instruction, 21*(2), 175-179.

Bransford, J. D., Brown, A. L., & Cocking, R. R. (2000). *How people learn.* Washington, DC: National Academy Press.

Bransford, J. D., & Schwartz, D. L. (1999). Rethinking transfer: A simple proposal with multiple implications. *Review of Research in Education, 24*, 61-100.

Brophy, J. (2004). *Motivating students to learn.* Routledge.

Brophy, J. (2005). Goal theorists should move on from performance goals. *Educational Psychologist, 40*(3), 167-176.

Brown, A. L. (1990). Domain-specific principles affect learning and transfer in children. *Cognitive Science, 14*(1), 107-133.

Browne, M. W. & Cudeck, R. (1993). Alternative ways of assessing model fit. In: Bollen, K. A. & Long, J. S. (Eds.) Testing Structural Equation Models. pp. 136–162. Beverly Hills, CA: Sage.

Bulgren, J. A., Deshler, D. D., Schumaker, J. B., & Lenz, B. K. (2000). The use and effectiveness of analogical instruction in diverse secondary content classrooms. *Journal of Educational Psychology, 92*(3), 426-441.

Burke, L. A., & Hutchins, H. M. (2007). Training transfer: An integrative literature review. *Human Resource Development Review, 6*(3), 263.

Byrne, B.M. (2004). Testing for multigroup invariance using AMOS graphics: a road less traveled. *Structural Equation Modeling*, 11(2): 272-300.

Campione, J. C., Shapiro, A. M., & Brown, A. L. (1995). Forms of transfer in a community of learners: Flexible learning and understanding. In A. McKeough, J. L. Lupart& A. Marini (Eds.), *Teaching for transfer: Fostering generalization in learning* (pp. 35–68) Erlbaum.

Carraher, D., & Schliemann, A. (2002). The transfer dilemma. *Journal of the Learning Sciences, 11*(1), 1-24.

Cattell, R. B. (1966). The scree test for the number of factors. Multivariate Behavioral Research, 1(2), 245-276.

Chang, C. Y. (2010). Does problem solving= prior knowledge reasoning skills in earth science? An exploratory study. *Research in Science Education, 40*(2), 103-116.

Cheung, G. W., & Rensvold, R. B. (1999). Testing factorial invariance across groups: A reconceptualization and proposed new method. *Journal of Management*, 25, 1-27.

Chi, M. T. H., & Bassok, M., W. (1989). Self-explanations: How students study and use examples in learning to solve problems. *Cognitive Science, 13*(2), 145-182.

Chi, M. T. H., De Leeuw, N., Chiu, M. H., & LaVancher, C. (1994). Eliciting self-explanations improves understanding. *Cognitive Science, 18*(3), 439-477.

Chi, M. T. H., Glaser, R., & Rees, E. (1982). Expertise in problem solving. *Advances in the Psychology of Human Intelligence, 1*, 1-75.

Church, M. A., Elliot, A. J., & Gable, S. L. (2001). Perceptions of classroom environment, achievement goals, and achievement outcomes. *Journal of Educational Psychology, 93*(1), 43-54.

Clarke, K. A. (2005). The phantom menace: Omitted variable bias in econometric research. *Conflict Management and Peace Science, 22*(4), 341-352.

Cox, B. D. (1997). The rediscovery of the active learner in adaptive contexts: A developmental-historical analysis of transfer of training. *Educational Psychologist, 32*(1), 41-55.

Creswell, J. W. (2003). (2nd Ed.). Thousand Oaks, CA: Sage Publications, Inc.

Creswell, J. W. (2009). *Research design: Qualitative, quantitative, and mixed methods approaches*. Thousand Oaks, CA: Sage Publications, Inc.

Crocker, L., & Algina, J. (1986). *Introduction to classical and modern test theory.* Orlando, FL: Holt, Rinehart and Winston.

Cureton, E. E., & Mulaik, S. A. (1975). The weighted varimax rotation and the promax rotation. *Psychometrika*, 40(2), 183-195.

Deci, E. L., & Ryan, R. M. (2000). The “what” and “why” of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry, 11*(4), 227-268.

Detterman, D. K., & Sternberg, R. J. (1993). *Transfer on trial*. Norwood, NJ: Ablex.

Dignath, C., Buettner, G., & Langfeldt, H. P. (2008). How can primary school students learn self-regulated learning strategies most effectively? A meta-analysis on self-regulation training programmes. *Educational Research Review, 3*(2), 101-129.

Dochy, F., Moerkerke, G., & Martens, R. (1996). Integrating assessment, learning and instruction: Assessment of domain-specific and domain-transcending prior knowledge and progress. *Studies in Educational Evaluation, 22*, 309-340.

Dochy, F. J. R. C., & Alexander, P. A. (1995). Mapping prior knowledge: A framework for discussion among researchers. *European Journal of Psychology of Education, 10*(3), 225-242.

Duncan, T. G., & McKeachie, W. J. (2005). The making of the motivated strategies for learning questionnaire. *Educational Psychologist, 40*(2), 117-128.

Dupeyrat, C., & Mariné, C. (2005). Implicit theories of intelligence, goal orientation, cognitive engagement, and achievement: A test of Dweck's model with returning to school adults. *Contemporary Educational Psychology, 30*(1), 43-59.

Dweck, C. S. (1986). Motivational processes affecting learning. *American Psychologist, 41*(10), 1040-1048.

Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological Review, 95*(2), 256-273.

D'Zurilla, T., & Nezu, A. (1982). Social problem-solving. *PC Kendall (Éd) Advances in Cognitive-Behavioral Research and Therapy,* 201-274.

Eden, D., & Aviram, A. (1993). Self-efficacy training to speed reemployment: Helping people to help themselves. *Journal of Applied Psychology, 78*(3), 352-360.

Egan, T. M., Yang, B., & Bartlett, K. R. (2004). The effects of organizational learning culture and job satisfaction on motivation to transfer learning and turnover intention. *Human Resource Development Quarterly, 15*(3), 279-301.

Elliot, A. J. (2006). The hierarchical model of approach-avoidance motivation. *Motivation and Emotion, 30*(2), 111-116.

Elliot, A. J., & Church, M. A. (1997). A hierarchical model of approach and avoidance achievement motivation. *Journal of Personality and Social Psychology, 72*(1), 218-232.

Elliot, A. J., & McGregor, H. A. (2001). A 2 x 2 achievement goal framework. *Journal of Personality and Social Psychology, 80*(3), 501-519.

Elliot, A. J., McGregor, H. A., & Gable, S. (1999). Achievement goals, study strategies, and exam performance: A mediational analysis. *Journal of Educational Psychology, 91*, 549-563.

Elliot, A. J., McGregor, H. A., & Gable, S. (1999). Achievement goals, study strategies, and exam performance: A mediational analysis. *Journal of Educational Psychology, 91*, 549-563.

Elliott, E. S., & Dweck, C. S. (1988). Goals: An approach to motivation and achievement. *Journal of Personality and Social Psychology, 54*(1), 5-12.

Ellis, A. B. (2007). A taxonomy for categorizing generalizations: Generalizing actions and reflection generalizations. *Journal of the Learning Sciences, 16*(2), 221-262.

Ellis, H. C. (1965). *The transfer of learning*. Macmillan: New York.

Enos, M. D., Kehrhahn, M. T., & Bell, A. (2003). Informal learning and the transfer of learning: How managers develop proficiency. *Human Resource Development Quarterly, 14*(4), 369-387.

Ericsson, K. A., & Smith, J. (1991). *Toward a general theory of expertise: Prospects and limits.* New York: Cambridge University Press.

Ericsson, K. A., & Simon, H. A. (1993). Protocol analysis; Verbal reports as data (revised edition). Cambridge, MA: Bradfordbooks/MIT Press.

Ericsson, K. A., & Simon, H. A. (1998). How to study thinking in everyday life: Contrasting think-aloud protocols with descriptions and explanations of thinking. Mind, Culture, & Activity, 5(3), 178-186.

Farrington-Darby, T., & Wilson, J. R. (2006). The nature of expertise: A review. *Applied Ergonomics, 37*(1), 17-32.

Filak, V. F., & Sheldon, K. M. (2003). Student psychological need satisfaction and college teacher-course evaluations. *Educational Psychology, 23*(3), 235-247.

Finney, S. J., & Schraw, G. (2003). Self-efficacy beliefs in college statistics courses. *Contemporary Educational Psychology, 28*(2), 161-186.

Fisher, S. L., & Ford, J. K. (1998). Differential effects of learner effort and goal orientation on two learning outcomes. *Personnel Psychology, 51*(2), 397-420.

Ford, J. K., Smith, E. M., Weissbein, D. A., Gully, S. M., & Salas, E. (1998). Relationships of goal orientation, metacognitive activity, and practice strategies with learning outcomes and transfer. *Journal of Applied Psychology, 83*(2), 218-233.

Fowler, F. J. (2009). *Survey research methods*. Sage Publications, Inc.

Fraenkel, J. R., & Wallen, N. E. (1993). *How to design and evaluate research in education.* New York: McGraw-Hill.

Fuchs, L. S., Fuchs, D., Prentice, K., Burch, M., Hamlett, C. L., Owen, R., et al. (2003). Enhancing third-grade students' mathematical problem solving with self-regulated learning strategies. *Journal of Educational Psychology, 95*(2), 306-315.

Gagné, M., Ryan, R. M., & Bargmann, K. (2003). Autonomy support and need satisfaction in the motivation and well-being of gymnasts. *Journal of Applied Sport Psychology, 15*(4), 372-390.

Gagne, R. M. (1985). *The conditions of learning*. New York: Holt, Rinehart & Winston.

Gentner, D. (1983). Structure-mapping: A theoretical framework for analogy. *Cognitive Science, 7*(2), 155-170.

Gentner, D., & Kurtz, K. J. (2006). Relations, objects, and the composition of analogies. *Cognitive Science: A Multidisciplinary Journal, 30*(4), 609-642.

Gentner, D., Loewenstein, J., & Thompson, L. (2003). Learning and transfer: A general role for analogical encoding. *Journal of Educational Psychology, 95*(2), 393-408.

Georghiades, P. (2000). Beyond conceptual change learning in science education: Focusing on transfer, durability and metacognition. *Educational Research, 42*(2), 119-139.

Gick, M. L., & Holyoak, K. J. (1980). Analogical problem solving. *Cognitive Psychology, 12*(3), 306-355.

Gick, M. L., & Holyoak, K. J. (1983). Schema induction and analogical transfer. *Cognitive Psychology, 15*(1), 1-38.

Gist, M. E. (1989). The influence of training method on self-efficacy and idea generation among managers. *Personnel Psychology, 42*(4), 787-805.

Gist, M. E., Stevens, C. K., & Bavetta, A. G. (1991). Effects of self-efficacy and post-training intervention on the acquisition and maintenance of complex interpersonal skills. *Personnel Psychology, 44*(4), 837-861.

Glaser, C., & Brunstein, J. C. (2007). Improving fourth-grade students' composition skills: Effects of strategy instruction and self-regulation procedures. *Journal of Educational Psychology, 99*(2), 297-310.

Glaser, R., & De Corte, E. (1992). Preface to the assessment of prior knowledge as a determinant of future learning. *Assessment of Prior Knowledge as a Determinant for Future Learning.*

Goldman, S. R. (2003). Learning in complex domains: When and why do multiple representations help? *Learning and Instruction, 13*(2), 239-244.

Goldstone, R. L., & Son, J. Y. (2005). The transfer of scientific principles using concrete and idealized simulations. *The Journal of the Learning Sciences, 14*(1), 69-110.

Goldstone, R. L., & Wilensky, U. (2008). Promoting transfer by grounding complex systems principles. *Journal of the Learning Sciences, 17*(4), 465-516.

Gollwitzer, P. M., & Oettingen, G. (2000). Motivation: History of the concept. In J. Smelser, & P. B. Baltes (Eds.), *International encyclopedia of the social & behavioral sciences* (pp. 10109-10112). Oxford, U.K: Elsevier.

Gonzalez-Pienda, J. A., Nunez, J. C., Gonzalez-Pumariega, S., Alvarez, L., Roces, C., & Garcia, M. (2002). A structural equation model of parental involvement, motivational and aptitudinal characteristics, and academic achievement. *The Journal of Experimental Education, 70*(3), 257-287.

Grant, H., & Dweck, C. S. (2003). Clarifying achievement goals and their impact. *Journal of Personality and Social Psychology, 85*(3), 541-553.

Greene, B. A., & Miller, R. B. (1996). Influences on achievement: Goals, perceived ability, and cognitive engagement. *Contemporary Educational Psychology, 21*(2), 181-192.

Greene, J. A., Costa, L. J., Robertson, J., Pan, Y., & Deekens, V. M. (2010). Exploring relations among college students' prior knowledge, implicit theories of intelligence, and self-regulated learning in a hypermedia environment. *Computers & Education, 55*(3), 1027-1043.

Grolnick, W. S., Ryan, R. M., & Deci, E. L. (1991). Inner resources for school achievement: Motivational mediators of children's perceptions of their parents. *Journal of Educational Psychology, 83*(4), 508-517.

Haavelmo, T. (1944). The probability approach in econometrics. *Econometrica: Journal of the Econometric Society, 12.*

Hailikari, T., Nevgi, A., & Lindblom-Ylänne, S. (2007). Exploring alternative ways of assessing prior knowledge, its components and their relation to student achievement: A mathematics based case study. *Studies in Educational Evaluation, 33*(3-4), 320-337.

Hailikari, T. K., & Nevgi, A. (2010). How to diagnose at-risk students in chemistry: The case of prior knowledge assessment. *International Journal of Science Education, 32*(15), 2079-2095.

Hall, R. J., Snell, A. F., & Foust, M. S. (1999). Item parceling strategies in SEM: Investigating the subtle effects of unmodeled secondary constructs. *Organizational Research Methods, 2*(3), 233.

Hall, S., & Vance, E. A. (2010). Improving self-efficacy in statistics: Role of self-explanation & feedback. *Journal of Statistics Education, 18*(3)

Halpern, D. F. (1998). Teaching critical thinking for transfer across domains: Dispositions, skills, structure training, and metacognitive monitoring. *American Psychologist, 53*, 449-455.

Hamilton, R.J., & Akhter, S. (2009). Construct Validity of the Motivated Strategies For Learning Questionnaire. *Psychological Reports, 104*(3), 711-722.

Harp, S. F., & Mayer, R. E. (1997). The role of interest in learning from scientific text and illustrations: On the distinction between emotional interest and cognitive interest. *Journal of Educational Psychology, 89*(1), 92-102.

Harrison, A. W., Rainer, R. K., Hochwarter, W. A., & Thompson, K. R. (1997). Testing the self-Efficacy-Performance linkage of Social-Cognitive theory. *The Journal of Social Psychology, 137*(1), 79-87.

Haskell, R. E. (2001). *Transfer of learning: Cognition, instruction, and reasoning*. San Diego: Academic Press.

Hatano, G., & Oura, Y. (2003). Commentary: Reconceptualizing school learning using insight from expertise research. *Educational Researcher, 32*(8), 26-29.

Hausmann, R. G. M., & Vanlehn, K. (2007). Explaining self-explaining: A contrast between content and generation. *Artificial Intelligence in Education: Building Technology Rich Learning Contexts that Work, 158*, 417-424.

Hayduk, L., Cummings, G., Boadu, K., Pazderka-Robinson, H., & Boulianne, S. (2007). Testing! testing! one, two, three-testing the theory in structural equation models! *Personality and Individual Differences*, 42(5), 841-850.

Haynes, S. N., Richard, D. C. S., & Kubany, E. S. (1995). Content validity in psychological assessment: A functional approach to concepts and methods. *Psychological Assessment, 7*(3), 238-247.

Heckman, J. (1990). Varieties of selection bias. *The American Economic Review, 80*(2), 313-318.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the Econometric Society,* 153-161.

Heckman, J. J. (1985). Selection bias and self-selection. *The New Palgrave: A Dictionary of Economics,* 287–96.

Hidi, S. (1990). Interest and its contribution as a mental resource for learning. *Review of Educational Research, 60*(4), 549.

Hidi, S. (2001). Interest, reading, and learning: Theoretical and practical considerations. *Educational Psychology Review, 13*(3), 191-209.

Hidi, S., & Renninger, K. A. (2006). The four-phase model of interest development. *Educational Psychologist, 41*(2), 111-127.

Hoffman, B., & Spatariu, A. (2008). The influence of self-efficacy and metacognitive prompting on math problem-solving efficiency. *Contemporary Educational Psychology, 33*(4), 875-893.

Holladay, C. L., & Quiñones, M. A. (2003). Practice variability and transfer of training: The role of self-efficacy generality. *Journal of Applied Psychology, 88*(6), 1094-1103.

Hoyle, R. H., & Panter, A. T. (1995). Writing about structural equation models. *Structural Equation Modeling: Concepts, Issues, and Applications,* 158-176.

Hu, L., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods*, 3, 424–453.

Huang, S. C. (2008). Assessing motivation and learning strategies using the motivated strategies for learning questionnaire in a foreign language learning context. *Social Behavior and Personality: An International Journal, 36*(4), 529-534.

Huitt, W. (2003). The information processing approach to cognition. *Educational Psychology Interactive,* 2004-2012.

Ilardi, B. C., Leone, D., Kasser, T., & Ryan, R. M. (1993). Employee and supervisor ratings of motivation: Main effects and discrepancies associated with job satisfaction and adjustment in a factory setting. *Journal of Applied Social Psychology, 23*(21), 1789-1805.

Jang, H., Reeve, J., Ryan, R. M., & Kim, A. (2009). Can self-determination theory explain what underlies the productive, satisfying learning experiences of collectivistically oriented Korean students? *Journal of Educational Psychology, 101*(3), 644-661.

Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. *Journal of Consumer Research, 30*(2), 199-218.

Jonassen, D. H., Tessmer, M., & Hannum, W. H. (1999). *Task analysis methods for instructional design.* Lawrence Erlbaum Associates.

Jourden, F. J., Bandura, A., & Banfield, J. T. (1991). The impact of conceptions of ability on self-regulatory factors and motor skill acquisition. *Journal of Sport and Exercise Psychology, 13*(3), 213–226.

Kaiser, H. F. (1958). The varimax criterion for analytic rotation in factor analysis. Psychometrika, 23(3), 187-200.

Kaplan, A., & Maehr, M. L. (2007). The contributions and prospects of goal orientation theory. *Educational Psychology Review, 19*(2), 141-184.

Kasser, T., Davey, J., & Ryan, R. M. (1992). Motivation and employee-supervisor discrepancies in a psychiatric vocational rehabilitation setting. *Rehabilitation Psychology, 37*(3), 175.

Kehr, H. M., Bles, P., & Rosenstiel, L. (1999). Self-regulation, self-control, and management training transfer. *International Journal of Educational Research, 31*(6), 487-498.

Keith, T. Z. (2006). *Multiple regression and beyond.* Boston, MA: Pearson Education.

Kilpatrick, J., Swafford, J., & Findell, B. (2001). *Adding it up: Helping children learn mathematics*. National Academies Press.

Kim, J. S., & Frees, E. W. (2006). Omitted variables in multilevel models. *Psychometrika, 71*(4), 659-690.

Kline, R. B. (2010). *Principles and practice of structural equation modeling*. New York: Guilford Press.

Kozlowski, S. W. J., Gully, S. M., Brown, K. G., Salas, E., Smith, E. M., & Nason, E. R. (2001). Effects of training goals and goal orientation traits on multidimensional training outcomes and performance adaptability. *Organizational Behavior and Human Decision Processes, 85*(1), 1-31.

Kozma, R. (2003). The material features of multiple representations and their cognitive and social affordances for science understanding. *Learning and Instruction, 13*(2), 205-226.

Krapp, A. (1999). Interest, motivation and learning: An educational-psychological perspective. *European Journal of Psychology of Education, 14*(1), 23-40.

Krapp, A., Hidi, S., & Renninger, K. A. (1992). The role of interest in learning and development. *Interest, learning, and development* (pp. 3-25) Hillsdale, NJ: Erlbaum.

Krathwohl, D. R. (1998). *Methods of educational & social science research: An integrated approach*. Reading, MA: Addison Wesley Longman.

Ku, H. Y., & Sullivan, H. J. (2002). Student performance and attitudes using personalized mathematics instruction. *Educational Technology Research and Development, 50*(1), 21-34.

Larson, R. W. (2000). Toward a psychology of positive youth development. *American Psychologist, 55*(1), 170-183.

Lave, J. (1988). *Cognition in practice: Mind, mathematics, and culture in everyday life*. New York: Cambridge University Press.

Lee, C. Y., & Chen, M. P. (2009). A computer game as a context for non-routine mathematical problem solving: The effects of type of question prompt and level of prior knowledge. *Computers & Education, 52*(3), 530-542.

Lee, J. C. K., Zhang, Z., & Yin, H. (2010). Using multidimensional Rasch analysis to validate the Chinese version of the motivated strategies for learning questionnaire (MSLQ-CV). *European Journal of Psychology of Education, 25*(1), 141-155.

Levesque, C., Zuehlke, A. N., Stanek, L. R., & Ryan, R. M. (2004). Autonomy and competence in German and American university students: A comparative study based on self-determination theory. *Journal of Educational Psychology, 96*(1), 68-84.

Light, R. J., & Pillemer, D. B. (1984). *Summing up: The science of reviewing research*. Cambridge, MA: Harvard University Press.

Lim, J., Reiser, R. A., & Olina, Z. (2009). The effects of part-task and whole-task instructional approaches on acquisition and transfer of a complex cognitive skill. *Educational Technology Research and Development, 57*(1), 61-77.

Linnenbrink, E. A. (2005). The dilemma of performance-approach goals: The use of multiple goal contexts to promote students' motivation and learning. *Journal of Educational Psychology, 97*(2), 197-213.

Linnenbrink-Garcia, L., Durik, A. M., Conley, A. M. M., Barron, K. E., Tauer, J. M., Karabenick, S. A., et al. (2010). Measuring situational interest in academic domains. *Educational and Psychological Measurement, 70*(4), 647.

Little, T. D., Lindenberger, U., & Nesselroade, J. R. (1999). On selecting indicators for multivariate measurement and modeling with latent variables: When "good" indicators are bad and "bad" indicators are good. *Psychological Methods, 4*, 192-211.

Lobato, J. (2003). How design experiments can inform a rethinking of transfer and viceversa. *Educational Researcher, 32*(1), 17.

Lobato, J. (2006). Alternative perspectives on the transfer of learning: History, issues, and challenges for future research. *The Journal of the Learning Sciences, 15*(4), 431-449.

MacCallum, R. C., & Austin, J. T. (2000). Applications of structural equation modeling in psychological research. *Annual Review of Psychology, 51*(1), 201-226.

Marsh, H.W. (1994) Confirmatory factor analysis models of factorial invariance: a multifaceted approach. *Structural Equation Modeling*, 1(1): 5-34.

Marsh, H. W., Roche, L. A., Pajares, F., & Miller, D. (1997). Item-specific efficacy judgments in mathematical problem solving: The downside of standing too close to trees in a forest. *Contemporary Educational Psychology, 22*, 363-377.

Mathieu, J. E., Martineau, J. W., &Tannenbaum, S. I. (1993). Individual and situational influences on the development of self-efficacy: Implications for training effectiveness. *Personnel Psychology, 46*(1), 125-147.

Mayer, R. E. (1998). Cognitive, metacognitive, and motivational aspects of problem solving. *Instructional Science, 26*(1), 49-63.

Mayer, R. E. (2006). The role of domain knowledge in creative problem solving. *Creativity and Reason in Cognitive Development,* 145–158.

Mayer, R. E., & Wittrock, M. C. (1996). Problem-solving transfer. In D. C. Berliner, & R. C. Calfee (Eds.), *Handbook of educational psychology* (pp. 47-62). New York: Simon & Schuster.

McDonald, R. P., & Ringo Ho, M. H. (2002). Principles and practice in reporting structural equation analyses. *Psychological Methods, 7*(1), 64-82.

McInerney, D. M., Roche, L. A., McInerney, V., & Marsh, H. W. (1997). Cultural perspectives on school motivation: The relevance and application of goal theory. *American Educational Research Journal, 34*(1), 207.

McIntosh, C. N. (2007). Rethinking fit assessment in structural equation modeling: A commentary and elaboration on Barrett (2007). *Personality and Individual Differences*, 42(5), 859-867.

Mestre, J. P. (2005). *Transfer of learning from a modern multidisciplinary perspective.* Greenwich, CT: Information Age.

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *V, 63*, 81-97.

Moos, D. C., & Azevedo, R. (2008). Exploring the fluctuation of motivation and use of self-regulatory processes during learning with hypermedia. *Instructional Science, 36*(3), 203-231.

Moos, D. C., & Azevedo, R. (2009). Self-efficacy and prior domain knowledge: To what extent does monitoring mediate their relationship with hypermedia learning? *Metacognition and Learning, 4*(3), 197-216.

Mulaik, S. (2007). There is a place for approximate fit in structural equation modeling. *Personality and Individual Differences*, 42(5), 883-891.

Muis, K. R., Winne, P. H., & Jamieson-Noel, D. (2007). Using a multitrait-multimethod analysis to examine conceptual similarities of three self-regulated learning inventories. *British Journal of Educational Psychology, 77*(1), 177.

Murphy, P. K., & Alexander, P. A. (2000). A motivated exploration of motivation terminology. *Contemporary Educational Psychology, 25*(1), 3-53.

Murphy, P. K., & Alexander, P. A. (2002). What counts? The predictive powers of subject-matter knowledge, strategic processing, and interest in domain-specific performance. *The Journal of Experimental Education, 70*(3), 197-214.

Muthén, B. (1994). Multilevel covariance structure analysis. In J. Hox & I. Kreft (eds.), Multilevel Modeling, a special issue of Sociological Methods & Research, 22, 376-398.

Muthén, B. & Asparouhov, T. (2011). Beyond multilevel regression modeling: Multilevel analysis in a general latent variable framework. In J. Hox& J.K. Roberts (eds), Handbook of Advanced Multilevel Analysis, pp. 15-40. New York: Taylor and Francis.

Muthén, L.K. & Muthén, B.O. (2002). How to use a Monte Carlo study to decide on sample size and determine power. *Structural Equation Modeling*, 9(4), 599-620.

National Council of Teachers of Mathematics. (2010). *Standards & focal points.* Retrieved December, 2010, from http://www.nctm.org/standards/default.aspx?id=58

Newman, R. S., & Schwager, M. T. (1995). Students' help seeking during problem solving: Effects of grade, goal, and prior achievement. *American Educational Research Journal, 32*(2), 352-376.

Niemiec, C. P., Lynch, M. F., Vansteenkiste, M., Bernstein, J., Deci, E. L., & Ryan, R. M. (2006). The antecedents and consequences of autonomous self-regulation for college: A self-determination theory perspective on socialization. *Journal of Adolescence, 29*(5), 761-775.

Niemiec, C. P., Ryan, R. M., Patrick, H., Deci, E. L., & Williams, G. C. (2010). The energization of health-behavior change: Examining the associations among autonomous self-regulation, subjective vitality, depressive symptoms, and tobacco abstinence. *The Journal of Positive Psychology, 5*(2), 122-138.

Noe, R. A. (2000). Toward an integrative theory of training motivation: A meta-analytic path analysis of 20 years of research. *Journal of Applied Psychology, 85*(5), 678-707.

Nokes, T. J. (2009). Mechanisms of knowledge transfer. *Thinking & Reasoning, 15*(1), 1-36.

Novick, L. R. (1988). Analogical transfer, problem similarity, and expertise. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14*(3), 510-520.

Obama, B. (2009, Sept 8). Prepared Remarks of President Barack Obama: Back to School Event. Arlington, VA. Retrieved March 10, 2012 from the White House Media Resources Archives: http://www.whitehouse.gov/MediaResources/PreparedSchoolRemarks.

Osman, M. (2008). Positive transfer and negative transfer/antilearning of problem-solving skills. *Journal of Experimental Psychology General, 137*(1), 97.

Pajares, F. (1996). Self-efficacy beliefs and mathematical problem-solving of gifted students. *Contemporary Educational Psychology, 21*, 325-344.

Pajares, F. (1996). Self-efficacy beliefs in academic settings. *Review of Educational Research, 66*(4), 543.

Pajares, F., & Graham, L. (1999). Self-efficacy, motivation constructs, and mathematics performance of entering middle school students. *Contemporary Educational Psychology, 24*, 124-139.

Pajares, F., & Miller, M. D. (1994). Role of self-efficacy and self-concept beliefs in mathematical problem solving: A path analysis. *Journal of Educational Psychology, 86*, 193-193.

Pape, S. J., & Wang, C. (2003). Middle school children's strategic behavior: Classification and relation to academic achievement and mathematical problem solving. *Instructional Science, 31*(6), 419-449.

Patrick, B. C., Skinner, E. A., & Connell, J. P. (1993). What motivates children's behavior and emotion? Joint effects of perceived control and autonomy in the academic domain. *Journal of Personality and Social Psychology, 65*(4), 781-791.

Pea, R. D. (1987). Socializing the knowledge transfer problem. *International Journal of Educational Research, 11*(6), 639-663.

Pearson. (2008). *New York state regents examination in integrated algebra: Technical report on reliability and validity* (Technical Report. Albany, NY: The University of the State of New York. Office of Assessment Policy, Development, and Administration.

Perels, F., Gürtler, T., & Schmitz, B. (2005). Training of self-regulatory and problem-solving competence. *Learning and Instruction, 15*(2), 123-139.

Pieschl, S., Stahl, E., & Bromme, R. (2008). Epistemological beliefs and self-regulated learning with hypertext. *Metacognition and Learning, 3*(1), 17-37.

Pintrich, P. R. (1988). A process-oriented view of student motivation. *Improving Teaching and Learning through Research: New Directions for Instructional Research, 57*, 65-79.

Pintrich, P. R. (1989). The dynamic interplay of student motivation and cognition in the college classroom. In C. Ames, & M. Maehr (Eds.), *Advances in motivation and achievement: Vol 6. Motivation enhancing environments* (pp. 117-160). JAI Press.

Pintrich, P. R. (1999). The role of motivation in promoting and sustaining self-regulated learning. *International Journal of Educational Research, 31*(6), 459-470.

Pintrich, P. R. (2000). Multiple goals, multiple pathways: The role of goal orientation in learning and achievement. *Journal of Educational Psychology, 92*(3), 544.

Pintrich, P. R. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. *Educational Psychology Review, 16*(4), 385-407.

Pintrich, P. R., Cross, D. R., Kozma, R. B., & McKeachie, W. J. (1986). Instructional psychology. *Annual Review of Psychology, 37*(1), 611-651.

Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology, 82*(1), 33-40.

Pintrich, P. R., & Schunk, D. (2002). The role of goals and goal orientation. *Motivation in Education: Theory, Research and Application (2nd Ed., Pp.190–242).* Englewood Cliffs, NJ: Simon & Schuster.

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the motivated strategies for learning questionnaire (MSLQ). *Educational and Psychological Measurement, 53*(3), 801.

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1991). A manual for the use of the motivated strategies for learning questionnaire (MSLQ). *Ann Arbor, Michigan.*

Pólya, G., & Conway, J. H. (2004). *How to solve it: A new aspect of mathematical method* Princeton, NJ: Princeton University Press.

Preacher, K. J., Zyphur, M. J., & Zhang, Z. (2010). A general multilevel SEM framework for assessing multilevel mediation. *Psychological Methods*, 15, 209-233.

Pugh, K. J., & Bergin, D. A. (2006). Motivational influences on transfer. *Educational Psychologist, 41*(3), 147-160.

Reigeluth, C. M. (1983). *Instructional-design theories and models: An overview of their current status*. New York: Lawrence Erlbaum.

Renkl, A. (2002). Learning from worked-out examples: Instructional explanations supplement self-explanations. *Learning & Instruction, 12*(5), 529-556.

Richman-Hirsch, W. L. (2001). Post-training interventions to enhance transfer: The moderating effects of work environments. *Human Resource Development Quarterly, 12*(2), 105-120.

Rittle-Johnson, B., Star, J. R., & Durkin, K. (2009). The importance of prior knowledge when comparing examples: Influences on conceptual and procedural knowledge of equation solving. *Journal of Educational Psychology, 101*(4), 836-852.

Riverside Publishing Company. (2008). *New York state regents examination in integrated algebra: Test design and development technical manual* (Technical Report. Albany, NY: The University of the State of New York. Office of Assessment Policy, Development, and Administration.

Rosenbaum, P. R. (2002). *Observational studies*. Springer Verlag.

Rosenthal, R. (1979). The “file drawer problem” and tolerance for null results. *Psychological Bulletin, 86*(3), 638-641.

Rosenthal, R., & Rosnow, R. L. (2009). The volunteer subject. *Artifacts in Behavioral Research: Robert Rosenthal and Ralph L.Rosnow's Classic Books,* 48.

Ross, S. M., & Anand, P. G. (1987). A computer-based strategy for personalizing verbal problems in teaching mathematics. *Educational Technology Research and Development, 35*(3), 151-162.

Ross, S. M., McCormick, D., Krisak, N., & Anand, P. (1985). Personalizing context in teaching mathematical concepts: Teacher-managed and computer-assisted models. *Educational Technology Research and Development, 33*(3), 169-178.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68-78.

Ryan, R. M., Patrick, H., Deci, E. L., & Williams, G. C. (2008). Facilitating health behaviour change and its maintenance: Interventions based on self-determination theory. *The European Health Psychologist, 10*, 2-5.

Ryan, R. M., Plant, R. W., & O'Malley, S. (1995). Initial motivations for alcohol treatment: Relations with patient characteristics, treatment involvement, and dropout. *Addictive Behaviors, 20*(3), 279-297.

Ryan, R. M., Stiller, J. D., & Lynch, J. H. (1994). Representations of relationships to teachers, parents, and friends as predictors of academic motivation and self-esteem. *The Journal of Early Adolescence, 14*(2), 226.

Salomon, G., & Perkins, D. N. (1987). Transfer of cognitive skills from programming: When and how? *Journal of Educational Computing Research, 3*(2), 149-169.

Salomon, G., & Perkins, D. N. (1989). Rocky roads to transfer: Rethinking mechanism of a neglected phenomenon. *Educational Psychologist, 24*(2), 113-142.

Sansone, C., & Thoman, D. B. (2005). Interest as the missing motivator in self-regulation. *European Psychologist, 10*(3), 175-186.

Sansone, C., Weir, C., Harpster, L., & Morgan, C. (1992). Once a boring task always a boring task? Interest as a self-regulatory mechanism. *Journal of Personality and Social Psychology, 63*(3), 379.

Saris, W.E., A. Satorra and W. van der Veld (2009), Testing Structural Equation Models or Detection of Misspecifications? *Structural Equation Modeling*, 16, 561-582.

Schiefele, U. (1991). Interest, learning, and motivation. *Educational Psychologist, 26*(3), 299-323.

Schiefele, U., Krapp, A., & Winteler, A. (1992). Interest as a predictor of academic achievement: A meta-analysis of research. *The Role of Interest in Learning and Development,* 183-212.

Schoenfeld, A. H. (1992). Learning to think mathematically: Problem solving, metacognition, and sense making in mathematics. *Handbook of Research on Mathematics Teaching and Learning,* 334-370.

Schraw, G., Horn, C., Thorndike-Christ, T., & Bruning, R. (1995). Academic goal orientations and student classroom achievement. *Contemporary Educational Psychology, 20*(3), 359-368.

Schraw, G., & Lehman, S. (2001). Situational interest: A review of the literature and directions for future research. *Educational Psychology Review, 13*(1), 23-52.

Schumacker, R. E., & Lomax, R. G. (2004). *A beginner's guide to structural equation modeling* New York: Lawrence Erlbaum.

Schunk, D. H. (1995). Inherent details of self-regulated learning include student perceptions. *Educational Psychologist, 30*(4), 213-216.

Schwartz, D. L., Bransford, J. D., & Sears, D. (2005). Efficiency and innovation in transfer. *Transfer of Learning from a Modern Multidisciplinary Perspective,* 1-51.

Shadish, W. R., & Cook, T. D. (1999). Comment-design rules: More steps toward a complete theory of quasi-experimentation. *Statistical Science, 14*(3), 294-300.

Shapiro, A. M. (2004). How including prior knowledge as a subject variable may change outcomes of learning research. *American Educational Research Journal, 41*(1), 159-189.

Shoemaker, P. J., Tankard, J. W., & Lasorsa, D. L. (2004). *How to build social science theories.* Sage Publications, Inc.

Singley, M. K., & Anderson, J. R. (1989). *The transfer of cognitive skill*. Cambridge, MA: Harvard University Press.

Snow, R. E. (1994). Individual differences in conflation: Selected constructs and measures. *Motivation: Theory and Research,* 71–99.

Snow, R. E., Corno, L., & Jackson, D. (1996). Individual differences in affective and conative functions. *Handbook of Educational Psychology, 9*, 243-310.

Star, J. R., & Rittle-Johnson, B. (2008). Flexibility in problem solving: The case of equation solving. *Learning and Instruction, 18*(6), 565-579.

Stevens, C. K., & Gist, M. E. (1997). Effects of self-efficacy and goal orientation training on negotiation skill maintenance: What are the mechanisms? *Personnel Psychology, 50*(4), 955-978.

Sweller, J. (2008). Human cognitive architecture. *Handbook of Research on Educational Communications and Technology,* 369-381.

Sweller, J., Van Merrienboer, J. J. G., & Paas, F. G. W. C. (1998). Cognitive architecture and instructional design. *Educational Psychology Review, 10*(3), 251-296.

Syracuse University Office of Institutional Research & Assessment. (2010). *Facts brochure 2009-2010.* Retrieved December, 2010, from https://oira.syr.edu/Reporting/Facts.htm

Thoemmes, F., MacKinnon, D.P., & Reiser, M.R. (2010). Power Analysis for Complex Mediational Designs Using Monte Carlo Methods. *Structural Equation Modeling*, 17(3), 510-534.

Thorndike, E. L. (1906). *The principles of teaching: Based on psychology*. AG Seiler.

Thorndike, E. L., & Woodworth, R. S. (1901). *The influence of improvement in one mental function upon the efficiency of other functions.* New York: MacMillan.

Thorndike, E. L., & Woodworth, R. S. (1901). The influence of improvement in one mental function upon the efficiency of other functions. *Psychological Review, 8*, 247-261.

Tomarken, A. J., & Waller, N. G. (2005). Structural equation modeling: Strengths, limitations, and misconceptions. *Clinical Psychology, 1*, 31-65.

Trendler, G. (2009). Measurement theory, psychology and the revolution that cannot happen. *Theory & Psychology, 19*(5), 579.

Tuomi-Gröhn, T., Engeström, Y., & Young, M. (2003). From transfer to boundary-crossing between school and work as a tool for developing vocational education: An introduction. *Between School and Work: New Perspectives on Transfer and Boundary-Crossing,* 1–15.

Usher, E. L., & Pajares, F. (2008). Sources of self-efficacy in school: Critical review of the literature and future directions. *Review of Educational Research, 78*(4), 751.

van der Meij, J., & de Jong, T. (2006). Supporting students' learning with multiple representations in a dynamic simulation-based learning environment. *Learning and Instruction, 16*(3), 199-212.

van Merriënboer, J. J. G. (1997). *Training complex cognitive skills: A four-component instructional design model for technical training*. Englewood Cliffs, NJ: Educational Technology Publications.

Vandewalle, D. (1997). Development and validation of a work-domain, goal-orientation instrument. *Educational and Psychological Measurement, 57*(6), 995.

VandeWalle, D., Cron, W. L., & Slocum, J. W. (2001). The role of goal orientation following performance feedback. *Journal of Applied Psychology, 86*(4), 629-640.

Vansteenkiste, M., & Deci, E. L. (2003). Competitively contingent rewards and intrinsic motivation: Can losers remain motivated? *Motivation and Emotion, 27*(4), 273-299.

Veenman, M. V. J., Van Hout-Wolters, B. H. A. M., & Afflerbach, P. (2006). Metacognition and learning: Conceptual and methodological considerations. *Metacognition and Learning, 1*(1), 3-14.

Veenman, M., Prins, F., & Elshout, J. (2002). Initial inductive learning in a complex computer simulated environment: The role of metacognitive skills and intellectual ability. *Computers in Human Behavior, 18*(3), 327.

Vollmeyer, R., & Rheinberg, F. (2000). Does motivation affect performance via persistence? *Learning and Instruction, 10*(4), 293-309.

Wagner, J. F. (2006). Transfer in pieces. *Cognition and Instruction, 24*(1), 1-71.

Weiner, B. (1985). An attributional theory of achievement motivation and emotion. *Psychological Review, 92*(4), 548-573.

Wigfield, A. (1994). Expectancy-value theory of achievement motivation: A developmental perspective. *Educational Psychology Review, 6*(1), 49-78.

Williams, G. C., & Deci, E. L. (1996). Internalization of biopsychosocial values by medical students: A test of self-determination theory. *Journal of Personality and Social Psychology, 70*(4), 767-779.

Williams, G. C., Saizow, R., Ross, L., & Deci, E. L. (1997). Motivation underlying career choice for internal medicine and surgery. *Social Science & Medicine, 45*(11), 1705-1713.

Williams, G. C., Wiener, M. W., Markakis, K. M., Reeve, J., & Deci, E. L. (1994). Medical students' motivation for internal medicine. *Journal of General Internal Medicine, 9*(6), 327-333.

Wilson, B. D. (2006). *Contextual student differences and scoring patterns of the motivated strategies for learning questionnaire (MSQL).* Unpublished doctoral dissertation. Oklahoma State University,

Winne, P. H. (1995). Inherent details in self-regulated learning. *Educational Psychologist, 30*(4), 173-187.

Winne, P. H. (2001). Self-regulated learning viewed from models. *Self-Regulated Learning and Academic Achievement: Theoretical Perspectives,* 153.

Winters, F. I., Greene, J. A., & Costich, C. M. (2008). Self-regulation of learning within computer-based learning environments: A critical analysis. *Educational Psychology Review, 20*(4), 429-444.

Wolters, C. A. (2004). Advancing achievement goal theory: Using goal structures and goal orientations to predict students' motivation, cognition, and achievement. *Journal of Educational Psychology, 96*(2), 236-250.

Wong, R. M. F., Lawson, M. J., & Keeves, J. (2002). The effects of self-explanation training on students' problem solving in high-school mathematics. *Learning and Instruction, 12*(2), 233-262.

Yamkovenko, B., & Holton, E. (2010). Toward a theoretical model of dispositional influences on transfer of learning: A test of a structural model. *Human Resource Development Quarterly, 21*(4), 381-410.

Zeldman, A., Ryan, R. M., & Fiscella, K. (2004). Motivation, autonomy support, and entity beliefs: Their role in methadone maintenance treatment. *Journal of Social and Clinical Psychology, 23*(5), 675-696.

Zimmerman, B. J. (1995). Self-regulation involves more than metacognition: A social cognitive perspective. *Educational Psychologist, 30*(4), 217-221.

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13-40). New York: Guilford Press.

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal, 45*(1), 166.

Zimmerman, B. J., & Martinez-Pons, M. (1990). Student differences in self-regulated learning: Relating grade, sex, and giftedness to self-efficacy and strategy use. *Journal of Educational Psychology, 82*(1), 51-59.

VITA

John A. Gonzalez

AREAS OF EXPERTISE
Core Competencies: Research design, instructional design theory, educational technology, advanced quantitative methods, evaluation theory, data management, data systems, project management
Applications: SAS, SPSS, R, Excel, Power Point, Word, AMOS, Tableau, MS Project, Dreamweaver, Flash, Photoshop, Blackboard, Moodle, Premiere, Screenflow, Camtasia
Programming Languages: PHP, HTML, XML, Visual Basic, VbScript, ASP, Java, JavaScript, VBA, Python, C++, Lingo, ActionScript, Eiffel, Perl

EDUCATION

Ph.D. Instructional Design, Development and Evaluation June 2012
Syracuse University, Syracuse NY
Dissertation: Mechanisms of Transfer: Modeling Motivational and Self-Regulatory Processes of Mathematical Problem-Solving

M.S. Mathematics Education August 2006
City University of New York at Brooklyn College, Brooklyn NY

B.S. Information Technology May 2002
Rochester Institute of Technology, Rochester NY
Concentrations: Learning Performance Technologies and Technical Communications

RELEVANT EXPERIENCE

Senior Research Associate – Progress Reports August 2011 – Present
New York City Department of Education, New York, NY

- Supported policy-making process by providing methodological and statistical guidance
- Managed development, implementation, and support of multiple products use to evaluate and communicate performance data with multiple stakeholders
- Conducted forecasting and simulation analysis to assess immediate and long-term impact of Progress Report policies

University / McNair Doctoral Fellow September 2007 – May 2011
Syracuse University, Syracuse, NY

- Managed implementation of longitudinal research project that included supervising junior graduate students, and coordinating project logistics
- Led analytical efforts that produced publications and papers presented at national conferences
- Developed, data collection instruments, and administered research protocols and surveys

Instructional Technologist May 2008 – December 2010
Syracuse University Project Advance (SUPA), Syracuse, NY

- Conducted needs assessments and front-end analysis activities in order to design instructional solutions. These activities included interviews with faculty and students, document analysis, and review of existing materials
- Collaborated with faculty and assistant directors to design, develop, and evaluate instructional materials to support a college learning strategies course
- Supported faculty implementation of various instructional projects that required used of advanced technologies such as blogging, podcasting, collaborative journaling, filming, and editing

Mathematics Teacher and Technology Coordinator June 2004 – August 2007
New York City Department of Education, New York, NY

- Taught mathematics and technology courses with emphasis on the development of problem-competencies
- Delivered professional development sessions on the use of various tools to enhance instruction

Junior Project Manager Sept 2002 – April 2003
IBM, Westford, MA

- Supported development operations across a large software development team by coordinating logistics, updating project plans, and managing technical resources
- Generated state of the business reports, and security plan implementations for software development product lines
- Developed and implemented metrics-reporting tools and reports that were used by management and other stakeholders to assess status of software products

PUBLICATIONS

- Gonzalez, J., Koszalka, T.A., Arnone, M., & Bellini, J. (In preparation). Conceptualizing and Measuring Transfer in a Theme-Based After School Program
- Gonzalez, J. (In preparation). Interest, Goals, and Self-Efficacy: A Motivational Approach to Transfer of Learning
- Gonzalez, J., & Bellini, J.L. (In preparation). The Fit Question: A Primer for Diagnosing Sources of Misfit in Structural Equation Modeling.

REFEREED CONFERENCE PRESENTATIONS

- Gonzalez, J. (Nov 2010). Mechanisms of Knowledge Transfer: Modeling Motivational & Prior Knowledge Effects. Association for Educational Communications and Technology, Anaheim, CA.
- Gonzalez, J. (Nov 2009). Lessons learned from developing a knowledge transfer measurement instrument and methodology. Association for Educational Communications and Technology. Louisville, KY
- Koszalka, T., Arnone, M., & Gonzalez, J (Nov 2009). Exploring Curiosity Creek©: Interdisciplinary design-based research creating instructional resources for informal learning. Association for Educational Communications and Technology. Louisville, KY
- Koszalka, T., Arnone, M., & Gonzalez, J (Nov 2009). AECT Design and Development Showcase: Innovative Training and Educational Programs for Curiosity Creek. Association for Educational Communications and Technology. Louisville, KY
- Gonzalez, J., Wu, C.P., & Wu, Y. (Oct 2007). Evaluating teacher knowledge in technology-integrated instruction – TPCK. Syracuse University Research Symposium. Syracuse University, Syracuse, NY

OTHER PROFESSIONAL PRESENTATIONS

- Gonzalez, J., & Souders, D. (July 2010). Visualizing Fractions: Linking Multiple Representations with Auditory Guidance. LearnLab Summer School. Carnegie Mellon University, Pittsburgh, PA
- Gonzalez, J. (Oct 2008). Educational Simulations: Elements that affect the transfer of knowledge. IDD&E brown bag seminar, Syracuse, NY
- Gonzalez, J., Wu, C.P., & Wu, Y. (Oct 2007). Evaluating teacher knowledge in technology-integrated instruction – TPCK. Graduate seminar presentation to visiting teachers and administrators from Thailand, Syracuse, NY
- Gonzalez, J. & Raphael, J. (Feb 2008). Reinventing the Workshop Model: Techniques to teach algebraic systems of equations. Professional development session. Frederick Douglas Academy VII, Brooklyn, NY.
- Gonzalez, J. (Oct 2006). Instructional uses of the Smartboard. Professional development session. Frederick Douglas Academy VII, Brooklyn, NY
- Gonzalez, J., & Purtill, M. (March 2006). Creating a digital community through partnerships: ON_DEC tech academy featuring City of the Future. Celebration of Teaching and Learning, New York, NY.
- Winter, L., Gonzalez, J. & Purtill, M. (January 2006). The ON_DEC tech academy: Lego Robotics. Presentation to Sleigh Middle School, Tampa, FL

SERVICE ACTIVITIES

- March 2012: Founder and Coordinator, Analytics Club. New York City Department of Education. New York, NY
- November 2011 – Present: Member, Institutional Review Board. New York City Department of Education. New York, NY
- March 2010: Proposal Reviewer, AECT

- Nov 2009: Student Volunteer, AECT Annual Conference. Louisville, KY
- Fall 2009 – Spring 2010 Co-chair, Qualifying exams study group. IDD&E. Syracuse University
- Summer 2009 Chair, Student Orientation Planning Committee. IDD&E. Syracuse University
- Spring 2009 – Fall 2009: Student Representative, Tenure & Promotion Teaching committee for Dr. E. Dekaney. School of Education. Syracuse University.
- Fall 2008 – Present: Co-chair, Student Activities Committee. IDD&E. Syracuse University
- Nov 2008: Student Volunteer, AECT Annual Conference. Orlando, Fl
- Sep 2008 – May 2009: Doctoral Student Body Representative, IDD&E. Syracuse University
- Aug 2008: Orientation Committee Volunteer, IDD&E. Syracuse University
- Spring 2008: ID competencies data analyst. IDD&E. Syracuse University
- Spring 2008: IDD&E Faculty Search Committee Volunteer, IDD&E. Syracuse University
- Spring 2008: Co-organizer, Small Group Collaboration Study Group, IDD&E. Syracuse University
- Spring 2008 : Co-Chair, Research Seminar Coordinating Committee, IDD&E. Syracuse University
- Fall 2007 : Brown bag planning committee, IDD&E, Syracuse University

TEACHING

- Summer 2010: Adjunct Instructor. ITT Technical Institute. College Mathematics I and II
- Spring 2010: Graduate Teaching Assistant. Syracuse University Future Professoriate Program. EDU 792: Advanced Quantitative Methods. Supervised by Dr. J. Bellini
- Fall 2009: Graduate Teaching Assistant. Syracuse University Future Professoriate Program. IDE 621: Principles of Instruction & Learning. Supervised by Dr. T. Koszalka

OTHER PROFESSIONAL ACTIVITIES

- Aug 2009 – Oct 2009: Research Assistant – Performed mixed-methods data analysis activities for a sponsored research project.
- Feb 2009 – May 2009: Technology Consultant – David Grover Professional Therapies.
- Feb 2008 – May 2008: External Evaluator E*Lit Project – Center for Digital Literacy
- Sep 2007 – Apr 2008: SAT Tutor - Huntington Learning Center
- Sep 2006 – May 2007: Stock Market Game Student Advisor - Frederick Douglass Academy VII
- Oct 2006 – May 2007: Math Regents Tutor – Frederick Douglass Academy VII
- Nov 2004 – May 2006: Teacher Advisor - Ditmas Middle School City of the Future Program
- Jan 2005 – Aug 2005: Lead Teacher - Ditmas Middle School Lego Robotics Enrichment Program

MEMBERSHIPS

- Association for Educational Communications and Technology (AECT)
- American Educational Research Association (AERA)
- Society of Hispanic Professional Engineers (SHPE)

CERTIFICATIONS

- New York State Professional Certification in Mathematics Grades 5-9

AWARDS

- 2010 – 2011 McNair Scholar
- 2007 – 2010 Syracuse University Graduate Fellowship
- 2008 - 2009 William Millard Instructional Technology Graduate Scholarship
- 2004 – 2005 Americorps Education Service Award
- 2004 – 2006 New York City Teaching Fellowship
- 1998 – 2002 RIT Presidential Scholarship