Motivation correlates of academic achievement: Exploring how motivation influences academic achievement in the PISA 2003 dataset

by

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B.Sc., University of Victoria, 1994

M.A., University of Victoria, 2003

A Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

DOCTOR OF PHILOSOPHY

in the Department of Educational Psychology and Leadership Studies

Supervisory Committee

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Abstract

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The relationship between achievement motivation and academic achievement is complex, but generally, the more a student is motivated to do an academic task, the greater the effort, persistence, and use of cognitive strategies expended on the task, and the better the performance on the task (Pintrich, 2003). The majority of achievement motivation research has been conducted in Western countries (Kumar, 2004). This is a concern as North American classrooms are become increasingly culturally diverse. The present study looked at the relationships between motivation and academic achievement in two distinct cultures: Western (Canada, the United States, and the United Kingdom) and Asian (Hong Kong-China, Japan, and Korea). Hierarchical linear modeling (HLM) was used to analyze data from the Programme for International Student Assessment 2003 (PISA; OECD, 2004). The outcome measures used for all countries were achievement scores in mathematics, science, reading, and problem-solving. The variables examined at the student level were instrumental and intrinsic motivation, performance orientation, and self-efficacy. The variables examined at the school level were teacher support, student morale, and teacher behaviours affecting school climate. In the null models, the intraclass correlations for the Western countries were consistently lower (ranging from .17 to .27) than for the Asian countries (ranging from .36 to .53). In the final HLM models, at Level 1, intrinsic motivation predicted an increase in scores for all six of the Asian country models in which it was significant, but results were inconsistent for the Western country models. Instrumental motivation predicted an increase in scores in seven of the Western country models, but was not significant in any of the Asian country models. Performance orientation predicted a decrease in score in all of the Western country models and in seven of the Asian country models. Self-efficacy predicted increased scores for all models for all countries. All Level 1 results were similar across all academic domains. At Level 2, teacher support was significant in the models for Japan only. Results for teacher behaviours were inconsistent. Student morale was significant in all models for all countries. The findings from this study demonstrate that there are some distinct cultural differences in the relationships between achievement motivation and academic achievement.

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Acknowledgments

There are several people who helped in the process of writing and completing this dissertation. First, my deeply felt thanks and appreciation for all of the time and encouragement given to me by my supervisor, Dr. John O. Anderson. I could not ask for a better mentor. I would also like to thank my committee members, Dr. C. Brian Harvey, Dr. Allyson Hadwin, and Dr. Ronald Skelton, for the time they contributed, and for the valuable feedback and guidance they gave me in my research. A special thank you also to Dr. Larry Yore, who was a generous supporter of my research.

My gratitude also goes out to several members of the department. The faculty and support staff have been instrumental in my success in graduate school, especially Zoria Crilly, who has been a great graduate secretary and cheering section. I would not have completed this dissertation without the help of my fellow graduate students, particularly my fellow research lab member, Todd Milford.

I would further like to acknowledge the Social Sciences and Humanities Research Council of Canada for awarding me a SSHRC Doctoral Fellowship, which partially funded the writing of this dissertation, and for providing funding to the COLO project, which funded the research that preceded this dissertation. Funding was also generously provided by the National Sciences and Engineering Research Council of Canada (through the CRYSTAL Project).

Finally, I express my deepest thanks to my family: to my husband and children, for their love, patience, and support; and to my parents, who have been unfailingly helpful and encouraging.

Dedication

This dissertation is dedicated to the little people:

- to Robert, who has spent his first decade hanging out at the University of Victoria, and has been there with me through two graduate degrees and teacher training;

- to Ross, who arrived at the beginning of my doctoral program, and helped me keep my sense of humour;

- to Piper, who arrived at the end, and has been very patient about sharing her Mom with the computer.

And to Greg, a great “civilian” husband.

Chapter 1: Introduction

Educators, particularly those who work with adolescents, are charged with a difficult task: to deliver a set curriculum to a group of students who often do not want to be in the classroom. This is important since the curriculum being taught lays a foundation for future formal education. How can a teacher get a group of students to engage with the material being taught? How can a teacher get students to want to master and fully understand the material, rather than learn just enough to pass a test or assignment and move on? It is with the aim of understanding what is involved in getting students to engage more fully and deeply with classroom material and tasks that educational psychologists seek to understand motivation.

Motivation has long been of interest to research psychologists and educators. Initial psychological research into motivation examined the idea of needs, goals or incentives, and direction. Both Hull's Drive Theory (Hull, 1951) and Lewin's Field Theory (Lewin, 1936), reduced motivation to mathematical formulae aimed at predicting behavior. This work evolved over time to include more complex human behaviours across a spectrum of domains. In particular, Atkinson's Theory of Achievement Motivation (1964) expanded research in motivation to include the idea of individual differences. While Atkinson intended to develop a general theory of motivation (Atkinson, 1964), his research focused on academic tasks.

Educational researchers have continued the work begun by psychological researchers, particularly Atkinson, but refined the target of motivation to the area of academic achievement; primarily, the examination of what motivates students in the classroom. Several theories have been developed that attempt to explain how and why students are motivated: self-efficacy theory (Bandura, 1986, 1997), self-worth theory (Covington, 1984), expectancy-value theory (Eccles, 2005), attribution theory (Weiner, 1985), and achievement goal theory (Ames & Archer, 1988; Dweck & Leggett, 1988; Midgely et al., 1998; Nicholls, 1984). Research findings from studies based in these various theories have increased our understanding of the advantages and positive consequences of motivation.

One of the universal findings from the motivation research discussed above is that increased motivation in students leads to the use of deeper processing strategies and more complete understanding of material taught in classrooms (Pintrich & DeGroot, 1990; Wolters et al., 1996; Zimmerman et al., 1992). These students usually show better achievement on assigned tasks and tests (e.g., O'Sullivan and Howe, 1996; Zimmerman & Bandura, 1994). Evidence suggests that increased motivation in students can lead to improved overall academic achievement.

A limitation of research linking motivation to improved academic achievement is that it has predominantly focused on North America and other Western cultures; there are limited studies of motivation in other cultures (Kumar, 2004). This is of concern, as North American classrooms are becoming increasingly diverse; in particular, one third of immigrants to Canada and the United States are originally from Asian countries (Citizenship and Immigration Canada, 2006; Department of Homeland Security, 2006). There are only a handful of studies of academic motivation in Asian students studying in Western classrooms (e.g., d'Ailly, 2003; Dandy & Nettlebeck, 2000; Eaton & Dembo, 1999); there are even fewer studies published in English examining motivation in Asian students in classrooms in their home countries (e.g., Lam, Yim, Law, & Cheung, 2004; Leung, 2002; Rao, Moely, & Sachs, 2000; Rogers, 1998). Studies of motivation in Asian students have found that while the same relationships exist between motivation and deeper learning strategies, low motivation does not necessarily mean low academic achievement (Eaton & Dembo, 1999). This discrepancy bears further investigation if we are to understand how and why to foster motivation in a culturally diverse classroom.

One avenue for examining the relationship between motivation and student achievement across cultures is provided by large scale assessments, such as the Programme for International Student Assessment (PISA), conducted by the Organisation for Economic Co-operation and Development (OECD; OECD, 2004). The PISA program is a large scale assessment of academic achievement that targets three academic domains: reading, mathematical, and scientific literacy. PISA is conducted on a three year cycle; each cycle focuses on one academic domain, but students answer questions from across all three academic domains. The first PISA administration was in 2000, and primarily focused on reading literacy with a limited set of questions addressing mathematical and scientific literacy. PISA 2003 focused primarily on mathematical literacy, and introduced a cross-disciplinary problem-solving domain. The 2006 administration of PISA focused on scientific literacy. Forty-three countries participated in the PISA 2000 cycle, 41 countries participated in the PISA 2003 cycle, and 57 countries participated in the PISA 2006 cycle.

In addition to academic assessment, students are also asked questions about their home and school learning environments, demographic information, and their attitudes and beliefs about school and learning. Principals of participating schools also answered questions about the school and its environment, as well as the demographics of the area in which the school is located.

The PISA dataset provides data for examining the correlates of student achievement both within and across countries. The inclusion of student self-reports of attitudes and beliefs about school and school subjects allows researchers to examine how select attitudes and beliefs, such as motivation and self-efficacy, contribute or are related to academic outcomes. The nature of the assessment – a standardized test given under the same conditions to all students in all participating countries – also allows for comparison of findings across or among participating countries. Most importantly, the size of the sample from each participating country increases confidence in generalizing findings (OECD, 2003).

The purpose of this study is to examine the relationship between motivation and student achievement in reading, math, and science across six different countries. Specifically, this research examines the relationship between student level instrumental and intrinsic motivation, self-efficacy, and performance orientation indices and academic achievement as measured in the PISA 2003 dataset across Canada, the United States, the United Kingdom, Hong Kong-China, Japan, and Korea. This study also explores how school climate, teacher support, and student morale and commitment influence those relationships. The findings from this study are expected to allow for an examination of the generalizability of some components of theories of motivation, as well as provide some insight into the relationship of motivation to student achievement in both Western and Asian countries.

Chapter 2: A review of achievement motivation research

In psychology, motivation is defined as “a construct used to describe the strength or willingness with which an animal engages in behaviour” (Toates, 1987, p.7). Motivation has been defined in two ways: as a *trait* (Dykman, 1998) or individual set personality characteristic; or as a *state* (Bandura, 1986) or temporary domain-specific response to a specific task. The definition depends on the perspective of the research being conducted. In the context of educational research, motivation is one of the factors contributing to the way students approach an academic task. Students usually do not have a choice as to whether or not they complete a task in the classroom; if it is assigned, and the student wants to pass, the student must complete the task. Pintrich and Schunk (2002) suggest that when discussing motivation in the classroom, the focus shifts from traditional views of intrinsic or extrinsic motivation in psychology, i.e., whether a task is completed because of external rewards or internal satisfaction, because the task itself must be completed whether the student wants to do it or not. Rather, in the academic context, educational researchers are not interested in whether or not, or why, the student is motivated to do the task, but are instead interested in the process and behaviours that students demonstrate as they complete the task (Pintrich & Schunk, 2002). In the academic context, motivation concerns how thoroughly and deeply a student learns while completing a required academic task. In this context, motivation consists of: (a) *choices* that a student makes in how to approach the task, such as meeting a minimum standard or fully engaging in a deeper understanding and learning of the topic of the task; (b) *persistence* at the task, including continuing to work at the task even in the face of challenge or potential failure; and (c) *effort* on the task, including deciding what interim and long-term goals to set (implicitly or explicitly) as the student progresses through the task, and how the student decides that the task is complete. Educational and social psychology researchers examining motivation in this context refer to “achievement motivation” (Maehr, 1984).

Achievement motivation is comprised of three stages, which happen in the context of an academic task: initiation of a behaviour, direction of the behaviour (either towards or away from completing the task), and persistence at the task (Pintrich, 2003). Generally, the more a student is motivated to do a task, the more deeply the student learns, and the better the performance on the task. The precise metacognitive or learning processes involved in completing a specific task are not always of direct concern to theorists in achievement motivation; rather, achievement motivation focuses on the relationship between motivation and learning through the choice of task, persistence at the task, effort expended on a task, and response upon completion of a task.

Research into achievement motivation proceeds from a variety of theoretical frameworks, all of which have the same general goal: to discover how motivation in the classroom can be instilled, increased or improved, with the aim of improving student learning and performance. This goal is sought through theory development, based on both classroom and laboratory experiments. The findings from these types of experiments form the building blocks for further development of the theory in which a experiment is grounded; when hypotheses are supported or found to be unsupported by the data, researchers gain further understanding of achievement motivation. Three theories that are referred to repeatedly in academic motivation research are expectancy-value theory, achievement goal theory, and self-efficacy theory. The following sections describe some of this research, as well as similarities among some of the theories. Classroom influences on student motivation are considered, as well as cultural differences in motivation. Finally, some ways of examining cultural differences in motivation are discussed.

Current constructs in motivation research

In examining achievement motivation using the PISA 2003 dataset, research is constrained by the variables available in the dataset. Motivation in the PISA dataset is directly measured as instrumental motivation, intrinsic motivation, self-efficacy, and performance orientation (measured by preference for competitive learning situations) (OECD, 2003). These variables are founded in three current predominant theories of achievement motivation: expectancy-value theory (Eccles & Wigfield, 2002), achievement goal theory (goal orientation) (Ames, 1992; Dweck & Leggett, 1988; Nichols, 1984), and self-efficacy theory (Bandura, 1986). This section provides a description of each theory; a brief examination of the similarities amongst the theories; and a discussion of how the relationship between school and classroom environment and motivation in students.

A brief historical overview of motivation

The earliest theories of motivation were based around the idea of needs, goals or incentives, and direction. Both Hull’s Drive Theory (Hull, 1951) and Lewin’s Field Theory (Lewin, 1936, as cited in Graham & Weiner, 1996) reduced motivation to mathematical formulae aimed at predicting behavior. Hull’s work looked at basic laws of motivation across organisms;

Lewin's work examined complex human behavior. Work based in both these theories laid the foundation for the experimental examination of motivation.

Tolman and his colleagues (Tolman, 1952; Tolman & Postman, 1954) introduced the idea of expectancies – that animals learn what will happen after a certain response is made, and develop expectancies for the results of that response. Tolman also introduced the idea that types of incentives influence behaviour. This concept began to replace the idea of habits in learning, and indicated a shift to a cognitive view of motivation. Tolman's work laid the foundation for expectancy-value theory: the response or behavior in a situation depends both on the probability that one's actions will lead to a specific goal, and on the value of that goal to the individual performing the behaviour.

Atkinson's Theory of Achievement Motivation (1964) expanded research in motivation to include the idea of individual differences. Atkinson also expanded the idea of expectancy, by suggesting that expectancy varies depending on the difficulty of a task. While Atkinson intended to develop a general theory of motivation (Atkinson, 1964), his research focused on academic tasks. This has resulted in Atkinson having a strong influence on educational psychologists, and his concept of expectancy is incorporated in current motivational constructs.

Expectancy-value theory

Using Atkinson's theory as a foundation, Eccles and colleagues developed expectancy-value theory (Eccles, 2005; Eccles & Wigfield, 2002; Wigfield & Eccles, 1992, 2000). This theory states that the tasks that a learner chooses and persists at, as well as the learner's performance on the chosen task, is explained by both the beliefs a student holds about their expectations for success on a task, and by the degree of value that the learner places on the task. These expectancies and values will affect what tasks a learner chooses, performance on the task, and persistence on the task in face of challenge or tedium. Expectancies as described in this theory are similar to those in Atkinson (1964); it is in the area of task value that Eccles and colleagues have expanded on classical expectancy-value frameworks.

According to Eccles and Wigfield's (2002) series of studies with United States school children and college students, choice of task is based on the characteristics of the task (difficulty level), and all choices have a cost (because making one choice usually eliminates another possible choice). Because of the cost of making a choice, the value of the task and the expectancies for success on the task determine what task a learner will choose. The task-specific beliefs that a learner has, such as beliefs about their own competence, and perceptions of the difficulty of the task and its alternatives, and the outcomes that the learner expects (positive or negative), will also affect task choice and persistence. The learner exists in a social milieu, so expectancies and values are also related to perceptions of others' expectations. Finally, the learner's previous experiences will also influence his or her expectancies for success.

Eccles and colleagues (see Eccles & Wigfield, 2002) suggest that task-value has four dimensions. These dimensions are "attainment value", or the importance to the individual (their self-worth or self-schema) of accomplishing the task, "intrinsic value", or the enjoyment derived from the task, "utility value", or the relevance of the task to present or future goals, and "cost", the potential negative impacts of the task, which includes the effort needed, the anxiety induced by the task, and the loss of other opportunities that result from choosing one task over another.

The expectancy-value model has been used to explain the decline in motivation as students progress through school. Eccles and colleagues (1998) found that students' beliefs in their own competence, and their expectancies for success also decline, as they move from elementary school to middle school in the American school system. They also found that the children in their studies valued certain academic tasks less as they got older (Eccles et al., 1998; Wigfield & Eccles, 1992). While the causes for these declines vary, it is possible that children become more realistic in their self-judgments as they mature (Stipek & MacIver, 1989), and that the increasingly competitive atmosphere in higher grades will lead to a decrease in students' self-assessments of their own abilities (Eccles et al., 1993).

In their research with students in mathematics classrooms, Eccles and colleagues found that the value that students place on a task predicts intentions and decisions to persist in mathematics (Meece, Wigfield, & Eccles, 1990; Wigfield & Eccles, 2000). As well, students' ability beliefs and expectancies for success were found to be strong predictors of grades in mathematics, even when previous experience was controlled for (Wigfield & Eccles, 2000).

While the expectancy-value theory research described above has been mostly theory development, rather than predicting achievement, other researchers have examined discrete parts of the expectancy-value theory model, particularly the concept of utility value. Utility value of a task is the value the task holds in attaining a bigger goal, such as a career goal (Wigfield & Eccles, 1992). An example of the influence of utility value would be a student who works very hard at a physics course and places high utility value on the course, not out of any intrinsic interest in physics, but because the course is a required prerequisite for veterinary college. Placing a high utility value on a task has been found to predict increased use of cognitive strategies (Pokay & Blumenfeld, 1990), and improved performance (Simons, DeWitte, & Lens, 2003).

The findings from expectancy-value theory are valuable in understanding differences in motivation, but expectancy-value theory is not a comprehensive theory of achievement motivation – and the theory is based predominantly on work with students in the United States.

Achievement Goal Theory

Achievement goal theory (or "goal theory") has become one of the leading perspectives in the study of motivation (Maehr, 2002; Pintrich & Schunk, 2002). The theory is based on the idea that individuals adopt implicit goals, or goal orientations, when faced with a task, and combines elements of self-efficacy, self-worth, attributions, and expectancy-value. There are two main goal orientations: the goal to look good as compared to others, and the goal to learn, to improve skills, or to gain knowledge (Ames & Archer, 1988; Dweck, 1999; Dweck & Leggett, 1988; Kaplan et al., 2002). Terminology varies across goal theory researchers; a performance goal is also known as an ego goal (Nichols, 1984), an ability-focused goal (Ames, 1992), an extrinsic goal (Pintrich et al., 1993), or a competitive goal (Roberts et al., 1996); a mastery goal is also called a learning goal (Dweck, 1999), a task goal (Nicholls, 1984), and an intrinsic goal (Pintrich et al., 1993). In this dissertation, the terms learning and performance goal orientation will be used.

Within performance goal orientation, a further bifurcation has been proposed (Elliot, 1999): performance-approach goal orientation, where an individual wants to do something because the individual knows he or she will do well; and performance-avoid goal orientation, where an individual avoids doing something because of a fear of failure and looking poorly as compared to others (Elliot, 1999, 2005). While this division has support amongst achievement motivation theorists (Elliot & Church, 1997; Elliot & Harackiewicz, 1996; Middleton & Midgley, 1997), the results from research have been mixed, and there is still debate about the ways that performance goals are operationalized and examined (Brophy, 2005).

The underlying reasons for the adoption of either a learning goal or a performance-avoid or -approach goal are thought to be perceptions and beliefs of self such as implicit theories of intelligence (Dweck & Leggett, 1988), feelings of self-worth (Covington, 1984, 2000), and fear of failure or of looking bad or low in ability (Elliot & Church, 1997; Elliot & Harackiewicz, 1996).

Research based in achievement goal theory has found that a learning goal orientation is positively related to self efficacy and task value (Midgley et al., 1998; Roeser et al., 1996; Wolters et al., 1996), cognitive strategy use (Bandalos et al., 2003; Patrick et al., 2001), self-regulated learning (Wolters et al., 1996), and other adaptive patterns of learning (see Urdan, 1997, for a review).

Performance-approach goals have been found to predict positive task value, self-efficacy, and use of cognitive and self-regulatory strategies (Wolters et al., 1996), and to predict final course grade (Harackeiwicz et al., 2002). Performance-avoid goals are not consistently predictive of positive academic functioning, and are generally considered to be related to maladaptive strategies and learning patterns (Elliot & Harackiewicz, 1996; Middleton & Midgley, 1997).

Most recent research in achievement goal theory has proposed multiple goals – the idea that performance-approach goals can combine with learning goals (Harackiewicz et al., 2002; Linnenbrink, 2005; Pintrich, 2000). Research from this field of study shows promise for producing more consistent results regarding performance goals (Harackiewicz & Linnenbrink, 2005; Riveiro et al., 2001), although some researchers have proposed that performance goals be completely re-evaluated to determine their predictive utility (Brophy, 2005).

Criticism of achievement goal theory has been directed at the resemblance of the theory to attribution theory, a theory of motivation proposed by Weiner (1985) that states that achievement motivation and emotion are inseparable, in that learners have emotional responses to the outcomes of a task, and that these response will affect and guide expectancies in the future. Weiner states that the reasons, or attributions, that a learner attributes to outcomes will affect how the learner will approach a similar task in the future. Performance-avoid goal orientation looks similar to consequences of stable attributions for failure, where learners blame unchangeable circumstances for their failures (Weiner, 1985). There is also a lack of consensus among achievement goal researchers regarding the number and dimensions of goal orientation (Harackiewicz et al., 2002; Elliott and Thrash, 2001), and whether performance goals are adaptive or mal-adaptive (Linnenbrink, 2005; Wolters, 2004). Recently, it has been suggested that the performance goal orientation dimension be dropped (Brophy, 2005).

Finally, a major criticism of goal theory is that some researchers operationalize goal orientations as domain-specific (Midgley et al, 1998), and state that goal orientation will vary depending on the specific task that students are working on. Others define goal orientations as dispositional traits (for example, Newton & Duda, 1999), and state that students have a characteristic way of approaching all academic tasks. This view of goal orientation is more akin to a personality trait than a case by case task-specific goal orientation as viewed by domain-specific researchers. This difference in the way that goal orientation is operationalized makes it difficult to compare studies, or to be certain that the same variable is being examined or measured.

Self-efficacy theory

Originally conceived as one component of Bandura's (1986, 1997) social-cognitive theory, self-efficacy is individual "judgments of … capabilities to organize and execute courses of action required to attain designated types of performances" (Bandura, 1986, p. 391). Self-efficacy is highly domain-specific, and varies from task to task, and even from time to time on the same sort of task. Bandura coined the term "self-efficacy" to encompass both the belief about personal ability in the face of a task, and the ideas of self-perception, domain-specific viewpoint, and goal-directed behaviour. Self-efficacy is positively related to effort, persistence, and resiliency; when self-efficacy is high, learners will exert effort in the face of difficulty, persist as long as they believe they have the skills to complete a task, and become more cognitively engaged when they perceive a task to be difficult (Bandura, 1986, 1997; Schunk, 1991;

Zimmerman, 2000). Self-efficacy affects individual choice of activities, motivation, and achievement outcomes (Bandura, 1997); in other words, as stated by Bandura, self-efficacy is not a theory of motivation, but self-efficacy is related to motivation. As a construct, self-efficacy is similar to task-specific self-concept from expectancy-value theory (Eccles et al., 1998). The key difference is that self-efficacy is much more situation-specific and changeable; Pintrich and Schunk (2002) refer to self-efficacy as a "microlevel instability of beliefs" (p. 165). According to Pintrich and Schunk (2002), self-efficacy varies by task, even within a specific academic context. For example, a student may have high self-efficacy for the problem-solving questions on a math test, but low self-efficacy for the straight computational problems on the same test. Overall motivation to do well (or poorly) on the test will probably not be influenced by the task-specific self-efficacy on the different types of problems, although persistence on the computational problems may not be as high as on other parts of the test.

As described by Bandura (1986), self-efficacy involves both a learner's judgment of "Can I do it? Do I have the skills and the competence?" and the learner's judgment of the anticipated outcome (such as satisfaction, a good grade, or praise). While it is optimal for motivation for a learner to be high in both self-efficacy and outcome expectations, it is possible to have any combination of self-efficacy and outcome expectation. When self-efficacy is low and outcome expectations are high, there can be affective consequences such as feelings of depression (Pintrich & Schunk, 2002); when both self-efficacy and outcome expectations are low, the learner can experience feelings of learned helplessness (Alloy et al., 1984), which has been consistently found to be detrimental to learning (Dweck & Leggett, 1988).

As learners experience success, their self-efficacy increases; as they experience failure, their self-efficacy decreases. When a task is novel or in the early stages, effort attributions on the part of learners, or incorporated in feedback, cause self-efficacy to increase. As skills develop, learners with high self-efficacy move to ability attributions, where they attribute outcomes to their own abilities (Bandura, 1997; Pintrich & Schunk, 2002). A meta-analysis of the relationship between self-efficacy and academic outcome by Multon, Brown, and Lent (1991) found a significant effect size for a positive relationship between self-efficacy and successful academic outcome. This suggests that self-efficacy plays a role in motivation and learning.

Researchers have found links between self-efficacy and achievement in mathematics (Pajares & Miller, 1994; Schunk, Hanson, & Cox, 1987), and in reading (Schunk, 1981). Zimmerman and colleagues (1992) found that self-efficacy for self-regulated learning affected students' self-efficacy for academic achievement, the goals students set for learning, and their eventual academic outcomes, with higher self-efficacy for self-regulated learning leading through these relationships to higher academic achievement. Higher self-efficacy beliefs lead to students setting higher goals for themselves (such as a self-reported expectation of a high grade on an assignment), and self-efficacy and goal-setting were predictive of final grades. Zimmerman and Bandura (1994) also found that setting high personal academic goals and self-efficacy were predictive of final grades in a college writing course. In a review of self-efficacy and learning, Zimmerman (2000) cites several examples of research that support the role of self-efficacy in self-regulated learning and successful achievement outcomes.

Self-efficacy may play a role in academic achievement by having an affect on strategy use. Pintrich and DeGroot (1990), and Zimmerman, Bandura, and Martinez-Pons (1992) found that among elementary and secondary school students, self-efficacy beliefs were positively related to strategy use, across all domains investigated.

Research using the self-efficacy construct has lately been concerned with how self-efficacy correlates with other achievement motivation variables, and the role self-efficacy plays in self-regulated learning, rather than on self-efficacy as a motivator in and of itself. Bong (1996;

2001) found that self-efficacy, task value, and achievement goals are all related to each other and to academic achievement, but that the relationships change depending on the age of students and the academic domain being investigated. Schunk (1991) offers a comprehensive review of this literature, which consistently finds support for the findings of Zimmerman and colleagues described above.

Self-efficacy theory is not a stand-alone theory of motivation; rather, “efficacy beliefs play a central role in the cognitive regulation of motivation” (Bandura, 1997, p. 122). Self-efficacy can be thought of as an essential component of motivation (Schunk & Pajares, 2005; Seifert, 2004), interacting with attributions, values, and goals in the process of student motivation (Bandura, 1997; Bong, 2001; Seifert, 2004). In this study, self-efficacy will be measured in addition to three other motivation constructs to examine the pattern of the relationships between motivation, self-efficacy, and academic achievement.

Commonalities among the theories

The strongest commonality among these theories is the idea of intrinsic motivation. The concept of intrinsic motivation has existed for decades; it is the idea of doing a task for the enjoyment of it. Intrinsic motivation has been presented in the form of a theory by both Deci and Ryan (1980, 2000; Ryan & Deci, 2000) and Harter (1981). However, intrinsic motivation is a construct that runs through all theories of motivation, and is consistent in its definition across all theories. Intrinsic motivation is positively related to self-efficacy (Bandura, 1997) and adaptive attributions (Stipek, 1996), and is a key component of adopting a learning goal orientation in achievement goal theory (Dweck & Leggett, 1988). Finally, expectancy-value theory incorporates the concept of intrinsic motivation in the four dimensions of task-values (Eccles & Wigfield, 2002).

In addition to the pervasive presence of intrinsic motivation in all of the theories presented above, there are other commonalities. There is considerable overlap between self-efficacy and expectancies, and between expectancy-value and both performance goal orientation and mastery goal orientation. None of the theories discussed above stand in isolation from each other, despite the fact that they are often presented alone (Seifert, 2004). Nor do any of the theories discussed above give a comprehensive model of all of the dynamics and facets of motivation (Bong, 1996). While each theory has contributed valuable information to our understanding of achievement motivation, the findings within each theoretical framework are like pieces to a jigsaw puzzle. Perhaps to truly understand the process and mechanisms of action of motivation in school, we need to step back and look at how all of the pieces fit together. As stated by Pintrich (2003), " …we need research to understand how they (motivational constructs) work together, rather than horse-race research that attempts to determine which is the best predictor of motivated behavior" (p. 675).

The similarities between theories of motivation are particularly important when examining the relationship of motivation to academic achievement across cultures. Few studies of motivation and academic achievement focus on just one of the theories above; rather, researchers look at relationships between such things as goal orientation and self-efficacy, or task value and self-efficacy (Bandura, 1997; Bong, 2001; Seifert, 2004). It is for this reason that this study examines motivation using items based in three achievement motivation theories, and compares findings across six countries.

Cultural differences in motivation

The achievement motivation research discussed above is derived primarily from studies conducted with North American participants and, to a much lesser degree, some Western European contributions. The findings have been found to generalize fairly well across students in

Western society (Pintrich & Schunk, 2002). However, little research has been done on how well motivation theories generalize to non-Western students, particularly students from Asian countries.

Research into the relationship between Eastern Asian (Confucian Heritage countries such as Korea, China, and Japan; Biggs, 1996) students' achievement and their attitudes and motivations towards academic tasks have revealed some different results than for Western students. Leung (2002) found that while students from Japan, Hong Kong, Singapore, and Korea outperformed all other countries on the Third International Mathematics and Science Study (TIMMS), these same students did not report correspondingly high levels of liking mathematics, positive attitudes towards mathematics, nor of having high levels of confidence in being able to do well in mathematics. A similar result was found by Gu (2006), who found that while Hong Kong-Chinese students outperformed Canadian students mathematics literacy on the Programme for International Student Assessment 2003 (OECD, 2004), the Hong Kong-Chinese students reported lower mathematics self-concept than their Canadian counterparts. Mathematics self-concept was significantly positively related to academic achievement for both Canadian and Hong Kong-China students, but the relationship was stronger for Canadian students than for Hong Kong-China students. Also, school environment had more influence on mathematics self-concept for Hong Kong-China students than for Canadian students.

Whang and Hancock (1994) compared mathematics achievement between Chinese-American and non-Asian-American Grade 4-6 students, and found that while the Chinese-American students achieved higher mathematics scores, they showed lower mathematics self-concept that their non-Asian-American counterparts. Whang and Hancock also found significantly different patterns of predictors for mathematics achievement between the two groups: mastery and performance goal orientation, causal attributions for failure and self-concept of ability (respectively) were found to predict mathematics achievement of the Chinese-American students, while self-concept of ability, perception of mathematics, and mastery goal orientation (respectively) were found to predict mathematics achievement for non-Asian-American students.

The role of self-efficacy in academic achievement has been studied between cultures. Chen and Stevenson (1996) found that Chinese students are more likely to report lower self-efficacy beliefs than North American students. Rao, Moely, and Sachs (2000) did not find a relationship between self-efficacy and achievement in mathematics for Hong Kong-Chinese students attending school in Hong Kong, contrary to findings in North American studies. Eaton and Dembo (1999) found that Asian-American students reported lower self-efficacy than their non-Asian-American counterparts, but outperformed them on a novel achievement task (unscrambling words by locating the words in two novel reading passages).

Research examining goal orientation across cultures has also found that patterns described in research with North American students do not always hold true in studies with students of Asian backgrounds. In particular, Tanzer (1995) found that while Singapore Chinese and Australian students showed similarities in their responses to self-concept items (similar to mastery and performance items), the Chinese students were uncomfortable answering items where there was an element of self-praise. Rogers (1998) administered goal orientation scales to students in China, and a matched sample of students in England, and found that while among the UK students, mastery and performance orientations were independent of each other, for the Chinese students, mastery and performance orientations were positively correlated (i.e., those with high mastery orientation also showed high performance orientation).

A study by Lam and colleagues (2004) found that, similarly to what is found in Western students, Hong Kong secondary students were more likely to demonstrate performance goals when placed in a competitive environment (consistent with achievement goal theory, as described above). Unfortunately, this study is flawed by the way in which performance goals were measured: students completed a preliminary test in a competitive atmosphere, then were asked to choose between an easy task where they could do well, or a harder task where they would learn more, but were less likely to perform well. If a student chose the easy task, they were classified as “performance-oriented”; if they chose the difficult test, they were classified as “mastery-oriented”. No questionnaire or interview check was done to confirm whether students were choosing between tasks due to goal orientation. This procedural issue makes the results of this study difficult to interpret as to how well it demonstrates similarities in motivation between cultures.

This brief review of motivation research between North American and Asian cultures suggests that there are discrepancies in how motivation theories apply to students of different cultural backgrounds. Research is needed in this area, to inform and expand our understanding of motivation in academic contexts, for students of all cultures, so that theories are generalizable and applicable across all students. This is important as immigration continues to change the make-up of classrooms across Western society, and teachers need to adjust their teaching, assessment, and classroom cultures to ensure that all students are getting the best education possible. The relationship between the school learning climate and student motivation is discussed briefly in the next section.

Classroom and school influences on motivation

Students do not exist in isolation. They are members of a community – their classroom, their school, and their district (via its policies that directly affect schools) all have roles in shaping the experiences a student has in an academic context. An important factor in student achievement is the learning climate. While the PISA 2003 dataset does not contain classroom level data, it does contain information about the participating schools as reported by both students and principals. These data give information about the learning climate in the school, specifically teacher support (as reported by students), student morale, and school climate (both as perceived by principals). These variables were chosen for this study because they best reflect the variables used in primary research on learning climate and its relationship to motivation.

Learning climate has been studied, and operationalized, in a variety of ways. The majority of research on how schools and classrooms affect student academic motivation has focused on instructional practices that enhance or detract from motivation (Brophy, 2004; Perry, Turner, & Meyer, 2006; Pintrich & Schunk, 2002; Stipek, 1996). A less well-explored area of study is directed at the climate of the school. This field of research examines less direct influences on student motivation; rather than looking at specific instructional practices, this field of research looks at the relationship between motivation and such school elements as teacher support (Klem & Connell, 2004), school belongingness (Goodenow, 1992, 1993), and student morale (Goodenow, 1992). School climate research encompasses a broad range of school characteristics; a common theme through all of this research, however, is the role of teachers in the school climate (Anderson, 1982).

One of the most consistent findings in research into school climate is the importance of teacher support. Teacher support is found as a characteristic of school belongingness (Goodenow, 1992; Anderman & Freeman, 2004) and school climate (Anderson, 1982). At all levels of education, teacher support is positively related to student motivation and academic achievement (Freeman, Anderman, & Jensen, 2007). Teacher support in the literature has been variously defined, but operational definitions generally include the following characteristics: caring, friendliness, understanding, dedication, and dependability (Patrick, Anderman, & Ryan, 2001).Higher perceived levels of teacher support are associated with more positive school engagement and higher levels of scholastic achievement, for both elementary and middle school students (Klem & Connell, 2004). Midgley and colleagues (1998) found that students' perceptions of teacher support were related to the value that students placed on mathematics when the students transitioned from elementary school to middle school. When students moved from a less supportive teacher to a more supportive teacher, they valued mathematics more and reported higher levels of intrinsic interest. Moving from a more supportive teacher to a less supportive teacher showed the reverse effect. This relationship between teacher support and intrinsic motivation was stronger for low-achieving students than for higher-achieving students.

Another area of research into school climate looks at characteristics of teachers' relationships to their students and their schools. Wentzel (1997) found that when students perceived teachers as being committed, respectful, and having specific expectations of their students, the students participated more fully in class and were more willing to make an effort in class. In her research on school belongingness, Goodenow (1993) found that perceived teacher support was the strongest predictor of self-reported motivation. Ryan and Patrick (2001) found that when students reported feeling that their teachers were supportive and caring, the students showed higher levels of motivation and increased use of cognitive strategies.

The expectations that teachers hold for their students are also important. Teachers who have high expectations of their students' potential for academic achievement have been found to elicit good academic outcomes from their students (Brophy, 2004). Creating a challenging atmosphere and being willing to adapt teaching to promote learning has also been found to have a positive relationship with student achievement (Blumenfeld, 1992; Henningsen & Stein, 1997).

The teacher characteristics described above contribute to a positive school climate (Haynes, Emmons, & Ben-Avie, 1997). Part of school climate is also teacher morale. When teachers' morale in a school is high, there is generally a positive impact on student achievement and attitude across the students in the school (Miller, 1981; Zigarelli, 1996); conversely, low teacher morale in a school is associated with less positive outcomes, such as loss of enthusiasm in preparing for class, poor attitude towards students, and a focus on leaving the teaching profession, all of which have a negative impact on students' achievement (Black, 2001).

The literature cited above supports the idea that the school and classroom environment in which students find themselves can have a substantial effect on student motivation. As with the motivation theory research described earlier, however, all of the research cited above was conducted with students in North American and European (Western) schools. Research is needed into the relationship of school, teacher, and classroom characteristics on students from other cultures.

Examining achievement motivation across cultures

Research on cultural differences in motivation has focused mainly on students of different nationalities taking schooling in Western school systems (Eaton & Dembo, 1999), or, more rarely, comparing small samples of students from one country to a matched sample from another country (D'Ailly, 2003). This research has produced valuable results, as outlined in the section above; however, the numbers make generalizations difficult. One way to examine similarities and differences in the relationship of achievement motivation to academic outcomes (positive and negative) is to use data from large-scale, standardized international assessments. These assessments, such as the Trends in International Mathematics and Science Study (TIMSS; assesses students in Grades 4 and 8) (Leung, 2002) and the Programme for International Student Assessment (PISA; assesses 15 year old students) (OECD, 2003), collect demographic and individual differences data from students (such as attitudes and beliefs about schooling) and academic achievement data from students in several countries. All students in all participating countries complete similar assessments in mathematics, science (PISA and TIMMS), reading and problem-solving (PISA only). Both of these large-scale assessments use carefully designed sampling procedures for good representation of student populations in the participating countries.

The value of these types of datasets lies in the fact that all students in all countries also complete questionnaires that address soci-economic variables, school climate, and personal attitudes and beliefs about school. Having this same data for all students in all countries who complete the academic assessments allows analyses that would not be feasible practically or economically for most researchers. This study used data from the PISA 2003 dataset to examine the relationship between motivation, and academic achievement across six countries. The next section details the value of secondary data analysis, such as using data from large-scale assessment datasets, in educational research.

Secondary data analysis

Secondary data analysis is the analysis of data that has been collected by others. The sources of data can be previously published results, or large-scale datasets comprised of survey data. Datasets can be those collected with a specific hypothesis in mind such as the individual studies used in a meta-analysis, or can be large datasets collected expressly as a resource for researchers (Brooks-Gunn et al., 1991). Occasionally, secondary data analysis can include supplementary data, such as interviews with a group of participants from the original pool of participants in a large-scale, national survey (Reiss, Plomin, & Hetherington, ongoing, as described in Brooks-Gunn et al., 1991). The aim of secondary data analysis is to analyze existing datasets with the intention of either combining studies to reinforce findings from research with small groups of participants, or to research different questions than those asked in the original research. Secondary data analysis is intended to either reinforce previous findings (common in medical research, where the participant numbers in individual studies are too small to generalize) or to arrive at different interpretations of the data, making it possible to derive new knowledge of the subject in question (Hakim, 1982). Most theories in educational research are derived and clarified using data from laboratories or classrooms. In the case of laboratory studies, participants are usually undergraduate students, who tend to be a demographically homogenous population (Wintre, North, & Sugar, 2001). This can lead to difficulty in generalizing theories. Being able to examine theories using large-scale datasets where the data has been collected from a diverse group of students in a variety of schools can lead to better understanding of how a theory looks in the target population (assuming the target population is the one represented by the large-scale dataset).

As outlined above, secondary data analysis offers promise for furthering our understanding of how and why students learn. This type of research allows for the examination of the relationships between variables affecting the classroom and students on a much larger scale (across more students and more classrooms) than is possible in primary research. However, there are also drawbacks to secondary data analysis. In this section, the advantages and disadvantages of secondary data analysis are discussed, with an emphasis on the PISA dataset.

Advantages of secondary data analysis

The first advantage of secondary data analysis is the quality of the data available through most large-scale data collection projects, such as TIMMS and PISA (Gonzales et al., 2004; OECD, 2003). These datasets are carefully constructed: the variables are chosen based on findings from primary research, sampling is done systematically to ensure generalizability, and administration is standardized across all sampling locations.

The second major advantage of secondary data analysis is the cost savings, both in real money and in personnel, of this type of research (Kiecolt & Nathan, 1985). Conducting primary research costs either money or time, usually both. Collecting data means finding participants and carrying out the process of gathering information from them, which takes up the bulk of time in any research. Often, graduate students or research assistants are paid to do this work; participants are also recompensed in some way in many studies. Secondary data analysis eliminates this part of the research process. Researchers need be concerned only with analyzing and interpreting the results of the analysis of the data, rather than the administrative issues that surround the collection of original data.

Another time savings is in the elimination of the need for data entry. The databases available for secondary data analysis are usually already in a form to be analyzed (although this depends on the statistical analysis method used for the secondary analysis). Researchers can work independently, without the need for a team to assist in data entry.

The large-scale datasets usually used in secondary data analysis are typically nationally, or internationally, representative. These datasets are usually designed to represent a specific population, such as the 15 year olds targeted by the PISA study. The high response rates to studies such as these mean that researchers can assume good representation of the target population, and can generalize their findings across that target population when interpreting their results (Hofferth, 2005). Researchers are also spared the attendant administrative duties of making sure that sampling is accurate; large-scale datasets such as PISA are carefully administered to ensure that sampling occurs across a wide and diverse population range within the target population, with representation across such areas as socio-economic status and gender.

Additionally, for the PISA dataset, there is careful quality control at all points in the data collection and analysis. The achievement test items and the questionnaire items for each PISA cycle are developed based on current primary research, evaluated by experts in the respective fields, pilot tested with groups in various countries, and then field-tested before the final test booklets and questionnaires are created (OECD, 2003). Test administrators at each testing location are trained, and students and test administrators are asked quality control questions to ensure that proper procedures are followed at each testing location. Test scorers are also trained before the scoring, and there are inter-rater reliability checks on scoring (OECD, 2003). Before release, the raw data is analyzed using specifically designed subroutines that result in a comprehensive dataset that includes sampling weights to compensate for differences such as differing sample sizes or representation between countries, and score estimates to compensate for missing data.

Finally, secondary data analysis allows researchers to examine data that they could not reasonably collect themselves. The large-scale databases available for secondary data analysis include longitudinal studies involving hundreds or thousands of people over several years or decades, such as the National Longitudinal Survey of Youth in the United States (Brooks-Gunn et al., 1991), and the Canadian National Longitudinal Survey of Children and Youth (NLSCY; Special Surveys Division, 1996). Other large-scale datasets, such as PISA, contain information from data from tens of thousands of individuals across several countries. The cost and time involved in collecting such data by even a large team of independent researchers would be prohibitive.

Disadvantages of secondary data analysis

Despite all of the advantages of secondary data analysis, there are disadvantages and limitations to this type of research as well. Obtaining the data, and preparing it for certain types of analysis can take more time than researchers may expect (Anderson et al., 2006) – although this time is minimal compared to the time it would take to actually collect the data.

An extension of the data access problem is getting accurate information about items used in the data collection. Often, large-scale datasets have already been analyzed, and items from the original data have been grouped to form indexes, aggregates, or composite variables. This is the case for the PISA dataset; a number of variables are in the dataset are scaled as indices. The suitability of these data for answering specific research questions must then be evaluated. It is necessary, therefore, to seek out the raw data for the original items, which is not always available to researchers outside the original data analysis.

Finally, and perhaps the most significant challenge in secondary data analysis, is the limitation of the available variables. The measures used in collecting the data for the databases used for secondary data analysis are pre-determined, which can create a problem for researchers who wish to examine a particular variable (Hyman, 1972). Researchers need to match the research question to the available data, rather than collecting data that answers a specific research question. If the original operational definition of the variable differed from the current researcher's definition, there may be a measurement issue; as well, there may have been too few measures to provide the information that a researcher may need.

Similarly, there can be issues of data availability. In the PISA 2003 assessment, data is collected only at the student and school level for 15 year old students. This means that no classroom level analyses are possible, because there are no teacher data, nor are students clustered by classrooms. This limitation means that analysis of teaching practices is not possible using the PISA dataset (OECD, 2003), although there are data on students' perception of classroom practices, which can be used to do exploratory studies of the relationship between students' perceptions of classroom environments, and their academic outcomes. Further to this issue, there may be a lack of access to raw data. The data released to researchers has already been analyzed, weighted, and often individual items have been compressed into indices.

Although there are limitations to secondary data analysis, they are outweighed by the potential knowledge that can be gained by research such as is reported in this study. As secondary data analysis continues to gain in popularity, many of the disadvantages will become less prominent – mostly through the meticulous keeping of records, and the increased use of standard measures of commonly examined variables, such as motivation and cognitive learning strategies.

The PISA 2003 data set

The motivation items answered by 15 year old students in the PISA 2003 assessment allow for the examination of the relationship between some common components of motivation theories and academic achievement. This allows for exploration of both the patterns of relationships between these mathematics-specific motivation variables and mathematics achievement, and how these mathematics-specific motivation items relate to achievement in other domains (reading, scientific literacy, and problem-solving). The relationship between the school environment and motivation and achievement can also be explored. As well, the data available in the PISA 2003 dataset allows some preliminary investigation of similarities and differences in patterns of relationships between motivation and academic achievement, and how those variables are related to school environment, in several Western and non-Western countries.

The PISA 2003 dataset was deliberately chosen for this research over other large-scale assessment datasets. The decision to use data from PISA rather than TIMMS was based on the fact that the items in the PISA assessment are based in knowledge that students will need in pursuing careers in a technical world (OECD, 2003), rather than based in curriculum (Gonzales et al., 2004). This results in a broader and more meaningful set of assessment items that reflect whether students understand and apply basic concepts of mathematics, science, and problem-solving, rather than whether students completed the full curriculum as agreed upon between participating countries. The PISA dataset for 2003 was selected over other years because it is the most recent available dataset; as such, it represents the most current sampling and data collection procedures.

Research questions

This study will use hierarchical linear modeling (HLM; described in the data analysis section) to explore the relationships between motivation and academic achievement of students in relation to school environments. HLM is an exploratory statistical method, rather than a hypothesis-testing approach as is used is inferential statistics; as such, the relationships explored in this study are stated in the form of research questions, rather than hypotheses.

1. What are the relationships between student level instrumental and intrinsic motivation, performance orientation, and self-efficacy indices and academic achievement for 15 year olds in the PISA 2003 dataset for mathematics? Does this relationship vary between Canada, the United States, the United Kingdom, Hong Kong-China[1], Japan, and Korea?
2. What is the relationship between measures of mathematics instrumental and intrinsic motivation, mathematics performance orientation, self-efficacy, and achievement in reading, problem-solving, and scientific literacy for the countries listed above? Do we see the same patterns as with mathematics achievement? How do the relationships compare across achievement domains (e.g., mathematics and reading literacy)?
3. How do the school level indices (teacher support, student morale, and teacher behaviours affecting school climate) influence the student level motivation relationships in the same countries as above?

Chapter 3: Method

Ethical approval procedures

[1] Although Hong Kong-China is not a country, it is treated as such in data collection and analyses in PISA, and all students writing the PISA assessment in Hong Kong-China were grouped and analyzed as a country.

Pursuant to the requirements of the Human Ethics Research Board of the Office of Research Services at the University of Victoria, an Ethical Waiver was applied for and approved for this study (see Appendix A).

The dataset: PISA 2003

PISA is an international assessment of reading, mathematical and scientific literacy, and problem solving in 15 year olds across 30 OECD countries, plus over a dozen other participating countries, involving between 4500 and 29,000 students in each of the participating countries. The data is collected every three years, and each cycle focuses on a different literacy domain – all domains are included in every cycle, but the focus area of each cycle is assessed with greater accuracy through the administration of more items. For example, PISA 2003 collected reading and scientific literacy data, but only through a limited number of questions. The focus of PISA 2003 was on mathematical literacy, and the majority of the questions dealt with this area. In addition, PISA gathers background information on demographic and home supports for schooling variables, and information on student attitudes, engagement, and motivation regarding the focus of the assessment. Specifically, for PISA 2003, students answered a background questionnaire that used standardized, validated items from primary research (Marsh et al., 2006) to measure individual motivation and self-beliefs, as well as anxiety and learning strategies in the area of mathematics. As a result, PISA 2003 offers a wealth of data both in terms of student outcomes in mathematics, reading, science, and problem-solving, and in the possibility of examining the data for relationships between student academic outcomes in all domains and the motivation, self-beliefs, and self-regulated learning strategies self-reported by the students. Characteristics of student learning, using standard, validated items can be examined within countries, and across countries. The relationships between student characteristics, such as motivation, and student outcome across domains can be examined, and differences between countries can be explored. As well, the grounding of the student questionnaire development in educational theory means that researchers can ask questions that involve both replication and elaboration of existing research findings (Goldstein, 2004).

The data in the PISA datasets is hierarchical; there is data for students, there is data for the schools in which the students learn, and there is limited data about individual countries in which the schools are situated (other country data, particularly economic data, is available through other sources). The breadth of variables from the wide range of countries in this dataset allows researchers to explore questions that would not be possible in traditional research, where one researcher, or a small team of researchers, collect their own data. The dataset also lends itself to more complex data analysis, such as HLM (Raudenbush & Bryk, 2002), which is described more thoroughly in the data analysis section of this paper.

Countries to be examined in this study

Using HLM, this study models the relationship between motivation and academic achievement for each of six countries: Canada, the United States, the United Kingdom, Hong Kong-China, Japan, and Korea. The rationale for choosing these six countries for comparison is given below.

Canada was chosen because this research is being conducted with the broader aim of determining how well instruction based on achievement motivation theory serves the diverse ethnic student populations found in urban Canadian classrooms. The United States was chosen because it has been the source of most achievement motivation research and theory, and because Canada and the United States are close neighbors, and the United States in particular has an influence on the Canadian education system. There are distinct differences between the two countries, however; Canada does not have a centralized, federal education system, but rather individual provinces make decisions and govern their own provincial education systems. The

United Kingdom was chosen due to its close historical ties with Canada, and with the United States. Culturally and in terms of overall delivery of education, there are strong similarities between the United Kingdom and North America. In addition, a large amount of achievement motivation research has also been conducted with students in the United Kingdom (and to a lesser degree with students in Canada), although not to the same degree as in the United States. For this reason, it is expected that the final HLM models for these three countries will show similar motivation to achievement relationships.

Hong Kong-China was a British territory and member of the Commonwealth until recently. There are large emigrant Hong Kong-China populations in both the United Kingdom and North America. Hong Kong-China is in a unique position of straddling the Western and Eastern cultures, influenced by the West through previous government and other associations, but predominantly belonging to the Confucian Heritage Culture, and having a school system that is different from the Western countries in its organization, curriculum focus, and mode of instruction (Biggs, 1996). Japan and Korea are also both countries with a learning culture that is influenced by Confucian Heritage Culture (Biggs, 1996), and have similar schooling organization to Hong Kong-China. Both of these countries are traditionally high performing on international assessments such as PISA and TIMMS (Leung, 2002; OECD, 2004). Finally, in all three of these countries, there is an increasing interest in the study of achievement motivation (Huijun, Dejun, & Hongli, 2006; Takemura, Maehara, & Kobayashi 2007; Wakamatsu, Ohtani, & Konishi, 2004; Yanmei, Xiaoming, & Dejun, 2006). The majority of these studies are being published in non-English language journals, which impeded the author's ability to include the results of that research in this study.

Once the HLM models are created for each individual country, the models will be compared to examine whether the relationship between motivation and academic achievement varies between countries overall, and between the Eastern and the Western countries. It is expected that the relationships between achievement motivation and academic achievement will be similar in the Western countries (Canada, the United States, and the United Kingdom), and that the relationships between motivation and achievement will be similar in the Asian countries (Hong Kong-China, Japan, and Korea). What is to be determined, however, is whether the relationships between motivation and achievement will be similar between *both* Western and Asian countries, or whether there will be differences in the relationships that could be sttributed to cultural differences. The comparison of the models from each of these countries allows for evaluation of the generalizability of the relationships, and the generalizability of the theories themselves.

Measures of achievement in the PISA 2003 dataset

PISA uses an "incomplete or rotated-booklet design" (Willms & Smith, 2005). In this type of test design, no one student completes the entire set of achievement items – the full PISA achievement item pool is far too large to have any student complete the full set within feasible time limits. Each student completed two hours of testing, with a short break between hour one and hour two; in that time, the student completes a portion of the total PISA assessment.

The total PISA 2003 item set consisted of 167 items: 85 mathematics items, 35 science items, 28 reading items, and 19 problem-solving items. From these items, 13 item clusters were created. Each cluster consisted of a set of items that would take 30 minutes of test time to complete: approximately 13-18 items per cluster for mathematics, reading, and science, and 8-9 items for problem-solving. There were seven mathematics clusters, and two clusters each for science, reading, and problem-solving (OECD, 2004).

The clusters were distributed among 13 test booklets. Each booklet contained four clusters, with at least one of those clusters always being mathematics, so that every student in the PISA

2003 assessment completed a set of mathematics questions. Each cluster appeared in exactly four different booklets. This meant that each item in PISA 2003 appeared in four different booklets, in different combinations with other items from mathematics and from the other academic domains. This linked design allowed for the use of standard measurement techniques. For each academic domain, test scores were scaled to have a mean of 500 and a standard deviation of 100 for all the OECD countries participating.

As explained above, any one student completing the PISA 2003 assessment did not actually complete all items in the PISA 2003 item pool, but rather completed a sample of items. One parameter item response theory (IRT) analysis allowed for accurate achievement estimates on a common scale through the creation of five plausible values for each student on all domains and in each of the mathematical literacy subscales -- a total of 40 plausible values in all. Plausible value calculations are based on procedures used to impute missing data, such as bootstrapping (Beaton, 1987; Willms & Smith, 2005), and are commonly used in large scale assessment datasets, such as PISA and TIMMS (Wu, 2005). Plausible values represent the likely range of a student's ability, based on the ways the student has answered a set of items.

Plausible values are a statistically valid estimation of the range of abilities that a student might have, and provide reliable estimates of parameters for the student population (OECD, 2003). Plausible values allow for better estimates of country-level standard error. Statistical packages such as HLM6 contain an option to make calculations using plausible values. The statistical package replicates the analysis across all of the plausible values, and computes standard errors of the coefficients based on the full analysis (Willms & Smith, 2005).

Measures of motivation in PISA

There are four measures related to motivation in the PISA 2003 assessment: instrumental motivation, intrinsic motivation, self-efficacy, and performance goal orientation. These are derived indices based on four items each for instrumental and intrinsic motivation, eight items for self-efficacy, and five items for performance goal orientation. All items were field tested in a pilot assessment one year prior to the full assessment, and questions were modified or removed based on the field trial results. Students in the PISA 2003 assessment cycle answered the motivation items on a four point Likert-type scale, from “Strongly Disagree” to “Strongly agree” for the instrumental, intrinsic items, and performance goal orientation items, and from “Not very confident” to “Very confident” for the self-efficacy items. Responses were scaled across items to give a single score on each of instrumental and intrinsic motivation, performance goal orientation, and self-efficacy. The reliabilities for all the motivation variables are given in Table 1; reliabilities were calculated in the analyses for this study, and were found to be comparable to those in PISA publication.

Table 1

Reliabilities (α) For Instrumental And Intrinsic Motivation, Performance Orientation, And Self-Efficacy On PISA 2003 Assessment

Country	Instrumental Motivation (4 items)	Intrinsic Motivation (4 items)	Self-efficacy (8 items)	Performance Orientation (5 items)
Canada	.90	.91	.85	.86
Japan	.91	.90	.87	.87
Korea	.88	.91	.87	.83
Hong Kong-China	.88	.91	.87	.81
United Kingdom	.86	.90	.86	.84

United States	.89	.91	.86	.86

Instrumental motivation

The items used to measure instrumental motivation are based in the task-value work of Eccles and Wigfield (Eccles, 2005; Eccles et al., 1993; Eccles and Wigfield, 1995, 2002; Wigfield et al., 1998), and look at the practical aspects of approaching a task. The items are phrased specifically in the context of mathematics, as that was the focus of the assessment (see Table 2). As shown in Table 2, these items are similar to items that appear in the predominantly used scale that appears in primary research, developed by Eccles and colleagues (Eccles, Wigfield, Harold, & Blumenfeld, 1993). The items in the PISA 2003 assessment are phrased more specifically in the context of *why* mathematics is important, while the Eccles and colleagues items are phrased more generally.

Table 2

Instrumental Motivation Items From The PISA 2003 Dataset Compared To Items From A Scale Commonly Used In Primary Research

Items from PISA 2003	Items from primary research scales*
Making an effort in mathematics is worth it because it will help me in the work that I want to do later on.	Compared to most of your other activities, how important is it for you to be good at math?
Learning mathematics is worthwhile for me because it will improve my career <prospects, chances>.	In general, how useful is what you learn in math?
Mathematics is an important subject for me because I need it for what I want to study later on.	For me, being good at math is (not at all important to very important)
I will learn many things in	

mathematics that will help me get a job.	

*All items from the expectancy-value scale developed by Eccles et al., 1993.

Intrinsic motivation

The intrinsic motivation items used in the PISA 2003 assessment were developed through field trials, and reflect research in intrinsic motivation and interest (Lepper, 1988; Middleton & Spanias, 1999). The PISA 2003 intrinsic motivation items (Table 3) closely resemble intrinsic motivation items from scales commonly used in primary intrinsic value research (Eccles et al., 1993; Midgley et al., 1998). The reliabilities for these indices for the countries examined in this study range from α = .90 to α = .91 (see Table 1).

Table 3

Intrinsic Motivation Items From The PISA 2003 Dataset Compared To Items From A Scale Commonly Used In Primary Research

Items from PISA 2003	Items from primary research scales
I enjoy reading about mathematics.	
I look forward to my mathematics lessons.	How much do you like doing math (1 = a little, 7 = a lot). +
I do mathematics because I enjoy it.	An important reason I do my school work is because I enjoy it. *
I am interested in the things I learn in mathematics.	I do my school work because I am interested in it.*

+ “Interest in math” items from expectancy-value scales developed by Eccles et al., 1993.

* Task goal orientation items from Patterns of Adaptive Learning Survey scales developed by Midgley et al., 1998.

Self-efficacy

The self-efficacy items used in the PISA 2003 assessment (Table 4) are derived from items in the work of Bandura (1986) and others (Multon et al., 1991). The items were field-tested in pilot studies, and modified to improve reliability. The final set of eight questions are comparable to those seen in primary research, where students are asked how confident they are that they will be able to solve a specific problem, or do well on an exam (e.g.,Vancouver & Kendall, 2006). In the PISA 2003 dataset, the self-efficacy items relate directly to a student’s confidence in their ability to answer the specific types of questions asked in the mathematical literacy portion of the achievement test, which reflects the domain-specific nature of self-efficacy (Zimmerman, 2000). The reliabilities for these indices for the countries examined in this study range from α = .85 to α = .87 (see Table 1).

Table 4

Self-Efficacy Items From PISA 2003 Dataset

How confident do you feel about having to do the following mathematics tasks?
Using a <train timetable>, how long it would take to get from Zedville to Zedtown.
Calculating how much cheaper a TV would be after a 30 percent discount.
Calculating how many square meters of tiles you need to cover a floor.
Understanding graphs presented in newspapers.
Solving an equation like 3x + 5 = 17.
Finding the actual distance between two places on a map with a 1:10,000 scale.
Solving an equation like 2(x+3) = (x+3)(x-3).

Calculating the petrol consumption rate of a car.

Performance orientation

The performance goal orientation data in the PISA 2003 dataset were not collected specifically as performance goal items; rather, they were collected in the context of preferred learning environment (competitive versus cooperative), and were based on research by Owens and Barnes (1992; as cited in OECD, 2005). However, these items are almost identical to items that appear on scales used in primary data analysis to measure performance goal orientation (Table 5). Given the close match between these items and standard performance goal orientation items, these items are used in this study as performance goal orientation measures. The reliabilities for these indices for the countries examined in this study range from $\alpha = .81$ to $\alpha = .87$ (Table 1).

Table 5

Performance Goal Orientation Items From The PISA 2003 Dataset Compared To Items From A Scale Commonly Used In Primary Research

Items from PISA 2003	Items from primary research scales*
I would like to be the best in my class at math.	Doing better than other students in school is important to me.
I try very hard in math because I want to do better in the exams than others.	I would feel really good if I were the only one who could answer the teachers' questions in class.
I make a real effort in math because I want to be one of the best.	It's important to me that the other students in my classes think that I am good at my work.
	I would feel successful in school if I did better than most of the other students.

In math I always try to do better than the other students in my class.	I want to do better than other students in my classes.
I do my best work in math when I try to do better than others.	

*All items from the Patterns of Adaptive Learning Survey developed by Midgley et al., 1998.

School level indices in the PISA 2003 dataset

Three school-level indices will be used in the analyses: student morale and commitment (as reported by principals), teacher factors related to school climate (as reported by principals) and teacher support (derived as an aggregate from student-level responses). The school level indices are described below. The reliabilities for all indices are in Table 6.

Table 6

Reliabilities (α) For School Level Variables On PISA 2003 Assessment

Country	Student Morale (7 items)	Teacher-related factors (7 items)	Teacher Support* (5 items)
Canada	.86	.83	.85
Japan	.93	.80	.78
Korea	.89	.85	.75
Hong Kong-China	.84	.92	.83
United Kingdom	.91	.83	.88
United States	.85	.75	.83

* Reliabilities for this index are taken from the student-level data.

Students' Morale and Commitment (Principals' Views)

To measure students' morale and commitment to learning, principals responded to items on the School Questionnaire that addressed such areas as how well students enjoy school, how much enthusiasm students demonstrate, how much pride students take in the school, how much students value academic achievement, whether students demonstrate co-operation and respect, how much students value the education they are receiving, and whether students do their best to learn as much as possible. Principals' responses were scaled using IRT into one index; positive scores indicate higher agreement with higher student morale and commitment (OECD, 2003).

Teacher-Related Factors Affecting the School Climate (Principals' Perceptions)

To assess teacher influence on students from another perspective, and index of how teachers affected school climate was included in the Level 2 analyses. The School Questionnaire was completed by principals of schools taking part in the PISA 2003 data collection. One set of items examined principals' perceptions of teacher-related influences on school climate that limit or hinder how well students learn at school. These items were: absenteeism among teachers, teachers being resistant to change, teachers having low expectations of their students and not encouraging students to achieve their full potential, teachers not meeting students' needs, and poor teacher-student relations (OECD, 2003). IRT scaling was used to combine principals' responses on these items into a composite index of teacher-related factors affecting the school climate; as well, all items were inverted for scaling, so that positive numbers reflect positive evaluations of these areas, i.e. the more positive the index, the less the school climate is being affected by these teacher-related factors (OECD, 2003).

Teacher Support (students' perceptions)

In order to examine how teacher support of students affected motivation and achievement, an index of teacher support in mathematics was included in the Level 2 analyses. Students responded to "teacher support" items in the Student Questionnaire. These items consisted of five questions about the about the following: does the teacher show interest in every student's learning? Does the teacher give extra help when needed? Does the teacher help students with their learning? Does the teacher continue teaching until all students understand? Does the teacher give students opportunities to express opinions? The responses were scaled using IRT (item response theory) to create a scaled index centered at zero, and ranging from -3 to +3. Positive scores indicate that students perceived higher levels of teacher support (OECD, 2003).

Data analysis

Hierarchical linear modeling

Hierarchical linear modeling is known by a variety of names, often depending on the field of research where it is being used. Sociologists use the term multilevel linear models; biometricians use the term random-effects models or mixed-effects models, and statisticians call these models covariance components models (Raudenbush & Bryk, 2002).

Hierarchical linear modeling (HLM) is a statistical approach that allows for analysis of variables at a variety of levels. These levels result from the nesting of variables within each other – such as students nested within classrooms, classrooms nested within schools, schools nested within districts, etc. This is important because in using traditional linear regression statistics for analyzing classroom- or school-based research, researchers are often violating the assumption of independence of traditional linear models (Raudenbush & Bryk, 2002).

With HLM, the relationship between student-level variables can be modeled as a first level (which is a simple regression equation), and then the intercepts and slopes between variables within schools or classrooms can be modeled, (Raudenbush & Bryk, 2002). The calculation of HLM models is explained in the Results section.

One of the important features of hierarchical linear modeling is that it decomposes the variance accounted for at each level. This information is vital evaluating the final models. Analyses of the PISA 2003 data show that the variance accounted for at the school level ranges from around 4% for Iceland, up to 60% for the Netherlands, with an average of 34% across all OECD countries (Anderson et al., 2006). This type of information is important when making policy recommendations (such as funding decisions) based on findings from hierarchical linear modeling research – if schools are only accounting for 10% of the difference, it might be more practical to investigate how to make changes that will influence the student-level differences (such as changes in instructional practices).

The hierarchical nature of the PISA 2003 dataset allows examination of both the relationship of individual student variables (such as the motivation variables discussed above) to individual achievement, and of the relationship of Level 2 variables (here, school level variables) to the Level 1 relationships.

Chapter 4: Results

The results of this study describe, evaluate, and compare the relationships among students' motivation, learning environment at school, and academic achievement in Canada, the United States, the United Kingdom, Hong Kong-China, Japan, and Korea. Hierarchical linear modeling (HLM) was used to analyze the following: at the student level, the relationships between students' motivation (instrumental and intrinsic motivation, performance orientation, and self-efficacy, all answered in the context of mathematics) and academic achievement (in mathematics, reading, science and problem-solving), modeled for all six countries; at the school level, the analysis focused on how the learning environment at school (students' perceptions of teacher support, and principals' perceptions of student morale and teacher behaviours affecting school climate) affects average academic achievement across schools and moderates the relationships between students' motivation and achievement in all six countries separately. The results of the study are described and discussed in detail below.

The results below report only the general mathematics achievement scores. All analyses were carried out on each mathematics achievement domain (space and shape ability, change and relationships ability, uncertainty ability, and quantity ability), but no substantial difference was found for individual domains versus the general mathematics ability domain. For practical purposes, the individual mathematics ability domains are therefore not presented here.

Descriptive Statistics

Country Samples (student participants)

The descriptive statistics for the student sample from each country, as well as the number of schools sampled for each country, are given in Table 7. The samples from each country are acceptably consistent with PISA sampling standards in regards to age of participants and equal size of gender groups. It should be noted that the Japan sample was reduced by more than 20% due to missing data; however, the data was missing at random, so the analyses were not affected.

Table 7

Numbers Of Students, Descriptives Of Student Samples, And Number Of Schools In Each Country Sample

Country	Students		Gender		Age range (years)	Schools
	HLM*	Sample	Male	Female		
Canada	27,220	27,953 ^(330,436)	13,469	13,748	15.3 – 16.3	1,066
United States	5,455	5,456 ^(3,147,089)	2740	2715	15.2 – 16.3	262
United Kingdom	9,535	9,535 ^(698,579)	4663	4872	15.2 – 16.3	361
Hong Kong-	4,478	4,478	2219	2259	15.2 –	145

China		^(72,484)			16.3	
Japan	3,755	4,707 ^(1,240,054)	1876	1879	15.2 – 16.2	144
Korea	5,444	5,444 ^(533,504)	3211	2233	15.3 – 16.2	149

* Some of the students from each country sample were excluded from the HLM analyses if there was missing data.
^Weighted number of students. The weighted number of students in the sample indicates the number of students in the target population (as defined for each country) that the PISA sample represents.

Interpreting PISA index scores

The following sections give descriptive statistics for each of the independent variables used in this study. Each of these variables is reported as an index (which summarizes student responses to a set of related questions on the Student Questionnaire) (OECD, 2004). In the PISA dataset, a scale was constructed for each index, derived from a comparison of scores across countries using structural equation modeling. For each index, a student with an average level of interest (determined as an average across OECD countries) is given an index value of zero. About two thirds of the total OECD student population reported values that fall between -1 and 1 on the scale (because each index has a standard deviation of 1). This means that a negative value on the index does not necessarily mean that students responded negatively to the items that make up the index; rather, a negative index value means that students responded less positively than the average OECD student. Similarly, positive scores mean that students responded more positively than the average OECD student (OECD, 2004).

Student level variables

Instrumental motivation

Instrumental motivation, a scaled index with values centered at 0 and ranging from –3 to +2, was measured through the PISA 2003 Student Questionnaire. Positive values indicate that responses for the country are higher than the OECD average for instrumental motivation in mathematics. The histograms of instrumental motivation for all countries are shown in Appendix B, and show that instrumental motivation is roughly normally distributed for all countries (Figure B1).

Table 8

Descriptive Statistics Of Instrumental Motivation For All Countries

Country	Mean	SD	Skewness	Kurtosis
Canada	0.24	1.01	-0.26	0.03
United States	0.18	0.97	-0.17	-0.13
United Kingdom	0.17	0.94	-0.07	-0.27
Hong Kong	-0.12	0.86	0.04	0.45
Japan	-0.69	1.02	0.31	-0.15
Korea	-0.44	0.97	0.22	-0.01

Table 8 shows the mean, standard deviation, skewness, and kurtosis of instrumental motivation for all six countries examined. The Western countries showed more positive mean instrumental motivation than the OECD mean, with Canadian students on average reporting the most positive mean levels of instrumental motivation (.24), followed by the United States (.18) and the United Kingdom (.17). Students in the Asian countries reported lower mean levels of instrumental motivation than the OECD mean, with students in Japan reporting the least positive mean levels of instrumental motivation (-.69), followed by students in Korea (-.44) and students in Hong Kong-China (-.12). For all countries, there is no obvious violation to the normal distribution of instrumental motivation according to the values of skewness and kurtosis.

Intrinsic motivation

Intrinsic motivation, a scaled index with values centered at 0 and ranging from –2 to +3, was measured through the PISA 2003 Student Questionnaire. Positive values indicate that responses for the country are higher than the OECD average for intrinsic motivation in mathematics. The histograms of intrinsic motivation for all countries are shown in Appendix B, and show that intrinsic motivation is roughly normally distributed for all countries (Figure B2).

Table 9

Descriptive Statistics Of Intrinsic Motivation For All Countries

Country	Mean	SD	Skewness	Kurtosis
Canada	-0.01	1.02	-0.09	0.03
United States	0.04	1.04	0.08	-0.43
United Kingdom	-0.01	0.94	0.02	-0.18
Hong Kong	0.23	0.94	-0.13	-0.08
Japan	-0.41	1.00	0.42	-0.17
Korea	-0.13	1.00	0.21	-0.28

Table 9 shows the mean, standard deviation, skewness, and kurtosis of intrinsic motivation for all six countries examined. The Western countries showed similar mean instrumental motivation, grouped around the OECD mean. Students in the United States had the most positive mean intrinsic motivation (0.04), while students in Canada and the United Kingdom reported similar mean intrinsic motivation (-0.01). Students in the Asian countries reported differing mean levels of intrinsic motivation, with students in Japan reporting the least positive mean levels of intrinsic motivation (-.41), followed by students in Korea (-.13). Students in Hong Kong-China reported the most positive mean levels of intrinsic motivation for all countries in this study (0.23). For all countries, there is no obvious violation to the normal distribution of instrumental motivation according to the values of skewness and kurtosis.

Performance orientation

Performance orientation is taken from the Competitive Learning Environment scale from PISA. The Competitive Learning Environment scale is a scaled index with values centered at 0 and ranging from –3 to +3. Positive values indicate that responses for the country are higher than the OECD average for performance orientation in mathematics (a preference for being competitive with others in the mathematics classroom). The histograms of performance orientation for all countries are shown in Appendix B, and show that performance orientation is roughly normally distributed for all countries (Figure B3).

Table 10

Descriptive Statistics Of Performance Orientation For All Countries

Country	Mean	SD	Skewness	Kurtosis
Canada	0.18	0.98	0.10	0.03
United States	0.43	0.97	0.06	0.74
United Kingdom	0.20	0.94	-0.07	0.98
Hong Kong	0.11	0.86	-0.25	1.94
Japan	-0.49	1.16	-0.12	0.21
Korea	-0.06	0.93	-0.25	1.21

Table 10 shows the mean, standard deviation, skewness, and kurtosis of performance orientation for all six countries examined. The Western countries showed more positive mean performance orientation than the OECD mean, with students in the United Kingdom reporting the most positive mean levels of performance orientation (.43), followed by the United States (.20) and Canada (.18). Students in the Asian countries reported lower mean levels of performance orientation than the OECD mean, with students in Japan reporting the least positive mean levels of performance orientation (-.49), followed by students in Korea (-0.06). Students in Hong Kong-

China reported positive mean levels of performance orientation (.11). For all countries, there is no obvious violation to the normal distribution of instrumental motivation according to the values of skewness and kurtosis.

Self-efficacy

Self-efficacy, a scaled index with values centered at 0 and ranging from –4 to +3, was measured through the PISA 2003 Student Questionnaire. Positive values indicate that responses for the country are higher than the OECD average for self-efficacy in mathematics. The histograms of Self-efficacy for all countries are shown in Appendix B, and show that Self-efficacy is roughly normally distributed for all countries (Figure B4).

Table 11

Descriptive Statistics Of Self-Efficacy For All Countries

Country	Mean	SD	Skewness	Kurtosis
Canada	0.19	1.07	0.24	0.03
United States	0.24	1.06	0.33	1.11
United Kingdom	-0.02	0.99	0.63	0.98
Hong Kong	0.14	1.02	1.14	1.64
Japan	-0.57	1.03	-0.38	2.57
Korea	-0.43	0.99	0.27	2.61

Table 11 shows the mean, standard deviation, skewness, and kurtosis of self-efficacy for all six countries examined. The Western countries showed varying mean levels of self-efficacy. Students in the United States showed positive mean levels of self-efficacy (0.24), as did students in Canada (.19). Students in the United Kingdom reported less positive mean levels of self-efficacy (-0.02). Students in the Asian countries also reported varying mean levels of self-efficacy, with students in Japan reporting the least positive levels of self-efficacy (-.57), followed by students in Korea (-.43). Students in Hong Kong-China reported positive mean levels of self-efficacy (.14). For all countries, there is no obvious violation to the normal distribution of instrumental motivation according to the values of skewness and kurtosis.

School level variables

Student morale and commitment

Student morale and commitment, a scaled index with values centered at 0 and ranging from –3 to +3, was measured through principals' responses to the PISA 2003 School Questionnaire. Positive values indicate that responses for the country are higher than the OECD average for student morale and commitment. The histograms of student morale and commitment for all countries are shown in Appendix B, and show that student morale and commitment is roughly normally distributed for all countries (Figure B5).

Table 12

Descriptive Statistics Of Student Morale And Commitment For All Countries

Country	Mean	SD	Skewness	Kurtosis
Canada	0.35	0.95	0.21	0.57
United States	0.32	0.96	0.35	0.36
United Kingdom	0.43	1.01	0.38	0.25
Hong Kong	-0.15	0.96	0.14	-0.39
Japan	0.23	1.40	-0.04	-0.69
Korea	-0.08	1.25	-0.04	-0.34

Table 12 shows the mean, standard deviation, skewness, and kurtosis of student morale and commitment for all six countries examined. The Western countries showed varying mean levels of student morale and commitment. Principals in the United Kingdom reported the highest positive mean levels of student morale and commitment (0.43), followed by principals in Canada (0.35) and the United States (0.32). The Asian countries reported more varying mean levels of student morale and commitment, with principals in Japan reporting the least positive levels of student morale and commitment (-0.15), followed by principals in Korea (-0.08). Principals in Japan reported positive mean levels of student morale and commitment (.23). For all countries, there is no obvious violation to the normal distribution of instrumental motivation according to the values of skewness and kurtosis.

Teacher factors affecting school climate

Teacher factors affecting school climate, a scaled index with values centered at 0 and ranging from –5 to +3, was measured through principals' responses to the PISA 2003 School Questionnaire. Positive values indicate that responses for the country are higher than the OECD average. The way that the items were scaled is such that the more positive the value, the fewer negative teacher behaviours are occurring in the school. The histograms of teacher factors affecting school climate for all countries are shown in Appendix B, and show that Teacher factors affecting school climate is roughly normally distributed for all countries (Figure B6).

Table 13 shows the mean, standard deviation, skewness, and kurtosis of teacher factors affecting school climate for all six countries examined. The Western countries showed varying mean levels of teacher factors affecting school climate. Principals in Canada reported the highest positive mean levels of teacher factors affecting school climate (0.43), followed by principals in the United States (-0.04) and the United Kingdom (-0.12). The Asian countries reported more varying mean levels of teacher factors affecting school climate, with principals in Hong Kong-China reporting the least positive levels of teacher factors affecting school climate (-0.34), followed by principals in Japan (-0.23).

Table 13

Descriptive Statistics Of Teacher Factors Affecting School Climate For All Countries

Country	Mean	SD	Skewness	Kurtosis
Canada	0.16	0.89	0.51	0.46
United States	-0.04	0.80	0.44	0.36
United Kingdom	-0.12	0.84	0.57	0.74
Hong Kong	-0.34	1.34	-0.76	0.51
Japan	-0.23	0.90	0.88	1.44
Korea	0.36	1.16	-0.00	-0.45

Principals in Korea reported positive mean levels of student morale and commitment (0.36). For all countries, there is no obvious violation to the normal distribution of instrumental motivation according to the values of skewness and kurtosis.

Teacher support (aggregate)

Teacher support, a scaled index with values centered at 0 and ranging from –2 to +2, was measured through the PISA 2003 Student Questionnaire. Positive values indicate positive student beliefs about how supportive their teachers are. To determine how teacher support affects student-level motivation variables, student reports of teacher support at the student level were aggregated for each school, giving a school-level value of teacher support. The histograms of teacher support for all countries are shown in Appendix B, and show that teacher support is roughly normally distributed for all countries (Figure B7). The Asian countries reported more varying mean levels of teacher support, with students in Japan reporting the least positive levels of teacher support (-0.34), followed by students in Korea (-0.22) (Table 14). Students in Hong Kong-China reported positive mean levels of teacher support (0.03).

Table 14

Descriptive Statistics Of Teacher Support For All Countries

Country	Mean	SD	Skewness	Kurtosis
Canada	0.27	0.39	-0.01	0.90
United States	0.33	0.37	-0.35	0.78
United Kingdom	0.19	0.31	-0.02	0.09
Hong Kong	0.03	0.23	-0.01	-0.11
Japan	-0.34	0.29	-0.41	1.58
Korea	-0.22	0.19	0.33	1.20

Note: Mean is the mean of school means; the low SD is due to the student-level variable having been standardized to have an SD of 1 across students, not schools.

For all countries, there is no obvious violation to the normal distribution of instrumental motivation according to the values of skewness and kurtosis.

Achievement scores

For each student who participated in the PISA 2003, the dataset contains five plausible values (PV1 – PV5) for each domain assessed (see discussion of plausible values in the methodology section). These plausible values are used in the calculation of the HLM models. The descriptive statistics - maximum, minimum, mean, standard deviation, skewness, and kurtosis- for each of the five plausible values are very similar, and are detailed in Appendix C. Histograms of the five plausible values for each domain, for each country, are also given in Appendix C. For all countries and all domains, all five plausible values are roughly normally distributed, and satisfy statistical assumptions of skewness and kurtosis.

Student weights and school weights are available in the PISA dataset, and are used in the calculations to eliminate or reduce biases due to the sample design (Willms & Smith, 2005).Student weights and school weights were not used in the calculations reported in this study, as the weights in PISA are primarily to facilitate comparisons between countries on achievement (Willms & Smith, 2005). As the focus of this study is on relationships between motivation and achievement within each country, and then the comparison of those relationships between countries, using the student and school weights was determined to be unnecessary. All HLM calculations were carried out using unweighted values, and were then repeated using the weighted values. No substantive differences were found between the models. Unweighted models are reported here.

Mathematics Achievement

For each student who participated in the PISA 2003, there are five plausible values (PV1math – PV5math) in the datasets to indicate each student's general math ability achievement score. Scaling of the scores resulted in a mean of 500 points, and a standard deviation of 100 points for all OECD countries. The histograms of the general math ability scores for all countries are shown in Appendix C, Figure C1.

Table 15 shows that Japan achieved the highest average math scores (559 points), followed by Korea (555 points), Hong Kong-China (553 points), Canada (511 points), and the United Kingdom (512 points). The United States achieved lower than the OECD average of 500 points, with an average score of 470 points. There is no obvious violation to the normal distributions of all the five plausible values of math scores according to the corresponding skewness and kurtosis (see Appendix C, Table C1).

Science Achievement

For each student who participated in the PISA 2003, there are five plausible values (PV1scie – PV5scie) in the datasets to indicate each student's science literacy achievement score. Scaling of the scores resulted in a mean of 500 points, and a standard deviation of 100 points. The histograms of the science scores for all countries are presented in Appendix C, and show no violations of normal distribution, skewness or kurtosis.

Table 15

Mean Achievement Scores For All Domains And All Countries

Country	Mathematics	Science	Reading	Problem-solving
Canada	511	498	508	509
United States	470	481	485	466
United Kingdom	512	519	511	512
Hong Kong-China	553	544	516	551
Japan	559	572	525	570
Korea	555	551	543	561

Note 1: Mean scores are from the final HLM models and so have been adjusted for missing data (students with missing data were excluded from the analyses), and may differ slightly from the published mean country scores in PISA 2003 publications.

According to the histograms in Appendix C (Figure C2), all five plausible values for the science literacy score for all countries are roughly normally distributed. Table 15 shows that Japan achieved the highest average science literacy scores (572 points), followed by Korea (551 points), Hong Kong-China (544), and the United Kingdom (519 points). The United States and Canada achieved lower than the OECD average of 500 points, with average scores of 498 and 481 points respectively. There is no obvious violation to the normal distributions of all the five plausible values of math scores according to the corresponding skewness and kurtosis (Appendix C, Table C2).

Reading Achievement

For each student who participated in the PISA 2003, there are five plausible values (PV1read – PV5read) in the datasets to indicate each student's reading literacy achievement score. Scaling of the scores resulted in a mean of 500 points, and a standard deviation of 100 points. The histograms of the reading literacy scores for all countries are shown in Appendix C, Figure C3. The maximum, minimum, mean, standard deviation, skewness, and kurtosis of reading literacy scores for all countries are presented in Appendix C, Table C3.

According to the histograms in Appendix C (Figure C3), all five plausible values for the reading literacy score for all countries are roughly normally distributed. Table 15 shows that Korea achieved the highest average reading literacy scores (543 points), followed by Japan (525 points), Hong Kong-China (516 points), the United Kingdom (511 points), and Canada (508 points). The United States had the lowest average reading score, at 485 points. There is no obvious violation to the normal distributions of all the five plausible values of math scores according to the corresponding skewness and kurtosis (See Appendix C, Table C3).

Problem-solving Achievement

For each student who participated in the PISA 2003, there are five plausible values (PV1prob – PV5prob) in the datasets to indicate each student's problem-solving ability achievement score. Scaling of the scores resulted in a mean of 500 points, and a standard deviation of 100 points. The histograms of the problem-solving ability scores for all countries are shown in Appendix C, Figure C4. The maximum, minimum, mean, standard deviation, skewness, and kurtosis of problem-solving ability scores for all countries are also presented in Appendix C, in Table C4.

According to the histograms in Appendix C (Figure C4), all five plausible values for the problem-solving ability score for all countries are roughly normally distributed. Table 15 shows that Japan achieved the highest average problem-solving scores (570 points), followed by Korea

(561 points), Hong Kong-China, (551 points), the United Kingdom (512 points), and Canada (509 points). The United States achieved lower than the OECD average of 500 points, with an average score of 466 points. There is no obvious violation to the normal distributions of all the five plausible values of problem-solving scores according to the corresponding skewness and kurtosis (see Appendix C, Table C4).

Correlations

The correlations between variables at the student level and the school level were calculated using SYSTAT 11. Given that the means and distributions of each of the plausible values are very similar (and this is the case across all domains), only one plausible value (PV1) was used from each domain in calculating the correlations. The correlations at the student level are presented in Tables 16 to 21. At the student level, all the relationships between the variables are significant ($p < 0.05$) for all countries. Results for the correlations are presented by country at the student level first, followed by results for each country at the school level.

Student level

The results for Canada are shown in Table 16. At the student level, achievement scores in all literacy domains were highly positively correlated (r = .78 to .88). Looking at the relationships between the motivation variables and achievement, the strongest correlation was between self-efficacy and mathematics achievement (r = .54), followed by the correlations between self-efficacy and problem-solving (r = .48), science (r = .47), and reading literacy (r = .39) achievement. For the remainder of the motivation variables, moderate correlations were found between mathematics achievement and instrumental and intrinsic motivation (r = .25 for both), problem-solving and instrumental and intrinsic motivation (r = .25 and .23, respectively), and science achievement and instrumental and intrinsic motivation (r = .20 and .18, respectively), while less strong correlations were found between reading achievement and instrumental and intrinsic motivation (*r* = .19 and .12, respectively). Overall, performance orientation showed the lowest correlation with achievement, ranging from *r* = .07 (for reading achievement) to *r* = .16 (for mathematics achievement).

Moderate correlations were observed amongst the motivation variables themselves. Self-efficacy was moderately correlated with intrinsic motivation (*r* = .41), instrumental motivation (*r* = .37), and performance orientation (*r* = .31). Instrumental motivation was moderately correlated with intrinsic motivation (*r* = .59), and less strongly with performance orientation (*r* = .39). Finally, a moderate correlation was observed between intrinsic motivation and performance orientation (*r* = .39).

Table 16

Correlations Between Student Motivation Variables And Achievement Scores In All Literacy Domains For Canada

	1	2	3	4	5	6	7
1. Performance orientation	1.00						
2. Instrumental motivation	0.39	1.00					
3. Intrinsic motivation	0.42	0.59	1.00				
4. Self-efficacy	0.31	0.37	0.41	1.00			
5. Mathematics	0.16	0.25	0.25	0.54	1.00		
6. Reading	0.07	0.19	0.12	0.39	0.78	1.00	
7. Science	0.10	0.20	0.18	0.47	0.83	0.85	1.00
8. Problem-solving	0.13	0.25	0.23	0.48	0.88	0.85	0.82

Note: All correlations in the table are significant, $p<.05$

The results for the United States are shown in Table 17. At the student level, achievement scores in all literacy domains were highly positively correlated (*r* = .84 to .89). Looking at the relationships between the motivation variables and achievement, the strongest correlation was between self-efficacy and mathematics achievement (r = .52), followed by the correlations between self-efficacy and problem-solving (r = .50), science (r = .47), and reading literacy (r = .42) achievement.

Table 17

Correlations Between Student Motivation Variables And Achievement In All Literacy Domains For The United States

	1	2	3	4	5	6	7
1. Performance orientation	1.00						
2. Instrumental motivation	0.40	1.00					
3. Intrinsic motivation	0.44	0.61	1.00				
4. Self-efficacy	0.27	0.35	0.34	1.00			
5. Mathematics	0.03	0.14	0.09	0.52	1.00		
6. Reading	-0.02	0.11	0.01	0.42	0.84	1.00	
7. Science	-0.02	0.12	0.04	0.47	0.86	0.87	1.00
8. Problem-solving	0.02	0.15	0.10	0.50	0.90	0.86	0.84

Note: All correlations in the table are significant, $p<.05$

For the remainder of the motivation variables, only weak correlations were found. Of these, the least weak were between instrumental motivation and problem-solving (r = .15), mathematics (r = .14), science (r = .12), and reading (r = .11) achievement. For intrinsic motivation, correlations ranged from r = .10 with problem-solving achievement to r = .01 with reading achievement. For performance orientation, correlations were negative with reading and science achievement (r = -.02 for both), and weakly positive with mathematics (r = .03) and problem-solving achievement (r = .02).

Moderate correlations were observed amongst the motivation variables themselves. Self-efficacy was moderately correlated with instrumental motivation (r = .35), intrinsic motivation (r = .34), and performance orientation (r = .27). Instrumental motivation was moderately correlated with intrinsic motivation (r = .61), and less strongly with performance orientation (r = .40). Finally, a moderate correlation was observed between intrinsic motivation and performance orientation (r = .44).

The results for the United Kingdom are shown in Table 18. At the student level, achievement scores in all literacy domains were highly positively correlated (r = .84 to .92). Looking at the relationships between the motivation variables and achievement, the strongest correlation was between self-efficacy and mathematics achievement (r = .55), followed by the correlations between self-efficacy and problem-solving (r = .49), science (r = .48), and reading literacy (r = .39) achievement. For the remainder of the motivation variables, only weak correlations were found between mathematics achievement and intrinsic and instrumental motivation (r = .14 and .10, respectively), and problem-solving and intrinsic and instrumental motivation (r = .13 and .08, respectively), while less strong correlations were found between science achievement and intrinsic and instrumental motivation (r = .08 and .06, respectively), and reading achievement and instrumental and intrinsic motivation (r = .02 for both). Overall, performance orientation showed the lowest correlation with achievement, ranging from r = -.05 (for reading achievement) to r = .07 (for mathematics achievement). Moderate correlations were observed amongst the motivation variables themselves. Self-efficacy was moderately correlated with intrinsic motivation (r = .35), performance orientation (r = .30), and instrumental motivation (r = .29). Instrumental motivation was moderately correlated with intrinsic motivation (r = .54), and less strongly with performance orientation (r = .40). Finally, a moderate correlation was observed between intrinsic motivation and performance orientation (r = .42).

Table 18

Correlations Between Student Motivation Variables And Achievement In All Literacy Domains For The United Kingdom

	1	2	3	4	5	6	7
1. Performance orientation	1.00						
2. Instrumental motivation	0.42	1.00					
3. Intrinsic motivation	0.40	0.54	1.00				
4. Self-efficacy	0.30	0.29	0.35	1.00			
5. Mathematics	0.07	0.10	0.14	0.55	1.00		
6. Reading	-0.05	0.02	0.02	0.39	0.84	1.00	
7. Science	0.02	0.06	0.08	0.48	0.87	0.87	1.00
8. Problem-solving	0.02	0.08	0.13	0.49	0.92	0.86	0.85

Note: All correlations in the table are significant, $p<.05$

The results for Hong Kong-China are shown in Table 19. At the student level, achievement scores in all literacy domains were highly positively correlated (r = .81 to .91). Looking at the relationships between the motivation variables and achievement, the strongest correlation was between self-efficacy and mathematics achievement (r = .56), followed by the correlations between self-efficacy and problem-solving (r = .51), science (r = .49), and reading literacy (r = .40) achievement. For the remainder of the motivation variables, moderate correlations were found between mathematics achievement and intrinsic and instrumental motivation (r = .30 and .22 respectively), problem-solving and intrinsic and instrumental motivation (r = .26 and .19), and science achievement and intrinsic and instrumental motivation (r = .22 and .16, respectively), while less strong correlations were found between reading achievement and intrinsic and instrumental motivation (r = .16 and .14, respectively).

Performance orientation for Hong Kong-China differed from the Western countries discussed above, in that the correlations ranged from r = .10 (for reading achievement) to r = .19 (for mathematics achievement).

Moderate correlations were observed amongst the motivation variables themselves. Self-efficacy was moderately correlated with intrinsic motivation (r = .45), performance orientation (r = .38), and instrumental motivation (r = .35). Instrumental motivation was moderately correlated with intrinsic motivation (r = .61), and with performance orientation (r = .56). Finally, a moderate correlation was observed between intrinsic motivation and performance orientation (r = .56).

Table 19

Correlations Between Student Motivation Variables And Achievement In All Literacy Domains For Hong Kong-China

	1	2	3	4	5	6	7
1. Performance orientation	1.00						
2. Instrumental motivation	0.51	1.00					
3. Intrinsic motivation	0.56	0.61	1.00				
4. Self-efficacy	0.38	0.35	0.45	1.00			
5. Mathematics	0.19	0.22	0.30	0.56	1.00		
6. Reading	0.10	0.14	0.16	0.40	0.81	1.00	
7. Science	0.13	0.16	0.22	0.49	0.86	0.83	1.00
8. Problem-solving	0.15	0.19	0.26	0.51	0.91	0.85	0.84

Note: All correlations in the table are significant, $p<.05$

The results for Japan are shown in Table 20. At the student level, achievement scores in all literacy domains were highly positively correlated (r = .78 to .88). Looking at the relationships between the motivation variables and achievement, the strongest correlation was between self-efficacy and mathematics achievement ($r = .57$), followed by the correlations between self-efficacy and problem-solving ($r = .53$), science ($r = .50$), and reading literacy ($r = .44$) achievement. For the remainder of the motivation variables, moderate correlations were found between mathematics achievement and intrinsic and instrumental motivation ($r = .26$ and .25, respectively), problem-solving and instrumental and intrinsic motivation ($r = .24$ and .20, respectively), and science achievement and instrumental and intrinsic motivation ($r = .22$ and .20, respectively), while less strong correlations were found between reading achievement and instrumental and intrinsic motivation ($r = .17$ and .14, respectively).

As with Hong Kong-China, performance orientation showed a different pattern of correlations with achievement scores compared to Western countries. Performance orientation was positively correlated with mathematics ($r = .22$), problem-solving ($r = .20$), science ($r = .15$), and reading ($r = .13$) achievement. Moderate correlations were observed amongst the motivation variables themselves. Self-efficacy was moderately correlated with intrinsic motivation ($r = .42$), performance orientation ($r = .40$), and instrumental motivation ($r = .38$). Instrumental motivation was moderately correlated with intrinsic motivation ($r = .65$), and with performance orientation ($r = .52$). Finally, a moderate correlation was observed between intrinsic motivation and performance orientation ($r = .55$).

The results for Korea are shown in Table 21. At the student level, achievement scores in all literacy domains were highly positively correlated ($r = .77$ to .90). Looking at the relationships between the motivation variables and achievement, the strongest correlation was between self-efficacy and mathematics achievement ($r = .58$), followed by the correlations between self-efficacy and problem-solving and science ($r = .51$ for both), and reading literacy ($r = .45$) achievement. For the remainder of the motivation variables, unlike other countries, all of the motivation variables showed moderate correlations, even performance orientation. Moderate correlations were found between mathematics achievement and performance orientation (r = .40), intrinsic motivation (r = .39), and instrumental motivation (r = .35).

Table 20

Correlations Between Student Motivation Variables And Achievement In All Literacy Domains For Japan

	1	2	3	4	5	6	7
1. Performance orientation	1.00						
2. Instrumental motivation	0.52	1.00					
3. Intrinsic motivation	0.55	0.65	1.00				
4. Self-efficacy	0.40	0.38	0.42	1.00			
5. Mathematics	0.22	0.25	0.26	0.57	1.00		
6. Reading	0.13	0.17	0.14	0.44	0.78	1.00	
7. Science	0.15	0.22	0.20	0.50	0.82	0.88	1.00
8. Problem-solving	0.20	0.24	0.2	0.53	0.87	0.79	0.78

Note: All correlations in the table are significant, p<.05

For problem-solving, moderate correlations were found between problem-solving and performance orientation and intrinsic motivation (r = .34 for both), and instrumental motivation (r = .31). For science achievement, correlations were found between science achievement and performance orientation (r = .32), and intrinsic and instrumental motivation (r = .29 for both). Finally, correlations were found between reading achievement and performance orientation and intrinsic motivation (r = .34 for both), and instrumental motivation (r = .31).

Moderate correlations were observed amongst the motivation variables themselves. Self-efficacy was moderately correlated with performance orientation (r = .53), intrinsic motivation (r = .51), instrumental motivation (r = .45). Instrumental motivation was moderately correlated with intrinsic motivation (r = .65), and with performance orientation (r = .56). Finally, a moderate correlation was observed between intrinsic motivation and performance orientation (r = .62).

Table 21

Correlations Between Student Motivation Variables And Achievement In All Literacy Domains For Korea

	1	2	3	4	5	6	7
1. Performance orientation	1.00						
2. Instrumental motivation	0.56	1.00					
3. Intrinsic motivation	0.62	0.65	1.00				
4. Self-efficacy	0.53	0.45	0.51	1.00			
5. Mathematics	0.40	0.35	0.39	0.58	1.00		
6. Reading	0.32	0.26	0.26	0.45	0.77	1.00	
7. Science	0.32	0.29	0.29	0.51	0.86	0.83	1.00
8. Problem-solving	0.34	0.31	0.34	0.51	0.90	0.83	0.80

Note: All correlations in the table are significant, $p<.05$

School level correlations

The correlations at the school level are presented in Tables 22 to 27. All school level correlations are school means for each variable.

The results for Canada are shown in Table 22. At the school level, for Canada, most of the relationships between variables are positive and significant except for aggregate teacher support. None of the correlations with aggregate teacher support were significant except for the correlation between aggregate teacher support and principals' perceptions of teacher behaviours affecting school climate (r = .13). As at the student level, the strongest correlations were among

Table 22

Correlations Between School Level Variables And All Academic Achievement Domains For Canada.

	1.	2.	3.	4.	5.	6.
1. Mathematics	1.00					
2. Reading	0.93*	1.00				
3. Science	0.94*	0.96*	1.00			
4. Problem-solving	0.96*	0.94*	0.94*	1.00		
5. Aggregate Teacher Support	0.08	0.07	0.05	0.11	1.00	
6. Teacher behaviours	0.13*	0.14*	0.14*	0.15*	0.13*	1.00
7. Student morale	0.27*	0.26*	0.25*	0.27*	0.04	0.30

* Correlations are significant, $p<.05$

the scores on the academic domains; these correlations were all above $r = .90$. Moderate correlations were seen between students' morale and academic scores (ranging from $r = .25$ for science score to $r = .27$ for both mathematics and problem-solving scores), while lower correlations were found between principals' perceptions of teacher behaviours affecting school climate and scores on all academic domains (ranging from $r = .13$ for mathematics score to $r = .15$ for problem-solving scores).

For the United States, the results look similar to those for Canada (Table 23). At the school level, for the United States, most of the relationships between variables are positive and significant except for aggregate teacher support. None of the correlations with aggregate teacher support were significant. As at the student level, the strongest correlations were among the scores on the academic domains; these correlations were all above $r = .95$. Moderate correlations were seen between students' morale and academic scores (ranging from $r = .38$ for mathematics, reading, and science score to *r* = .39 for problem-solving score), while lower correlations were found between principals' perceptions of teacher behaviours affecting school climate and scores on all academic domains (ranging from *r* = .19 for reading score to *r* = .21 for both mathematics and problem-solving scores).

Table 23

Correlations Between School Level Variables In All Literacy Domains For The United States.

	1.	2.	3.	4.	5.	6.
1. Mathematics	1.00					
2. Reading	0.96*	1.00				
3. Science	0.97*	0.97*	1.00			
4. Problem-solving	0.98*	0.96*	0.96*	1.00		
5. Aggregate Teacher Support	0.12	0.14	0.12	0.15	1.00	
6. Teacher behaviours	0.21*	0.19*	0.21*	0.20*	0.12	1.00
7. Student morale	0.38*	0.38*	0.38*	0.39*	0.07	0.43*

* Correlations are significant, $p<.05$

Slightly different results were found for the United Kingdom (Table 24). In the United Kingdom, few relationships between variables are positive and significant. None of the correlations with aggregate teacher support were significant, and only one correlation with principals' perceptions of student morale was significant (student morale and principals' perceptions of teacher behaviours affecting school climate, *r* = 0.48). As at the student level, the strongest correlations were among the scores on the academic domains; these correlations were all above *r* = .95.

Table 24

Correlations Between School Level Variables In All Literacy Domains For The United Kingdom.

	1.	2.	3.	4.	5.	6.
1. Mathematics	1.00					
2. Reading	0.97*	1.00				
3. Science	0.97*	0.97*	1.00			
4. Problem-solving	0.98*	0.97*	0.96*	1.00		
5. Aggregate Teacher Support	0.05	0.06	0.07	0.07	1.00	
6. Teacher behaviours	0.16	0.15	0.14	0.16	-0.01	1.00
7. Student morale	0.07	0.06	0.08	0.07	0.08	0.48*

* Correlations are significant, $p<.05$

Hong Kong-China also shows different results from Canada and the United States. Most of the relationships between variables are positive and significant (Table 25), except for aggregate teacher support and principals' perceptions of teacher behaviours affecting school climate. None of the correlations with these two variables were significant. As at the student level, the strongest correlations were among the scores on the academic domains; these correlations were all above $r = .97$. Moderate correlations were seen between students' morale and academic scores (ranging from $r = .56$ for problem-solving score to $r = .57$ for mathematics, reading, and science score).

Table 25

Correlations Between School Level Variables In All Literacy Domains For Hong Kong-China.

	1.	2.	3.	4.	5.	6.
1. Mathematics	1.00					
2. Reading	0.97*	1.00				
3. Science	0.99*	0.98*	1.00			
4. Problem-solving	0.99*	0.98*	0.99*	1.00		
5. Aggregate Teacher Support	0.23	0.24	0.23	0.23	1.00	
6. Teacher behaviours	0.13	0.11	0.13	0.13	0.10	1.00
7. Student morale	0.57*	0.57*	0.57*	0.56*	0.33*	0.23

* Correlations are significant, $p<.05$

The results for Japan are different again from previous results. All of the relationships between variables are positive and significant (Table 26). As at the student level, the strongest correlations were among the scores on the academic domains; these correlations were all above $r = .97$. Moderate correlations were seen between students' morale and academic scores (ranging from $r = .61$ for problem-solving score to $r = .63$ for mathematics score). Moderate correlations were also seen between aggregate teacher support and academic score (ranging from $r = .41$ for problem-solving score to $r = .45$ for science score), and between principals' perceptions of teacher behaviours affecting school climate and academic score (ranging from $r = .50$ for reading, science, and problem-solving scores to $r = .52$ for mathematics score).

Table 26

Correlations Between School Level Variables In All Literacy Domains For Japan.

	1.	2.	3.	4.	5.	6.
1. Mathematics	1.00					
2. Reading	0.98*	1.00				
3. Science	0.99*	0.99*	1.000			
4. Problem-solving	0.99*	0.99*	0.98*	1.000		
5. Aggregate Teacher Support	0.43*	0.44*	0.45*	0.41*	1.000	
6. Teacher behaviours	0.52*	0.50*	0.50*	0.50*	0.26*	1.000
7. Student morale	0.63*	0.62*	0.61*	0.61*	0.34*	0.67*

* Correlations are significant, $p<.05$

The results for Korea are similar to those for Hong Kong-China. Most of the relationships between variables are positive and significant (Table 27), except for aggregate teacher support and principals' perceptions of teacher behaviours affecting school climate. None of the correlations with these two variables were significant, except for the correlation between principals' perceptions of teacher behaviours affecting school climate and student morale (r = .38). As at the student level, the strongest correlations were among the scores on the academic domains; these correlations were all above r = .92. Moderate correlations were seen between students' morale and academic scores (ranging from r = .53 for for reading score to r = .55 for problem-solving and science scores).

Table 27

Correlations Between School Level Variables In All Literacy Domains For Korea.

	1.	2.	3.	4.	5.	6.
1. Mathematics	1.00					
2. Reading	0.93*	1.00				
3. Science	0.99*	0.94*	1.000			
4. Problem-solving	0.99*	0.95*	0.98*	1.000		
5. Aggregate Teacher Support	0.14	0.13	0.14	0.15	1.000	
6. Teacher behaviours	0.17	0.20	0.20	0.19	0.07	
7. Student morale	0.54*	0.53*	0.55*	0.55*	0.16	0.38*

* Correlations are significant, p<.05

Hierarchical linear models

The results of the HLM models are presented in this section. The HLM models were created by entering all of the variables of interest into the models using HLM 6.0 (Raudenbush, Bryk, & Congdon, 2005). Any variables which were statistically non-significant were dropped from the models, and the models were run again. This process was carried out until only statistically significant variables remained in the models. Consequently, the results for each variable are conditioned on the other variables (and their respective statistical properties) in the model. Separate models for each country and each academic domain (e.g., a final model for mathematics achievement in Canada, a final model for science achievement in Canada, etc) were calculated using this method. A total of forty models were calculated, because separate models were calculated for each subdomain of mathematics ability (space and shape, change and relationships, uncertainty, and quantity). However, there were no differences between the subdomain models and the mathematics general ability models for any of the countries, and so each country's mathematics general ability HLM model is presented in this section.

The initial step in the HLM analysis is to create a null model. The null model is valuable in that it tells us how much of the variation in the outcome measure (in this case, achievement score) can be accounted for by the Level 2 units (here, schools) (Raudenbush & Bryk, 2002). The index of proportion of variance at Level 2 is the intra-class correlation coefficient.

The Null Model

The null model is calculated with unconditioned Level 1 and random effects at Level 2 (Raudenbush & Bryk, 2002). The null model separates the variability of the outcome variable into school and student components:

The equations of the Null Models are:

Student level (Level 1): $Y_{ij} = \beta_{0j} + r_{ij}$

School level (Level 2): $\beta_{0j} = \gamma_{00} + u_{0j}$

where

Y_{ij}, is the achievement score for student *i* and school *j*;

β_{0j} is the achievement score intercept, and it is calculated for each of *j* schools in the dataset;

r_{ij} is unique error associated with the student *i* and school *j*;

γ_{00} is mean achievement for all the students in the sample; and

u_{0j} is the unique error to the intercept associated with school *j*.

The outputs of the Null models are given in Appendix D. These tables are organized by domain, with each country's null model given for that domain. A summary of the intraclass correlations (the proportion of variance in scores accounted for by schools) is given in Table 28.

Table 28

Intraclass Correlations Derived From The Null Models For All Countries And All Domains

Country	Intraclass correlation for general math score	Intraclass correlation for science score	Intraclass correlation for reading literacy score	Intraclass correlation for problem-solving ability score
Canada	.19	.18	.17	.17
United States	.24	.21	.23	.22
United Kingdom	.27	.25	.26	.24
Hong Kong-China	.47	.46	.43	.40
Japan	.53	.46	.46	.47
Korea	.42	.38	.36	.38

The tables in Appendix D show that the average school scores for all domains vary significantly across schools for all countries. Table 28 summarizes these results. The amount of variability accounted for by schools varies from one country to another, with Japan having schools that tend to be less equitable for students (about 53% of the variability is accounted for by schools), and Canada having the most equitable schools (about 19% of the variability accounted for by schools). This means that in Japan, just over 50% of a student's expected math general ability score will be influenced by the school that student attends (leaving just under 50% of the variability accounted for by other factors, such as student attitudes and beliefs), while in Canada, just under 20% of a student's expected math general ability score will be influenced by the school that student attends, with the remaining variability resting with the student (and that student's individual factors) alone. Across all countries, schools in the Western countries are seen to account for less variability in students' scores (intraclass correlations ranging from 19% to 27%) than are schools in Asian countries (intraclass correlations ranging from 42% to 53%).

Random Coefficient Model

In the next series of HLM models, student-level variables were added into the equations to examine the estimated within-school variance, which is the proportion of the variance in achievement scores that can be accounted for by the student-level motivation variables (instrumental motivation, intrinsic motivation, performance orientation, and self-efficacy). All student-level variables were entered into the equations uncentered, and the estimated coefficients showed the within-school achievement score difference, controlling for other student-level variables. These models were then compared to the null model by examining the proportion of unexplained within-school variance that was accounted for after all the student-level predictors were included in the model.

The following is an example of the preliminary Level 1 model for general mathematics achievement for Canada. This intermediary Level 1 model includes all of the student level variables being examined in this study.

$$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{PERFORT}) + \beta_{2j}\,{*}(\text{INSTMOT}) + \beta_{3j}\,{*}(\text{INTMAT}) + \beta_{4j}\,{*}(\text{MATHEFF}) + r_{ij}$$

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + u_{1j}$$

$\beta_{2j} = \gamma_{20} + u_{2j}$

$\beta_{3j} = \gamma_{30} + u_{3j}$

$\beta_{4j} = \gamma_{40} + u_{4j}$

where

β_{1j} to β_{4j} are the parameters of the student-level variables of interest; and

γ_{00} to γ_{40} are the average regression slopes across students.

u_{0j} to u_{4j} is the error term unique to school $_j$

PERFORT: performance orientation

INSTMOT: Instrumental motivation

INTMAT: Intrinsic motivation

MATHEFF: Self-efficacy

The random coefficient models were run in conjunction with the random intercept and school slope models. In other words, the Level 2 variables were entered at the same time as the Level 1 variables, to create the final model, so the random coefficient model is not individually reported here. This was done for practical purposes in reporting the final results.

Random Intercept and School Slope Models

The final set of HLM analyses leading to the final models examined whether student achievement varied due to the Level 1 motivation variables and the Level 2 variables. The slopes for these variables were allowed to vary in the models. This model was used to answer what student- and school-level variables significantly explain the achievement variance across schools.

The following is an example of a preliminary random intercept and school slopes model for general mathematics achievement in Canada. This model was run until only the significant variables remained (see below).

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{PERFORT}) + \beta_{2j}*(\text{INSTMOT}) + \beta_{3j}*(\text{INTMAT}) + \beta_{4j}$

$*(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{AGGTS}) + \gamma_{02}\,(\text{STMORALE}) + \gamma_{03}\,(\text{TEACBEHA}) + u_{0j}$

$\beta_{1j} = \gamma_{10} + \gamma_{11}\,(\text{AGGTS}) + \gamma_{12}\,(\text{STMORALE}) + \gamma_{13}\,(\text{TEACBEHA}) + u_{1j}$

$\beta_{2j} = \gamma_{20} + \gamma_{21}\,(\text{AGGTS}) + \gamma_{22}\,(\text{STMORALE}) + \gamma_{23}\,(\text{TEACBEHA}) + u_{2j}$

$\beta_{3j} = \gamma_{30} + \gamma_{31}\,(\text{AGGTS}) + \gamma_{32}\,(\text{STMORALE}) + \gamma_{33}\,(\text{TEACBEHA}) + u_{3j}$

$\beta_{4j} = \gamma_{40} + \gamma_{41}\,(\text{AGGTS}) + \gamma_{42}\,(\text{STMORALE}) + \gamma_{43}\,(\text{TEACBEHA}) + u_{4j}$

After all analyses were run, the final model looked like this:

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{PERFORT}) + \beta_{2j}\,(\text{INSTMOT}) + \beta_{3j}\,(\text{INTMAT}) + \beta_{4j}\,(\text{MATHEFF}) +$

r_{ij}

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{STMORALE}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20}$

$\beta_{3j} = \gamma_{30} + u_{3j}$

$\beta_{4j} = \gamma_{40} + u_{4j}$

This final model indicates that for the intercept (conditioned school average general math achievement), only students' morale was significant at Level 2, and that there was significant variability across schools (because the error term is still in the model for the intercept). There was also significant variability across schools for the intrinsic motivation and self-efficacy slopes, whereas there was no school-level variation in the slopes for performance orientation and instrumental motivation.

In tabular form, this final model is depicted as shown in Table 29.

Table 29 shows that for general math achievement in Canada, in the student-level model, students who have higher instrumental and intrinsic motivation and higher self-efficacy are predicted to score higher in mathematics general ability than students who have lower levels of these motivation variables. Specifically, as the value of self-reported instrumental motivation increases by one unit, mathematics achievement score is predicted to increase by 5.50 points, and for intrinsic motivation, a one unit increase predicts a 2.84 point increase. As self-reported self-efficacy increases by one unit, students are predicted to score 38.47 points higher on the general mathematics ability assessment. A different trend is seen for performance orientation. For this variable, a one unit increase in self-reported performance orientation predicts a drop of 2.91 points on the general mathematics ability assessment. For all of these results, they hold true when all other variables are held constant.

The student-level model for general math achievement in the United States (Table 30) shows that students who have higher self-efficacy are predicted to score higher in mathematics general ability than students who have lower levels of self-efficacy. Specifically, as the value of self-reported self-efficacy increases by one unit, students are predicted to score 41.69 points higher on the general mathematics ability assessment. A different trend is seen for performance orientation. For this variable, a one unit increase in self-reported performance orientation predicts a drop of 5.39 points on the general mathematics ability assessment. For all of these results, they hold true when all other variables are held constant. For the school-level model, only student morale was significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the mathematics general ability assessment increased by 13.91 points when other variables were held constant. There was significant school variation in average school scores after controlling for students' morale. The self-efficacy slope varied significantly across schools. The proportion of variance in general mathematics achievement scores accounted for by the Level 2 model is 43%. This means that this final model (including the Level 2 variables) accounts for 43% of the total observed school-level variance in the null model.

Table 29

Final Model For General Mathematics Achievement For Canada

Variables	Coefficient	*SE*	*t*	*df*	*p*
	Parameter Estimates				
Fixed Effects					
Mathematics Intercept (γ_{00})	510.72	1.13	450.64	1056	.00
Student morale (γ_{01})	9.44	1.11	8.44	1056	.00
Performance Orientation Slope					
Intercept (γ_{10})	-2.91	0.63	-4.61	40	.00
Instrumental motivation Slope					
Intercept (γ_{20})	5.50	0.64	8.61	423	.00
Intrinsic Motivation Slope					
Intercept (γ_{30})	2.84	0.62	4.57	531	0.00
Self-efficacy Slope					
Intercept (γ_{40})	38.47	0.63	60.95	49	0.00

Random Effects	Variance Component	χ^2	*df*	*p*
Intercept (u_0j)	867.21	4292.27	1041	0.000
Intrinsic Motivation Slope (u_{3j})	40.45	1168.64	1042	0.004
Self-efficacy Slope (u_{4j})	42.94	1280.28	1042	0.000
Student-Level Effect (r_{ij})	4548.33			

Proportion of variance explained in the Level 2 model = $\frac{1532.4-(867.21+40.45+42.94)}{1532.4} = .38$

Table 30

Final Model For General Mathematics Achievement For United States

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Mathematics Intercept (γ_{00})	469.89	2.84	165.32	223	0.00
Student morale (γ_{01})	13.91	2.64	5.26	223	0.00
Performance Orientation Slope					
Intercept (γ_{10})	-5.39	1.26	-4.26	4385	0.00
Self-efficacy Slope					
Intercept (γ_{40})	41.69	1.29	32.28	224	0.00

Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	1138.02		1033.23	222	0.00
Self-efficacy Slope (u_{4j})	68.26		283.65	223	0.00
Student-Level Effect (r_{ij})	4881.38				

Proportion of variance explained in the Level 2 model = $\frac{2107.5-(1138+68.26)}{2107.5}$ = .43

The student-level model for general math achievement in the United Kingdom (Table 31) shows that students who have higher self-efficacy are predicted to score higher in mathematics general ability than students who have lower levels of this motivation variable. Specifically, as the value of self-reported self-efficacy increases by one unit, students are predicted to score 46.98 points higher on the general mathematics ability assessment. A different trend is seen for performance orientation and intrinsic motivation. For these variables, a one unit increase in self-reported performance orientation predicts a drop of 7.48 points on the general mathematics ability assessment, while a one unit increase in self-reported intrinsic motivation predicts a drop of 2.42 points on the general mathematics ability assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, student morale and teacher behaviour were significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the mathematics general ability assessment increased by 15.43 points, and as principals' reports of teacher behaviours which positively influenced school morale increased by one unit, the school average score on the mathematics general ability assessment increased by 6.23 points when other variables were held constant. Further, principals' reports of positive student morale had an influence on both the intrinsic motivation and the self-efficacy slopes. For the intrinsic motivation slope, principals' reports of positive student morale modified the slope, lessening the negative impact of intrinsic motivation on students' scores. For the self-efficacy slope, principals' reports of positive student morale also modified the slope, although in this case, the positive impact of higher self-efficacy was lessened (in other words, the slope was flattened).

There was significant school variation in average school scores after controlling for students' morale. The performance orientation and self-efficacy slopes varied significantly across schools. The proportion of variance in general mathematics achievement scores accounted for by the Level 2 model is 56%. This means that this final model (including the Level 2 variables) accounts for 56% of the total observed school-level variance in the null model.

Table 31

Final Model For General Mathematics Achievement For The United Kingdom

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Mathematics Intercept (γ_{00})	512.40	2.16	237.09	306	0.00
Student morale (γ_{01})	15.43	2.10	7.33	306	0.00
Teacher Behaviour (γ_{02})	6.23	2.64	2.36	306	0.00
Performance Orientation Slope					
Intercept (γ_{10})	-7.48	1.04	-7.22	308	0.00
Intrinsic Motivation Slope					
Intercept (γ_{20})	-2.42	1.12	-2.16	110	0.00
Student morale (γ_{21})	3.49	0.87	4.01	72	0.00
Self-efficacy Slope					
Intercept (γ_{30})	46.98	1.19	39.45	252	0.00
Student morale (γ_{31})	-3.33	1.07	-3.12	121	0.00
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	892.05		1650.94	306	0.00
Performance Orientation Slope (u_{1j})	53.79		389.16	308	0.00
Self-efficacy Slope (u_{3j})	61.10		433.65	307	0.00
Student-Level Effect (r_{ij})	4352.17				

Proportion of variance explained in the Level 2 model = $\frac{2283.6-(892.05+53.79+61.1)}{2283.6}$ = .56

The student-level model for general math achievement in the Hong Kong-China (Table 32) shows that students who have intrinsic motivation and higher self-efficacy are predicted to score higher in mathematics general ability than students who have lower levels of these motivation variables. Specifically, as the value of self-reported intrinsic motivation increases by one unit, mathematics achievement score is predicted to increase by 11.61 points, and as self-reported self-efficacy increases by one unit, students are predicted to score 30.83 points higher on the general mathematics ability assessment. A different trend is seen for performance orientation. For this variable, a one unit increase in self-reported performance orientation predicts a drop of 6.93 points on the general mathematics ability assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, student morale was significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the mathematics general ability assessment increased by 33.62 points. Further, principals' reports of positive student morale had an influence on the self-efficacy slope. For the self-efficacy slope, principals' reports of positive student morale modified the slope, and the positive impact of higher self-efficacy was lessened (in other words, the slope was flattened). There was significant school variation in average school scores after controlling for students' morale in this model. The proportion of variance in general mathematics achievement scores accounted for by the Level 2 model is 59%. This means that this final model (including the Level 2 variables) accounts for 59% of the total observed school-level variance in the null model. The student-level model for general math achievement in Japan (Table 33) shows that students who have higher intrinsic motivation and higher self-efficacy are predicted to score higher in mathematics general ability than students who have lower levels of these motivation variables.

Table 32

Final Model For General Mathematics Achievement For Hong Kong-China

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Mathematics Intercept (γ_{00})	553.51	3.87	142.79	142	0.00
Student morale (γ_{01})	33.62	3.68	9.14	142	0.00
Performance Orientation Slope					
Intercept (γ_{10})	-6.93	1.38	-5.03	287	0.00
Intrinsic Motivation Slope					
Intercept (γ_{20})	11.61	1.26	9.24	359	0.00
Self-efficacy Slope					
Intercept (γ_{30})	30.83	1.52	20.26	34	0.00
Student morale (γ_{31})	-3.41	1.28	-2.67	90	0.01
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	1873.78		2081.64	142	0.00
Student-Level Effect (r_{ij})	4015.88				

Proportion of variance explained in the Level 2 model = $\frac{4532.4 - 1873.78}{4532.4}$ = .59

Specifically, as the value of self-reported intrinsic motivation increases by one unit, the general mathematics ability assessment score is predicted to increase by 5.51 points. As self-reported self-efficacy increases by one unit, students are predicted to score 28 points higher on the general mathematics ability assessment. For all of these results, they hold true when all other variables are held constant.

Table 33

Final Model for General Mathematics Achievement for Japan

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Mathematics Intercept (γ_{00})	559.59	6.98	80.18	113	0.00
Student morale (γ_{01})	21.47	2.75	7.82	113	0.00
Aggregate teacher support (γ_{02})	46.50	13.61	3.42	113	0.00
Intrinsic Motivation Slope					
Intercept (γ_{10})	5.51	1.44	3.83	97	0.00
Self-efficacy Slope					
Intercept (γ_{20})	28.00	1.59	17.64	44	0.00

Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	1957.41		1870.03	113	0.00
Student-Level Effect (r_{ij})	3922.81				

Proportion of variance explained in the Level 2 model = $\frac{5266.4-1957.4}{5266.4}$ = .63

For the school-level model, student morale and aggregate student reports of teacher support were significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the mathematics general ability assessment increased by 21.47 points. Further, as aggregate student reports of positive teacher support increased by one unit, the school average score on the mathematics general ability assessment increased by 46.5 points.

There was significant school variation in average school scores after controlling for students' morale. The proportion of variance in general mathematics achievement scores accounted for by the Level 2 model is 63%. This means that this final model (including the Level 2 variables) accounts for 63% of the total observed school-level variance in the null model.

Table 34

Final Model for General Mathematics Achievement for Korea

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Mathematics Intercept (γ_{00})	555.15	3.44	161.21	146	0.00
Student morale (γ_{01})	19.77	2.85	6.94	146	0.00
Intrinsic Motivation Slope					
Intercept (γ_{10})	10.25	1.14	9.03	242	0.00
Self-efficacy Slope					
Intercept (γ_{20})	30.23	1.53	19.81	147	0.00

Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	1524.10		1500.44	146	0.00
Self-efficacy (u_{2j})	83.13		248.68	147	0.00
Student-Level Effect (r_{ij})	3946.88				

Proportion of variance explained in the Level 2 model = $\frac{3655.2-(1524.1+83.13)}{3655.2}$ = .56

The student-level model for general math achievement in Korea (Table 34) shows that students who have higher self-efficacy are predicted to score higher in mathematics general ability than students who have lower levels of this motivation variable. Specifically, as the value of self-reported intrinsic motivation increases by one unit, students are expected to score 10.25 points higher on the general mathematics ability assessment. Similarly, as self-reported self-efficacy increases by one unit, students are predicted to score 30.22 points higher on the general mathematics ability assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, only student morale was significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the mathematics general ability assessment increased by 19.77 points when other variables were held constant. There was significant school variation in average school scores after controlling for students' morale. The self-efficacy slope varied significantly across schools. The proportion of variance in general mathematics achievement scores accounted for by the Level 2 model is 56%. This means that this final model (including the Level 2 variables) accounts for 56% of the total observed school-level variance in the null model.

Science Achievement

The student-level model for science achievement in Canada (Table 35) shows that students who have higher instrumental motivation and higher self-efficacy are predicted to score higher in science than students who have lower levels of these motivation variables. Specifically, as the value of self-reported instrumental motivation increases by one unit, science achievement score is predicted to increase by 5.65 points, and for self-efficacy, a one unit increase predicts a 39.61 point increase. A different trend is seen for performance orientation. For this variable, a one unit increase in self-reported performance orientation predicts a drop of 6.47 points on the science assessment. For all of these results, they hold true when all other variables are held constant.

Table 35

Final Model for Science Achievement for Canada

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Science Intercept (γ_{00})	498.33	1.27	393.23	1055	0.00
Student morale (γ_{01})	8.78	1.35	6.51	368	0.00
Teacher behaviour (γ_{02})	3.07	1.49	2.06	1055	0.04
Performance Orientation Slope					
Intercept (γ_{10})	-6.47	0.80	-8.09	22	0.00
Instrumental motivation Slope					
Intercept (γ_{20})	5.65	0.67	8.50	691	0.00
Self-efficacy Slope					
Intercept (γ_{30})	39.61	0.70	56.80	65	0.00
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	1060.40		3843.39	1040	0.00
Instrumental Motivation Slope (u_{2j})	57.60		1181.22	1042	0.00
Self-efficacy Slope (u_{3j})	52.94		1227.12	1042	0.000
Student-Level Effect (r_{ij})	6536.81				

Proportion of variance explained in the Level 2 model = $\frac{1800-(1060.4+57.6+52.9)}{1800} = .35$

For the school-level model, student morale and teacher behaviour were significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the science assessment increased by 8.77 points, and as principals' reports of teacher behaviours which positively influenced school morale increased by one unit, the school average score on the science assessment increased by 3.07 points, when other variables were held constant.

There was significant school variation in average school scores after controlling for students' morale. The instrumental motivation and self-efficacy slopes varied significantly across schools. The proportion of variance in science achievement scores accounted for by the Level 2 model is 35%. This means that this final model (including the Level 2 variables) accounts for 35% of the total observed school-level variance in the null model.

The student-level model for science achievement in the United States (Table 36) shows that students who have higher instrumental motivation and higher self-efficacy are predicted to score higher in science achievement than students who have lower levels of these motivation variables. Specifically, as the value of self-reported instrumental motivation increases by one unit, science achievement score is predicted to increase by 5.94 points, and for self-reported self-efficacy, an increase of one unit predicts a score 42.07 points higher on the science assessment. A different trend is seen for performance orientation and intrinsic motivation. For these variables, a one unit increase in self-reported performance orientation predicts a drop of 10.29 points on the science assessment, while a one unit increase in self-reported intrinsic motivation predicts a drop of 7.16 points. For all of these results, they hold true when all other variables are held constant.

Table 36

Final Model for Science Achievement for The United States

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Science Intercept (γ_{00})	481.52	2.80	171.78	223	0.00
Student morale (γ_{01})	13.43	2.69	4.99	223	0.00
Performance Orientation Slope					
Intercept (γ_{10})	-10.29	1.78	-5.76	77	0.00
Instrumental motivation Slope					
Intercept (γ_{20})	5.94	1.88	3.17	128	0.00
Intrinsic Motivation Slope					
Intercept (γ_{30})	-7.16	1.71	-4.19	419	0.00
Self-efficacy Slope					
Intercept (γ_{40})	42.07	1.56	26.99	224	0.00

Random Effects	Variance Component	χ^2	*df*	*p*
Intercept (u_{0j})	1018.34	805.53	222	0.00
Self-efficacy Slope (u_{4j})	78.58	275.07	223	0.00
Student-Level Effect (r_{ij})	6128.08			

Proportion of variance explained in the Level 2 model = $\frac{2077-(1018.3+78.6)}{2077} = .47$

For the school-level model, only student morale was significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the science assessment increased by 13.43 points when other variables were held constant. There was significant school variation in average school scores after controlling for students' morale. The self-efficacy slope varied significantly across schools. The proportion of variance in science achievement scores accounted for by the Level 2 model is 47%. This means that this final model (including the Level 2 variables) accounts for 47% of the total observed school-level variance in the null model.

The student-level model for science achievement in the United Kingdom (Table 37) shows that students who have higher self-efficacy are predicted to score higher on the science assessment than students who have lower levels of this motivation variable. Specifically, as the value of self-reported self-efficacy increases by one unit, students are predicted to score 47.67 points higher on the science assessment. A different trend is seen for performance orientation and intrinsic motivation. For these variables, a one unit increase in self-reported performance orientation predicts a drop of 10.06 points on the science assessment, while a one unit increase in self-reported intrinsic motivation predicts a drop of 6.7 points on the science assessment. For all of these results, they hold true when all other variables are held constant.

Table 37

Final Model for Science Achievement for The United Kingdom

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Science Intercept (γ_{00})	518.77	2.56	202.50	306	0.00
Student morale (γ_{01})	17.90	2.38	7.53	306	0.00
Teacher Behaviour (γ_{02})	6.71	3.16	2.12	306	0.03
Performance Orientation Slope					
Intercept (γ_{10})	-10.06	1.47	-6.86	36	0.00
Intrinsic Motivation Slope					
Intercept (γ_{20})	-6.70	1.37	-4.89	88	0.00
Student morale (γ_{21})	3.28	1.12	2.92	35	0.01
Self-efficacy Slope					
Intercept (γ_{30})	47.67	1.31	36.53	307	0.00
Student morale (γ_{31})	-2.97	1.27	-2.35	67	0.02
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	1191.27		1627.73	306	0.00
Performance Orientation Slope (u_{1j})	57.82		368.03	308	0.01
Self-efficacy Slope (u_{3j})	66.36		406.88	307	0.00
Student-Level Effect (r_{ij})	6143.16				

Proportion of variance explained in the Level 2 model = $\frac{2711.3-(1191.3+57.8+66.4)}{2711.3}$ = .51

For the school-level model, student morale and teacher behaviour were significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the science assessment increased by 17.9 points, and as principals' reports of teacher behaviours which positively influenced school morale increased by one unit, the school average score on the science assessment increased by 6.71 points, when other variables were held constant. Further, principals' reports of positive student morale had an influence on both the intrinsic motivation and the self-efficacy slopes. For the intrinsic motivation slope, principals' reports of positive student morale modified the slope, lessening the negative impact of intrinsic motivation on students' scores. For the self-efficacy slope, principals' reports of positive student morale also modified the slope, although in this case, the positive impact of higher self-efficacy was lessened (in other words, the slope was flattened).

There was significant school variation in average school scores after controlling for students' morale. The performance orientation and self-efficacy slopes varied significantly across schools. The proportion of variance in science achievement scores accounted for by the Level 2 model is 51%. This means that this final model (including the Level 2 variables) accounts for 51% of the total observed school-level variance in the null model.

The student-level model for science achievement in Hong Kong-China (Table 38) shows that students who have intrinsic motivation and higher self-efficacy are predicted to score higher on the science assessment than students who have lower levels of these motivation variables. Specifically, as the value of self-reported intrinsic motivation increases by one unit, science achievement score is predicted to increase by 5.69 points, and as self-reported self-efficacy increases by one unit, students are predicted to score 25.37 points higher on the science assessment.

Table 38

Final Model for Science Achievement for Hong Kong-China

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Science Intercept (γ_{00})	544.29	3.68	148.05	142	0.00
Student morale (γ_{01})	32.43	3.65	8.88	142	0.00
Performance Orientation Slope					
Intercept (γ_{10})	-7.78	1.39	-5.59	88	0.00
Intrinsic Motivation Slope					
Intercept (γ_{20})	5.69	1.29	4.41	566	0.00
Self-efficacy Slope					
Intercept (γ_{30})	25.37	1.61	15.75	22	0.00
Student morale (γ_{31})	-3.33	1.16	-2.86	4428	0.01
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	1747.65		1947.59	142	0.00
Student-Level Effect (r_{ij})	4018.69				

Proportion of variance explained in the Level 2 model = $\frac{3880.1 - 1747.6}{3880.1}$ = .55

A different trend is seen for performance orientation. For this variable, a one unit increase in self-reported performance orientation predicts a drop of 7.78 points on the science assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, student morale was significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the science assessment increased by 32.43 points. Further, principals' reports of positive student morale had an influence on the self-efficacy slope. For the self-efficacy slope, principals' reports of positive student morale modified the slope, and the positive impact of higher self-efficacy was lessened (in other words, the slope was flattened).

There was significant school variation in average school scores after controlling for students' morale in this model. The proportion of variance in science achievement scores accounted for by the Level 2 model is 55%. This means that this final model (including the Level 2 variables) accounts for 55% of the total observed school-level variance in the null model.

The student-level model for science achievement in Japan (Table 39) shows that students who have higher self-efficacy are predicted to score higher in science than students who have lower levels of this motivation variable. Specifically, as the value of self-reported self-efficacy increases by one unit, science achievement score is predicted to increase by 28.41 points. A different trend is seen for performance orientation. For this variable, a one unit increase in self-reported performance orientation predicts a drop of 3.76 points on the science assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, student morale and aggregate student reports of teacher support were significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the science assessment increased by 22.25 points. Further, as aggregate student reports of positive teacher support increased by one unit, the school average score on the science assessment increased by 53.29 points.

There was significant school variation in average school scores after controlling for students' morale. The proportion of variance in science achievement scores accounted for by the Level 2 model is 62%. This means that this final model (including the Level 2 variables) accounts for 62% of the total observed school-level variance in the null model.

Table 39

Final Model for Science Achievement for Japan

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Science Intercept (γ_{00})	572.04	7.34	77.97	113	0.00
Student morale (γ_{01})	22.25	2.94	7.56	113	0.00
Aggregate teacher support (γ_{02})	53.29	14.21	3.75	113	0.00
Performance Orientation					
Intercept (γ_{10})	-3.76	1.56	-2.40	96	0.00
Self-efficacy Slope					
Intercept (γ_{20})	28.41	1.86	15.31	59	0.00
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	2075.62		1386.20	113	0.00
Student-Level Effect (r_{ij})	5757.23				

Proportion of variance explained in the Level 2 model = $\frac{5458.5 - 2075.62}{5458.5} = .62$

The student-level model for science achievement in Korea (Table 40) shows that students who have higher self-efficacy are predicted to score higher in science than students who have lower levels of this motivation variable. Specifically, as the value of self-reported self-efficacy increases by one unit, science achievement score is predicted to increase by 31.43 points. This result holds true when all other variables are held constant.

For the school-level model, student morale was significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the science assessment increased by 22.08 points.There was significant school variation in average school scores after controlling for students' morale. The self-efficacy slope varied significantly across schools. The proportion of variance in science achievement scores accounted for by the Level 2 model is 54%. This means that this final model (including the Level 2 variables) accounts for 54% of the total observed school-level variance in the null model.

Reading Literacy Achievement

The student-level model for reading literacy achievement in Canada (Table 41) shows that students who have higher instrumental motivation and higher self-efficacy are predicted to score higher in reading literacy than students who have lower levels of these motivation variables. Specifically, as the value of self-reported instrumental motivation increases by one unit, reading literacy achievement score is predicted to increase by 11.05 points. As self-reported self-efficacy increases by one unit, students are predicted to score 29.97 points higher on the reading literacy assessment. A different trend is seen for intrinsic motivation and performance orientation. For these variables, a one unit increase in self-reported intrinsic motivation predicts a 7.37 point drop in reading literacy score, while a one unit increase in self-reported performance orientation predicts a drop of 5.99 points on the reading literacy assessment. For all of these results, they hold true when all other variables are held constant.

Table 40

Final Model for Science Achievement for Korea

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Science Intercept (γ_{00})	550.61	3.70	148.75	146	0.00
Student morale (γ_{01})	22.08	2.99	7.39	146	0.00
Self-efficacy Slope					
Intercept (γ_{40})	31.43	1.69	18.65	29	0.00
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	1746.08		1261.19	146	0.00
Self-efficacy Slope (u_{4j})	53.26		198.99	147	0.00
Student-Level Effect (r_{ij})	5558.97				

Proportion of variance explained in the Level 2 model = $\frac{3923.7-(1746.1+53.26)}{3923.7}$ = .54

For the school-level model, student morale and teacher behaviour were significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the reading literacy assessment increased by 8.98 points when other variables were held constant. As principals' reports of teacher behaviours which positively influenced school morale increased by one unit, the intrinsic motivation slope was lessened, decreasing the negative impact on students' scores. There was significant school variation in average school scores after controlling for students' morale. The intrinsic motivation and self-efficacy slopes varied significantly across schools. The proportion of variance in reading literacy achievement scores accounted for by the Level 2 model is 31%. This means that this final model (including the Level 2 variables) accounts for 31% of the total observed school-level variance in the null model.

The student-level model for reading literacy achievement in the United States (Table 42) shows that students who have higher instrumental motivation and higher self-efficacy are predicted to score higher in reading literacy than students who have lower levels of these motivation variables. Specifically, as the value of self-reported instrumental motivation increases by one unit, reading literacy achievement score is predicted to increase by 9.18 points. As self-reported self-efficacy increases by one unit, students are predicted to score 35.32 points higher on the reading literacy assessment. A different trend is seen for intrinsic motivation and performance orientation. For these variables, a one unit increase in self-reported intrinsic motivation predicts a 11.11 point drop in reading literacy score, while a one unit increase in self-reported performance orientation predicts a drop of 7.55 points on the reading literacy assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, student morale was significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the reading literacy assessment increased by 15.22 points when other variables were held constant. There was significant school variation in average school scores after controlling for students' morale. The self-efficacy slope varied significantly across schools. The proportion of variance in reading literacy achievement scores accounted for by the Level 2 model is 44%. This means that this final model (including the Level 2 variables) accounts for 44% of the total observed school-level variance in the null model.

Table 41

Final Model for Reading Literacy Achievement for Canada

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Reading Intercept (γ_{00})	507.66	1.21	418.72	1056	0.00
Student morale (γ_{01})	8.98	1.15	7.84	1056	0.00
Performance Orientation Slope					
Intercept (γ_{10})	-5.99	0.70	-8.51	43	0.00
Instrumental motivation Slope					
Intercept (γ_{20})	11.05	0.76	14.52	252	0.00
Intrinsic Motivation Slope					
Intercept (γ_{30})	-7.37	0.72	-10.19	219	0.00
Teacher Behaviour (γ_{31})	1.50	0.66	2.25	1056	0.02
Self-efficacy Slope					
Intercept (γ_{40})o	29.97	0.61	48.82	218	0.00

Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	919.86		3937.56	1041	0.00
Intrinsic Motivation Slope (u_{3j})	50.01		1188.87	1041	0.00
Self-efficacy Slope (u_{4j})	35.42		1168.49	1042	0.00
Student-Level Effect (r_{ij})	5798.89				

Proportion of variance explained in the Level 2 model = $\frac{1448.9-(919.9+50+35.4)}{1448.9}$ = .31

Table 42

Final Model for Reading Literacy Achievement for The United States

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Reading Intercept (γ_{00})	485.48	3.10	156.36	223	0.00
Student morale (γ_{01})	15.22	2.78	5.47	223	0.00
Performance Orientation Slope					
Intercept (γ_{10})	-7.55	1.72	-4.40	242	0.00
Instrumental motivation Slope					
Intercept (γ_{20})	9.18	1.75	5.26	801	0.00
Intrinsic Motivation Slope					
Intercept (γ_{30})	-11.11	1.77	-6.26	228	0.00
Self-efficacy Slope					
Intercept (γ_{40})	35.32	1.57	22.54	224	0.00

Random Effects	Variance Component	χ^2	*df*	*p*
Intercept (u_{0j})	1173.51	863.01	222	0.00
Self-efficacy Slope (u_{4j})	69.67	261.01	223	0.00
Student-Level Effect (r_{ij})	6242.06			

Proportion of variance explained in the Level 2 model = $\frac{2234.8-(1173.5+69.7)}{2234.8} = .44$

The student-level model for reading literacy achievement in the United Kingdom (Table 43) shows that students who have higher self-efficacy are predicted to score higher on the reading literacy assessment than students who have lower levels of this motivation variable. Specifically, as the value of self-reported self-efficacy increases by one unit, students are predicted to score 36.02 points higher on the reading literacy assessment. A different trend is seen for performance orientation and intrinsic motivation. For these variables, a one unit increase in self-reported performance orientation predicts a drop of 13.58 points on the reading literacy assessment, while a one unit increase in self-reported intrinsic motivation predicts a drop of 7.35 points on the reading literacy assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, student morale and teacher behaviour were significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the reading literacy assessment increased by 16.77 points, and as principals' reports of teacher behaviours which positively influenced school morale increased by one unit, the school average score on the reading literacy assessment increased by 7.42 points, when other variables were held constant. Further, principals' reports of positive student morale had an influence on both the intrinsic motivation and the self-efficacy slopes. For the intrinsic motivation slope, principals' reports of positive student morale modified the slope, lessening the negative impact of intrinsic motivation on students' scores. For the self-efficacy slope, principals' reports of positive student morale also modified the slope, although in this case, the positive impact of higher self-efficacy was lessened (in other words, the slope was flattened).

Table 43

Final Model for Reading Literacy Achievement for The United Kingdom

Variables	Parameters Estimate				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Reading Intercept (γ_{00})	511.52	2.45	208.56	306	0.00
Student morale (γ_{01})	16.77	2.34	7.18	306	0.00
Teacher Behaviour (γ_{02})	7.42	2.94	2.5	306	0.01
Performance Orientation Slope					
Intercept (γ_{10})	-13.58	1.20	-11.31	182	0.00
Intrinsic Motivation Slope					
Intercept (γ_{20})	-7.35	1.20	-6.12	233	0.00
Student morale (γ_{21})	3.21	1.01	3.18	27	0.01
Self-efficacy Slope					
Intercept (γ_{30})	36.02	1.21	29.74	240	0.00
Student morale (γ_{31})	-2.77	0.93	-2.98	307	0.02
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	1044.90		1547.61	306	0.00
Performance Orientation Slope (u_{1j})	50.88		376.61	308	0.01
Self-efficacy Slope (u_{3j})	30.41		357.50	307	0.03
Student-Level Effect (r_{ij})	5440.47				

Proportion of variance explained in the Level 2 model = $\frac{2343.1 - (1044.9 + 50.9 + 30.4)}{2343.1} = .52$

There was significant school variation in average school scores after controlling for students' morale. The performance orientation and self-efficacy slopes varied significantly across schools. The proportion of variance in reading literacy achievement scores accounted for by the Level 2 model is 52%. This means that this final model (including the Level 2 variables) accounts for 52% of the total observed school-level variance in the null model.

Table 44

Final Model for Reading Literacy Achievement for Hong Kong-China

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Reading Intercept (γ_{00})	515.64	3.31	155.92	142	0.00
Student morale (γ_{01})	29.84	3.30	9.05	142	0.00
Performance Orientation Slope					
Intercept (γ_{10})	-3.66	1.35	-2.71	95	0.01
Self-efficacy Slope					
Intercept (γ_{20})	16.67	1.45	11.48	21	0.00
Student morale (γ_{21})	-3.11	1.13	-2.75	178	0.01
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	1435.27		1793.07	142	0.00
Student-Level Effect (r_{ij})	3613.45				

Proportion of variance explained in the Level 2 model = $\frac{2929.1 - 1435.3}{2929.1} = .51$

The student-level model for reading literacy achievement in Hong Kong-China (Table 44) shows that students who have higher self-efficacy are predicted to score higher in reading literacy than students who have lower levels of this motivation variable. Specifically, as the value of self-reported self-efficacy increases by one unit, reading literacy achievement score is predicted to increase by 16.67 points. A different trend is seen for performance orientation. For this variable, a one unit increase in self-reported performance orientation predicts a drop of 3.67 points on the reading literacy assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, student morale was significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the reading literacy assessment increased by 29.84 points. Further, principals' reports of positive student modified the self-efficacy slope; the positive impact of higher self-efficacy was lessened (in other words, the slope was flattened).

There was significant school variation in average school scores after controlling for students' morale. The proportion of variance in reading literacy achievement scores accounted for by the Level 2 model is 51%. This means that this final model (including the Level 2 variables) accounts for 51% of the total observed school-level variance in the null model.

The student-level model for reading literacy achievement in Japan (Table 45) shows that students who have higher self-efficacy are predicted to score higher in reading literacy than students who have lower levels of this motivation variable. Specifically, as the value of self-reported self-efficacy increases by one unit, reading literacy achievement score is predicted to increase by 33.52 points. A different trend is seen for performance orientation. For this variable, a one unit increase in self-reported performance orientation predicts a drop of 5.81 points on the reading literacy assessment. For all of these results, they hold true when all other variables are held constant.

Table 45

Final Model for Reading Literacy Achievement for Japan

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Reading Intercept (γ_{00})	524.66	6.3	83.26	1879	0.00
Student morale (γ_{01})	20.29	2.70	7.51	1680	0.00
Aggregate teacher support (γ_{02})	47.12	12.77	3.69	1680	0.00
Performance Orientation					
Intercept (γ_{10})	-5.81	1.78	-3.25	115	0.00
Self-efficacy Slope					
Intercept (γ_{20})	33.52	2.70	12.41	2000	0.00

Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_0j)	1802.81		646.69	113	0.00
Performance orientation (u_{1j})	209.92		286.81	113	0.00
Student-Level Effect (r_{ij})	84.64				

Proportion of variance explained in the Level 2 model = $\frac{5174.4-(1802.8+209.9)}{5174.4}$ = .61

For the school-level model, student morale and aggregate student reports of teacher support were significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the reading literacy assessment increased by 20.29 points. Further, as aggregate student reports of positive teacher support increased by one unit, the school average score on the reading literacy assessment increased by 47.12 points.

There was significant school variation in average school scores after controlling for students' morale. The proportion of variance in reading literacy achievement scores accounted for by the Level 2 model is 61%. This means that this final model (including the Level 2 variables) accounts for 61% of the total observed school-level variance in the null model.

Table 46

Final Model for Reading Literacy Achievement for Korea

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Science Intercept (γ_{00})	543.19	2.98	182.38	146	0.00
Student morale (γ_{01})	18.08	2.51	7.21	146	0.00
Self-efficacy Slope					
Intercept (γ_{40})	22.38	1.29	17.32	51	0.00
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_0j)	1129.03		1120.78	146	0.00
Self-efficacy Slope (u_4j)	27.36		187.11	147	0.00
Student-Level Effect (r_{ij})	3998.62				

Proportion of variance explained in the Level 2 model = $\frac{2502.4-(1129+27.4)}{2502.4}$ = .54

The student-level model for reading literacy achievement in Korea (Table 46) shows that students who have higher self-efficacy are predicted to score higher in reading literacy than students who report lower levels. Specifically, as self-reported self-efficacy increases by one unit, students are predicted to score 22.38 points higher on the reading literacy assessment. This result they holds true when all other variables are held constant.

For the school-level model, only student morale was significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the reading literacy assessment increased by 18.08 points when other variables were held constant. There was significant school variation in average school scores after controlling for students' morale. The self-efficacy slope varied significantly across schools. The proportion of variance in reading literacy achievement scores accounted for by the Level 2 model is 54%. This means that this final model (including the Level 2 variables) accounts for 54% of the total observed school-level variance in the null model.

Problem-solving Ability Achievement

The student-level model for problem-solving achievement in Canada (Table 47) shows that students who have higher instrumental motivation and higher self-efficacy are predicted to score higher in problem-solving than students who have lower levels of these motivation variables. Specifically, as the value of self-reported instrumental motivation increases by one unit, problem-solving achievement score is predicted to increase by 9.47 points, and for self-efficacy, a one unit increase predicts a 35.49 point increase. A different trend is seen for performance orientation. For this variable, a one unit increase in self-reported performance orientation predicts a drop of 4.32 points on the problem-solving assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, student morale was significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the problem-solving assessment increased by 8.77 points, when other variables were held constant.

Table 47

Final Model for Problem-Solving Ability Achievement for Canada

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Problem-solving Intercept (γ_{00})	509.45	1.14	447.26	429	0.00
Student morale (γ_{01})	9.37	1.11	8.47	827	0.00
Performance Orientation Slope					
Intercept (γ_{10})	-4.32	0.73	-5.88	22	0.00
Instrumental motivation Slope					
Intercept (γ_{20})	9.47	0.69	13.75	138	0.00
Self-efficacy Slope					
Intercept (γ_{40})	35.49	0.69	51.61	30	0.00

Random Effects	Variance Component	χ^2	*df*	*p*
Intercept (u_{0j})	781.87	4013.63	1051	0.00
Self-efficacy Slope (u_{4j})	27.38	1198.45	1052	0.00
Student-Level Effect (r_{ij})	5312.20			

Proportion of variance explained in the Level 2 model = $\frac{1388.4-(781.9+27.4)}{1388.4}$ = .42

There was significant school variation in average school scores after controlling for students' morale. The self-efficacy slope varied significantly across schools. The proportion of variance in problem-solving achievement scores accounted for by the Level 2 model is 42%. This means that this final model (including the Level 2 variables) accounts for 42% of the total observed school-level variance in the null model.

The student-level model for problem-solving achievement in the United States (Table 48) shows that students who have higher instrumental motivation and higher self-efficacy are predicted to score higher in problem-solving than students who have lower levels of these motivation variables. Specifically, as the value of self-reported instrumental motivation increases by one unit, problem-solving achievement score is predicted to increase by 5.32 points, and for self-efficacy, a one unit increase predicts a 39.93 point increase. A different trend is seen for performance orientation. For this variable, a one unit increase in self-reported performance orientation predicts a drop of 9.73 points on the problem-solving assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, student morale was significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the problem-solving assessment increased by 14.96 points, when other variables were held constant.

There was significant school variation in average school scores after controlling for students' morale. The self-efficacy slope varied significantly across schools. The proportion of variance in problem-solving achievement scores accounted for by the Level 2 model is 45%. This means that this final model (including the Level 2 variables) accounts for 45% of the total observed school-level variance in the null model.

Table 48

Final Model for Problem-Solving Ability Achievement for The United States

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Problem-solving Intercept (γ_{00})	465.66	2.94	158.19	223	0.00
Student morale (γ_{01})	14.96	2.74	5.46	223	0.00
Performance Orientation Slope					
Intercept (γ_{10})	-9.73	1.71	-5.70	47	0.00
Instrumental motivation Slope					
Intercept (γ_{20})	5.32	1.57	3.34	237	0.00
Self-efficacy Slope					
Intercept (γ_{40})	39.93	1.41	28.29	224	0.00
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	1103.39		902.97	222	0.00
Self-efficacy Slope (u_{4j})	54.35		264.39	223	0.00
Student-Level Effect (r_{ij})	5513.86				

Proportion of variance explained in the Level 2 model = $\frac{2098.1 - (1103.4 + 54.4)}{2098.1} = .45$

The student-level model for problem-solving achievement in the United Kingdom (Table 49) shows that students who have higher self-efficacy are predicted to score higher on the problem-solving assessment than students who have lower levels of this motivation variable.

Specifically, as the value of self-reported self-efficacy increases by one unit, students are predicted to score 43.06 points higher on the problem-solving assessment. A different trend is seen for performance orientation. A one unit increase in self-reported performance orientation predicts a drop of 11.61 points on the problem-solving assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, student morale and teacher behaviour were significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the problem-solving assessment increased by 14.24 points, and as principals' reports of teacher behaviours which positively influenced school morale increased by one unit, the school average score on the problem-solving assessment increased by 4.92 points, when other variables were held constant. Further, principals' reports of positive student morale had an influence on both the self-efficacy slope. For the self-efficacy slope, principals' reports of positive student morale modified the slope, lessening the positive impact of higher self-efficacy (in other words, the slope was flattened).

There was significant school variation in average school scores after controlling for students' morale. The performance orientation and self-efficacy slopes varied significantly across schools. The proportion of variance in problem-solving achievement scores accounted for by the Level 2 model is 52%. This means that this final model (including the Level 2 variables) accounts for 52% of the total observed school-level variance in the null model.

Table 49

Final Model for Problem-Solving Ability Achievement for The United Kingdom

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Problem-solving Intercept (γ_{00})	511.94	2.21	231.14	306	0.00
Student morale (γ_{01})	14.24	2.08	6.83	306	0.00
Teacher behaviour (γ_{02})	4.92	2.50	1.97	306	0.05
Performance Orientation					
Intercept (γ_{10})	-11.61	1.11	-10.48	308	0.00
Self-efficacy Slope					
Intercept (γ_{20})	43.06	1.24	34.70	128	0.00
Student morale (γ_{21})	-2.47	1.02	-2.42	50	0.02
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	839.08		1395.78	306	0.00
Performance orientation (u_{3j})	79.67		398.36	308	0.00
Self-efficacy (u_{3j})	65.68		418.22	307	0.00
Student-Level Effect (r_{ij})	5007.75				

Proportion of variance explained in the Level 2 model = $\frac{2039.4-(839.1+79.7+65.7)}{2039.4}$ = .52

The student-level model for problem-solving achievement in the Hong Kong-China (Table 50) shows that students who have higher intrinsic motivation and higher self-efficacy are predicted to score higher in problem-solving than students who have lower levels of these motivation variables. Specifically, as the value of self-reported intrinsic motivation increases by one unit, problem-solving achievement score is predicted to increase by 9.08points, and as self-reported self-efficacy increases by one unit, students are predicted to score 28.23 points higher on the problem-solving assessment. A different trend is seen for performance orientation. For this variable, a one unit increase in self-reported performance orientation predicts a drop of 8.28 points on the problem-solving assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, student morale was significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the problem-solving assessment increased by 29.79 points. Further, principals' reports of positive student morale had an influence on the self-efficacy slope. For the self-efficacy slope, principals' reports of positive student morale modified the slope, and the positive impact of higher self-efficacy was lessened (in other words, the slope was flattened).

There was significant school variation in average school scores after controlling for students' morale in this model. The proportion of variance in problem-solving achievement scores accounted for by the Level 2 model is 58%. This means that this final model (including the Level 2 variables) accounts for 58% of the total observed school-level variance in the null model.

The student-level model for problem-solving achievement in Japan (Table 51) shows that students who have higher intrinsic motivation and self-efficacy are predicted to score higher in problem-solving than students who have lower levels of these motivation variables. Specifically, as the value of self-reported intrinsic motivation increases by one unit, problem-solving achievement score is predicted to increase by 9.41 points, and as self-efficacy increases by one unit, problem-solving achievement score is predicted to increase by 25.99 points.

Table 50

Final Model for Problem-Solving Ability Achievement for Hong Kong-China

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Problem-solving Intercept (γ_{00})	551.45	3.42	161.04	142	0.00
Student morale (γ_{01})	29.79	3.35	8.89	142	0.00
Performance Orientation Slope					
Intercept (γ_{10})	-8.28	1.64	-5.05	80	0.00
Intrinsic Motivation Slope					
Intercept (γ_{20})	9.08	1.49	6.09	114	0.00
Self-efficacy Slope					
Intercept (γ_{30})	28.23	1.48	19.09	69	0.00
Student morale (γ_{31})	-3.43	1.42	-2.41	49	0.02
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	1508.22		1508.32	142	0.00
Student-Level Effect (r_{ij})	4591.00				

Proportion of variance explained in the Level 2 model = $\frac{3608.7 - 1508.2}{3608.7}$ = .58

A different trend is seen for performance orientation. For this variable, a one unit increase in self-reported performance orientation predicts a drop of 3.71 points on the problem-solving assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, student morale and aggregate student reports of teacher support were significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on the problem-solving assessment increased by 21.78 points. Further, as aggregate student reports of positive teacher support increased by one unit, the school average score on the problem-solving assessment increased by 42.06 points.

There was significant school variation in average school scores after controlling for students' morale. The self-efficacy slope varied significantly across schools. The proportion of variance in problem-solving achievement scores accounted for by the Level 2 model is 60%. This means that this final model (including the Level 2 variables) accounts for 60% of the total observed school-level variance in the null model.

The student-level model for problem-solving achievement in Korea (Table 52) shows that students who have higher levels of intrinsic motivation and self-efficacy are predicted to score higher in problem-solving than students who report lower levels of these motivation variables. Specifically, as the value of self-reported intrinsic motivation increases by one unit, students are expected to score 6.83 points higher on the problem-solving assessment. Similarly, as self-reported self-efficacy increases by one unit, students are predicted to score 25.28 points higher on the problem-solving assessment. For all of these results, they hold true when all other variables are held constant.

For the school-level model, only student morale was significant in the final HLM model. As principals' reports of positive student morale increased by one unit, the school average score on problem-solving assessment increased by 18.81 points when other variables were held constant.

Table 51

Final Model for Problem-Solving Ability Achievement for Japan

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Problem-solving Intercept (γ_{00})	570.01	6.79	83.94	113	0.00
Student morale (γ_{01})	21.78	2.71	8.03	113	0.00
Aggregate teacher support (γ_{02})	42.06	13.28	3.17	113	0.00
Performance Orientation Slope					
Intercept (γ_{10})	-3.71	1.53	-2.42	115	0.02
Intrinsic Motivation Slope					
Intercept (γ_{20})	9.41	1.72	5.49	129	0.00
Self-efficacy Slope					
Intercept (γ_{30})	25.99	2.22	11.73	19	0.00
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0}j)	2042.31		1333.28	113	0.00
Performance orientation (u_{1}j)	40.37		151.82	115	0.01
Student-Level Effect (r_{ij})	4932.16				

Proportion of variance explained in the Level 2 model = $\frac{5184.1-(2042.3+40.4)}{5184.1}$ = .60

There was significant school variation in average school scores after controlling for students' morale. The self-efficacy slope varied significantly across schools. The proportion of variance in problem-solving achievement scores accounted for by the Level 2 model is 75%. This means that this final model (including the Level 2 variables) accounts for 75% of the total observed school-level variance in the null model.

Table 52

Final Model for Problem-Solving Ability Achievement for Korea

Variables	Parameter Estimates				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed Effects					
Problem-solving Intercept (γ_{00})	561.21	3.11	180.23	146	0.00
Student morale (γ_{01})	18.81	2.57	7.32	146	0.00
Intrinsic Motivation Slope					
Intercept (γ_{10})	6.83	1.27	5.37	27	0.00
Self-efficacy Slope					
Intercept (γ_{20})	25.28	1.59	15.88	51	0.00
Random Effects	Variance Component		χ^2	*df*	*p*
Intercept (u_{0j})	1182.5		1193.48	146	0.00
Self-efficacy (u_{2j})	45.08		207.74	147	0.00
Student-Level Effect (r_{ij})	4005.16				

Proportion of variance explained in the Level 2 model = $\frac{4694.8 - (1182.5 + 45.1)}{4694.8} = .75$

Cross-cultural Comparison

The primary comparisons of concern in this paper are the differences between the Western and the Asian countries, rather than between all of the countries individually. Consequently, this section outlines country differences in these broader terms.

Overall, the first key difference seen between the Western and Asian countries lies in the proportion of variance in students' achievement attributable to schools (Table 53). The proportion of students' achievement variance attributed to schools in the Western countries (ranging from .17 to .27) is less than half of that of the Asian countries (ranging from .36 to .53). These findings suggest that the effects of school characteristics on students' achievement are more homogenous in Western countries compared to Asian countries.

Table 53 summarizes the significant variables in both Level 1 and Level 2 of the final HLM models for the Western countries, while Table 54 presents the same findings for the Asian countries. There are some similarities among the final models for all countries. At Level 1, for all countries, and across all domains, self-efficacy was positively related to achievement – in some cases, predicting as much as half a standard deviation improvement in achievement score. With the exception of Korea (and mathematics achievement only for Japan), performance orientation appears in all of the models, and for all of the models it was negatively related to achievement score. This negative relationship is consistent across academic domains. At Level 2, student morale (principals' reports of positive student morale) appears in all final models for all countries and all domains, and predicts a large, positive increase in average school score. Finally, the patterns of relationships between the motivation variables and achievement at both Level 1 and Level 2 do not vary greatly between academic domains.

There are several differences between the final models for the Western and Asian countries. First, the variables that are significant at Level 1 differ between country groups. The most marked difference in this respect is the instrumental motivation variable. This variable appears in several of the Western countries' final models, but appears in only one of the final models for the Asian countries (Korea, problem-solving; Table 54). Another difference at Level 1 between Western and Asian countries' final models is the way that the intrinsic motivation variable acts on students' scores. In the Western countries, with the exception of Canada in general mathematics ability achievement, intrinsic motivation predicts a decrease in achievement score (Table 53). For Asian countries, however, intrinsic motivation always has a positive predictive value when it appears in the final model (Table 54).

At Level 2, there are differences between Western and Asian countries for the teacher behaviour variable (principals' reports of teacher behaviours which positively influenced school morale). Teacher behaviour appears at Level 2 in the final models for the United Kingdom (all domains) and Canada (science and reading) (Table 53), but does not appear in any of the final models for the Asian countries. Similarly, the aggregate teacher support variable (an aggregate of students' reports of positive teacher support) does not appear in any of the Western country final models (Table 53), but does appear in the final models for Japan (all academic domains).

Table 53
Comparison Of Significant Variables And Their Effect On Achievement For Each Academic Domain In Final HLM Models For All Western Countries

Country	Mathematics		Science		Reading		Problem-solving	
	Level 1	Level 2*	Level 1	Level 2*	Level 1*	Level 2*	Level 1*	Level 2*
Canada	Perf. (-) Instr. (+) Intrins (+) Self-eff. (+)	Student Morale ([†]intercept; +)	Perf. (-) Instr. (+) Self-eff. (+)	Student Morale (intercept; +) Teacher Behav. (intercept; +)	Perf. (-) Instr. (+) Intrins. (-) Self-eff. (+)	Student Morale (intercept; +) Teacher Behav. (intrinsic)	Perf. (-) Instr. (+) Self-eff. (+)	Student Morale (intercept; +)
United States	Perf. (-) Self-eff. (+)	Student Morale (intercept; +)	Perf. (-) Intrins. (-) Self-eff. (+)	Student Morale (intercept; +)	Perf. (-) Instr. (+) Intrins. (-) Self-eff. (+)	Student Morale (intercept; +)	Perf. (-) Instr. (+) Self-eff. (+)	Student Morale (intercept; +)
United Kingdom	Perf. (-) Intrins (-) Self-eff. (+)	Student Morale (intercept; +) Teacher Behav. (intercept; +) Student Morale (Intrinsic) Student Morale (Self-eff.)	Perf. (-) Intrins (-) Self-eff. (+)	Student Morale (intercept; +) Teacher Behav. (intercept; +) Student Morale (Intrinsic) Student Morale (Self-eff.)	Perf. (-) Intrins. (-) Self-eff. (+)	Student Morale (intercept; +) Teacher Behav. (intercept; +) Student Morale (Intrinsic) Student Morale (Self-eff.)	Perf. (-) Self-eff. (+)	Student Morale (intercept; +) Teacher Behav. (intercept; +) Student Morale (Self-eff.)

Perf. = performance orientation; Instr. = instrumental motivation; Intrins = intrinsic motivation; Self-eff. = self-efficacy.
Value in brackets next to each Level 1 variable is the direction of relationship to academic achievement score
[†] Intercept is the β_{0j}, and represents the influence on average school score.
*All Level 2 effects on slopes are to modify (flatten) the slope of the variable indicated

Table 54

Comparison Of Significant Variables And Their Effect On Achievement For Each Academic Domain In Final HLM Models For All Asian Countries

Country	Mathematics		Science		Reading		Problem-solving	
	Level 1	Level 2	Level 1	Level 2	Level 1	Level 2	Level 1	Level 2
Hong Kong-China	Perf. (-) Intrins. (+) Self-eff. (+)	Student Morale ([†]intercept; +) Student Morale (Self-eff.)	Perf. (-) Intrins. (+) Self-eff. (+)	Student Morale (intercept; +) Student Morale (Self-eff.)	Perf. (-) Self-eff. (+)	Student Morale (intercept; +) Student Morale (Self-eff.)	Perf. (-) Intrins. (+) Self-eff. (+)	Student Morale (intercept; +) Student Morale (Self-eff.)
Japan	Intrins. (+) Self-eff. (+)	Student Morale (intercept; +) Teacher Support (intercept; +)	Perf. (-) Self-eff. (+)	Student Morale (intercept; +) Teacher Support (intercept; +)	Perf. (-) Self-eff. (+)	Student Morale (intercept; +) Teacher Support (intercept; +)	Perf. (-) Intrins. (+) Self-eff. (+)	Student Morale (intercept; +) Teacher Support (intercept; +)
Korea	Intrins. (+) Self-eff. (+)	Student Morale (intercept; +)	Self-eff. (+)	Student Morale (intercept; +)	Self-eff. (+)	Student Morale (intercept; +)	Intrins. (+) Self-eff. (+)	Student Morale (intercept; +)

Perf. = performance orientation; Instr. = instrumental motivation; Intrins = intrinsic motivation; Self-eff. = self-efficacy.
Value in brackets next to each Level 1 variable is the direction of relationship to academic achievement score
[†] Intercept is the β_{0j}, and represents the influence on average school score.
*All Level 2 effects on slopes are to modify (flatten) the slope of the variable indicated

Chapter 5: Discussion

The relationship between motivation and academic achievement is complex, but generally, the more a student is motivated to do an academic task, and the more cognitive strategies the student will employ to learn how to accomplish the task, the better the performance is on the task (Pintrich & Schunk, 2002). Instructional recommendations that come out of academic motivation research are aimed at creating a classroom environment that encourages and fosters motivation, which should lead to improvements in learning outcomes (Bandalos et al., 2003; Patrick et al., 2001; Pintrich & DeGroot, 1990; Schraw et al., 1995; Zimmerman & Martinez-Pons, 1990). However, the majority of this research has been carried out with students from North America and the United Kingdom (Pintrich, 2003) The research described here examines how well findings from academic motivation research generalize to a non-Western culture.

In this study, the relationships between motivation and academic achievement were examined in two distinct cultures: Western (represented by Canada, the United States, and the United Kingdom) and Asian (represented by Hong Kong-China, Japan, and Korea). Exploring how patterns of motivation and self-efficacy compare between these cultures is of increasing interest to researchers and practitioners. In addition to adding to understanding of theory (are findings from motivation theories applicable across cultures?), there is great value in examining how Western and Asian cultures differ and are similar in the relationship between motivation and academic achievement. Western countries have been experiencing increasing immigration from Asian countries, with a concurrent increase in students of Asian cultural backgrounds in Western classrooms. Understanding what works, and what does not, for those students is essential to teachers and other education stakeholders to make sure that education systems are as equitable as possible for all students.

The primary aim of this study was to examine the relationship (at Level 1) between four motivation variables (instrumental and intrinsic motivation, performance orientation, and self-efficacy) and academic achievement across the six countries mentioned above using hierarchical linear modelling (HLM) to analyze the OECD's PISA 2003 database. At Level 2, three school level variables (teacher support, student morale, and teacher behaviours affecting school climate) were also examined to evaluate the relationship to motivation and achievement. These relationships were further examined across the four academic domains measured in PISA 2003 (mathematics, science, reading, and problem-solving).

Summary of findings from the analyses

The analyses carried out for this study uncovered a variety of differences, and some similarities among, the six countries examined. In this section, the findings are briefly summarized. Detailed discussion of the findings follows this broad summary of the differences and similarities between the countries that were found in the analyses.

The first finding of note is that there were no systematic differences by academic domain for any of the countries, despite the fact that all of the student-level motivation variable items were phrased in the context of mathematics. In other words, the motivation variables that were significant in the HLM models for each country were generally the same variables for each academic domain (mathematics, science, reading, and problem-solving). From a theoretical point of view, this is problematic in that all of the motivation variables were phrased in the context of mathematics classes [e.g., *I do mathematics* *because I enjoy it* for intrinsic motivation, and *How confident do you feel about having to do the following calculations*: (e.g.) *Solving an equation like 3x + 5 = 17* for self-efficacy (OECD, 2005)]. For some theories, particularly self-efficacy theory, motivation is domain- or task-specific, so self-efficacy for mathematics does not necessarily mean self-efficacy for reading, science, or problem-solving. These issues are addressed in the individual motivation variable sections that follow this summary. As a result of the lack of obvious differences by academic domain, this summary addresses the similarities and differences in which motivation variables were significant in the HLM models by country, and not by academic domain.

Several differences were found between Western and Asian countries. One primary difference was in the performance of each country on the achievement portion of the PISA data collection. As shown in Table 15, the United States consistently scored lower than the OECD average across all four academic domains. Canada and the United Kingdom performed almost equally well, with mean scores slightly above the OECD average. The exception was Canada's performance in science, which was slightly below the OECD average. By contrast, the Asian countries (Hong Kong-China, Japan, and Korea) showed mean scores of almost half a standard deviation higher than the OECD average across all domains (except for Hong Kong-China in reading).

Further differences between the countries were found in how students responded to the self-report questions about motivation and school climate. In particular, for instrumental motivation (Table 2), the students in Western countries reported means that were either approximately equal to, or higher than the OECD average, while the students in the Asian countries responded less positively than the OECD average. Similar self-report differences were found for Japan and Korea for intrinsic motivation (Table 3), performance orientation (Table 4), self-efficacy (Table 5), and perceptions of teacher support (Table 8).

Differences were also found in the correlation analyses. For all Western countries, the correlations between performance orientation and achievement in all academic domains were low (Tables 16-18). The correlations between academic achievement and both intrinsic and instrumental motivation were slightly higher than for performance orientation and academic achievement, but were still consistently below $r = .25$. This was not the case for the Asian countries, however, where the correlations between these motivation variables and academic achievement for all domains were consistently higher (Tables 19-21). For performance orientation, correlations with academic achievement ranged from $r = .10$ (Hong Kong-China, reading) to $r = .40$ (Korea, mathematics); for intrinsic motivation, correlations ranged from $r = .14$ (Japan, reading) to $r = .39$ (Korea, mathematics), and for instrumental motivation, correlations with academic achievement ranged from $r = .14$ (Hong Kong-China, reading) to $r = .35$ (Korea, mathematics).

These differences between countries carried through into the proportion of variance accounted for by schools. The intraclass correlations (the measure of how much variance is accounted for by the level 2 HLM model) for the Western countries were much lower than those for the Asian countries. This finding suggests that Western schools are more equitable for students – in other words, the school that students attend is not as important to achieving a better score; students themselves (and possibly the classrooms they are in) are accounting for much of the difference in achievement.

Finally, differences were found between Western and Asian countries in the results of the HLM analyses (Tables 53 and 54). Certain patterns of motivation appeared in the models of the relationship between motivation and academic achievement; there were patterns that were fairly consistent among the Western countries and there were different patterns that were fairly consistent among the Asian countries. At Level 1 for the Western countries, instrumental motivation tended to be a significant positive predictor in most (eight of the twelve) models. Instrumental motivation was not significant in any of the Asian country models. As well, intrinsic motivation was significant in seven of the twelve Western models, where it predicted a decrease in achievement scores (except for Canada mathematics, where it predicted an increase in achievement score). However, intrinsic motivation was a predictor of increased performance in all seven of the Asian country models in which it was significant. At Level 2, teacher behaviour was significant in five of the twelve Western country models, but was not significant in any of the Asian models. And teacher support was not significant in any Western country models, but was significant in all final models for Japan.

As mentioned above, some similarities amongst countries were found in the results. In the correlation analyses, the relationships between the motivation variables were moderate and significant for all countries, suggesting that there are some cross-cultural similarities in how instrumental and intrinsic motivation, performance orientation, and self-efficacy are related to each other in this academic context, although the strength of those relationships varies by country. As well, for all countries, achievement in all domains was highly significantly correlated. For the school-level variables, student morale was significantly correlated to all academic achievement domains for all countries except the United Kingdom.

The three most important similarities in this study were found in the results of the HLM analyses: 1) *Performance orientation* was a significant predictor of a decrease in academic achievement in almost all of the HLM models for all of the countries (i.e., for every unit increase in self-reported performance orientation, there was a predicted decrease in achievement scores). As will be discussed below, this follows the findings from primary achievement goal theory research, and supports the generalizability of the construct of performance orientation; 2) *Self-efficacy* was a significant and positive predictor of achievement in all of the models for all of the countries, in all domains. This finding is problematic for the task- and/or domain-specificity of theorized self-efficacy. The ramifications of this finding are discussed in more detail below, and; 3) *Student morale* as reported by principals was significant in all final models for all countries and all domains, and predicted a large, positive increase in average school score.

Level 1 motivational variables (student-level variables)

Instrumental motivation

Higher levels of self-reported instrumental motivation were found to predict higher scores in all academic domains for Canada, and higher scores in science, reading, and problem-solving for the United States. Instrumental motivation was not a significant variable in the models for any of the other countries examined in this study.

The items for the instrumental motivation measure in PISA 2003 (Table 2) reflect the “utility value” domain of expectancy-value theory (Eccles, 1994; Wigfield et al., 1998, according to OECD, 2005). In this context (PISA’s questionnaire), in the absence of the expectancy piece of the expectancy-value theory, instrumental motivation operates as an extrinsic motivation variable: mathematics is something you do as a means to an end, and that end goal is the incentive, or extrinsic motivator, driving the mathematics task performance behaviour (Artelt, 2005).

The observed positive relationship between this variable and mathematics performance does follow from the primary research on instrumental motivation: Pokay and Blumenfeld (1990) found that perceived utility value of a task indirectly predicted improved achievement by increasing cognitive strategy use. Simons, DeWitte, and Lens (2003) found that when students were encouraged to understand the utility value of a task in terms of how the task related to a future goal, performance on the task was enhanced. Similarly, Vansteenkiste and colleagues (2004) found that framing a task in the context of its utility in attaining future goals led to improved performance in the group of female students in Belgium who participated in the study. This is slightly different than the results of a study by DeBacker and Nelson (1999), who found that perceived utility value of a science predicted improved performance for male students, but not female students.

Part of the reason that instrumental motivation contributes to improved academic performance is suggested by the research conducted by Miller and colleagues (Miller, DeBacker, & Greene, 1999) who found that when students perceive the instrumental value of a task, they show higher levels of self-regulation and use of learning strategies. Husman and colleagues (2004) found the instrumental value of a task (as it pertained to a future goal) predicted the amount of time that students spent studying in a university course. Finally, in a study that used the PISA 2000 dataset, Artelt (2005) found that instrumental motivation for reading was associated with an increased use of adaptive learning strategies.

Instrumental motivation was found to be significant only for Canada and the United States; these are also the countries in which most of the expectancy-value research has been conducted (Eccles & Wigfield, 2002) with some research carried out in the United Kingdom and Europe; again, predominantly Western cultures. There is a dearth of research in this area with non-Western students.

Given the lack of data for non-Western students, interpretation of this finding remains speculative. Instrumental motivation may not be operable for students in countries where the cultural context of learning is from the Confucian tradition, because under that cultural tradition, all learning is a means to an end (Tweed & Lehman, 2002)[2]. In this context, the utility value of a particular subject is not going to matter: all academic subjects and tasks are valuable. Future research into the meaning of utility value for students from the Confucian Cultural Heritage (Biggs, 1986) could clarify this finding, and elucidate the ways in which theories involving instrumental motivation (such as expectancy-value theory) can be refined and expanded to improve cross-cultural validity.

Intrinsic motivation

Higher levels of self-reported intrinsic motivation for mathematics (Table 3) were found to predict: a) lower scores in mathematics, science, and reading for the United

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[2] Culture in this dissertation refers to "learning culture" (Tweed & Lehman, 2002), and refers to the traditions in learning culture that are idiosyncratic to Western (Socratic) and Eastern (Confucian) students. In the Socratic learning culture, students learn by questioning, challenging, and doubting what they are told. There is a strong tradition of questioning authority, making intuitive leaps, and self-generated knowledge is highly valued.

The Confucian learning culture, however, has some different traditions. Effortful learning, rather than intuitive leaps, is highly valued. The essentials are to be mastered, step by step, before any innovation occurs. In this sense, utility value would not be as relevant, because in the Confucian learning culture, it is understood that all learning is a means to an end.

Kingdom, b) lower scores in science and reading for the United States, c) higher scores in mathematics, but lower scores in reading for Canada, and d) higher scores in all academic domains for all Asian countries (except Korea in science and reading, where it was not a significant predictor in the HLM models for those academic areas).

Intrinsic motivation is a construct that runs through all theories of motivation, and is consistent in its definition across all theories. Intrinsic motivation is positively related to the use of cognitive strategies (Pintrich and DeGroot, 1990; Schiefele, 1996), and has been found repeatedly to be associated with better academic outcomes (Artelt, 2005; Deci et al., 1991; Deci & Ryan, 1985; Ryan & Deci, 2000; Vansteenkiste et al., 2004).

In this study, some of the findings for the relationship between intrinsic motivation and academic achievement appear, at first, to contradict previous research. Although the correlations carried out for this research showed that all of the correlations were significant and positive between intrinsic motivation and academic achievement, intrinsic motivation is a negative predictor in all but one of the models for Western countries, meaning that for many students in Canada, the United States, and the United Kingdom, the higher their self-reported intrinsic motivation, the stronger the negative effect on their academic achievement scores. This is the opposite effect that we would expect based on the work of researchers such as Deci and Ryan (1985), who have consistently found that intrinsic motivation improves academic achievement.

And yet, this same field of research may explain this finding. Large-scale assessment programs such as PISA may be seen as controlling, and situations in which students feel controlled have been found to reduce intrinsic motivation (Ryan & Deci, 2000). It is possible that in this specific context, those students who were intrinsically motivated to do mathematics tasks were at a disadvantage. These intrinsically motivated Western students may have been adversely affected by the controlled environment of test administration, and so showed lower performance. Asian students would not have exhibited the same behaviour because in Confucian culture, structured tasks are more accepted (Biggs, 1986; Tweed & Lehman, 2002). These students would therefore benefit from their intrinsic motivation, as appeared to be the case. A follow-up study to the research reported here could be to explore this finding via primary research with students.

Performance orientation

For all students in all academic domains in the Western countries, and for all students in all domains in Japan and Hong Kong-China (except for mathematics in Japan), higher levels of self-reported performance orientation were found to predict a drop in mean achievement score. Performance orientation did not appear as a significant predictor in any of the HLM models for any academic domains for Korea.

This finding supports much of the findings in the original achievement goal theory research, which found that a performance orientation is less likely to lead to positive academic outcomes than is a learning or mastery orientation (Dweck & Leggett, 1988; Elliot & Dweck, 1988; Kaplan & Midgley, 1997; Midgley & Urdan, 2001; Pintrich, Roeser, & DeGroot, 1994; Ryan & Patrick, 2001).

The decrease in achievement score seen when students reported higher levels of performance orientation may be a result of less use of effective learning strategies. Midgley, Anderman, and Hicks (1995) found that students who reported a learning or mastery orientation reported trying harder and persisting longer than did students who reported a performance orientation. Performance orientation has also been associated with avoiding help-seeking (Middleton & Midgley, 1997), having decreased interest in university classes (Harackiewicz et al, 2002), increased depression and anxiety (Dykman, 1998; Sideridis, 2005), and vulnerability to failure, with consequent decreases in willingness to persist at a task (Mueller & Dweck, 1998). This possibility can be explored in future research, as there are learning strategies items available in the PISA 2003 data.

Performance orientation does not always show a negative effect on academic outcomes, however. Several studies have shown a positive effect of performance orientation on grades (Harackiewicz et al., 2002), although often the positive effect is found when students report a combination of mastery and performance orientation (multiple goals; cf. Barron & Harackiewicz, 2000; Harakiewicz et al, 2002). In the last fifteen years, researchers have expanded achievement goal theory to include the concepts of approach and avoidance as finer distinctions of the original mastery and performance orientations (Elliot & Church, 1997; Elliot, 1999; Elliot & McGregor, 2001; Harackiewicz, Barron, & Pintrich, 2002; Midgley et al., 2001).

This revision of goal theory suggests that, in certain situations, individuals will approach or avoid tasks depending on their goals. For example, an individual can have a performance-approach goal when that individual knows that he or she can do something well, and wants to show others. This is particularly true in older adolescents who do not separate goals for learning from goals to get good grades because both are often necessary to achieve in high school and university, as such, similar motivational correlates are seen for both mastery orientation and performance-approach (Bong, 2008). Performance-approach goals predicted engagement in academic tasks for high school students (Hardre et al., 2007), and increased use of cognitive strategies for Taiwanese students (Shih, 2005). Shih also found that performance-avoid goals predicted self-handicapping (Shih, 2005). This mirrors the work of Elliot (1999), who found that individuals have a performance-avoidance goal when he or she knows that a task would not be done well, and so the individual will avoid the task to prevent others from seeing how badly the individual will do; this type of goal orientation leads to the classic negative academic outcomes seen in research based on early conceptions of achievement goal theory (Elliot, 1999).

A possible reason for the clear negative effect of performance orientation found in this study is the way that the items were worded (Table 5). The performance orientation items used here are from competitive learning environment scales, and not from achievement goal orientation scales. Even though the items strongly resemble the items from performance orientation scales, particularly the items that have been called relative ability goal orientation (Elliot & Harackiewicz, 1996; Wolters et al., 1996), a clear picture is lacking of whether students are reporting a performance-approach or a performance-avoid orientation. It could also be argued that performance orientation is a problematic construct, so these findings need to be interpreted with care (Brophy, 2005).

A final possibility is that the wording of the items is more closely matched to the idea of *effort* than performance goal orientation; i.e., is the student making an effort while writing the PISA assessment? A student who is self-reporting that they are choosing not to put much effort into writing the test (*I make a real effort in math because I want to be one of the* best; *In math I always try to do better than the other students in my class*; *I do my best work in math when I try to do better than others*) will also likely not do as well on the test.

The findings from this study do suggest that performance orientation is a construct which is valid cross-culturally. A possible reason for this is that achievement goal theory is currently one of the most researched theories, with several hundred articles published in the last seven years (Ross, 2006). These studies involved students from a range of countries and cultural backgrounds, including Asian countries (Bong, 2008; Gong & Fan, 2006; Hardre et al., 2006; Shen et al., 2007). Refinements to the theory based on findings from students from a variety of cultures have strengthened the cross-cultural validity of achievement goal theory.

Self-efficacy

For all students, across all academic domains, higher self-reported self-efficacy predicted higher mean student scores. This finding supports self-efficacy theory up to a point; the problem with this finding is that it is universal for all domains for all of the countries, despite the fact that self-efficacy is supposed to be task- and domain-specific, and the self-efficacy items in PISA 2003 are highly domain-specific for mathematics (Table 4).

Based on self-efficacy theory, self-efficacy should be related to mathematics achievement only. As described by Bandura (1986), self-efficacy is situation specific, and refers to an individual's confidence in their own ability and skills to perform a task to a specific criterion level. As self-efficacy theory has been developed, the domain- and situation-sensitive nature of self-efficacy has continued to be emphasized (Pajares, 1997; Zimmerman, 2000).

The relationship between self-efficacy and academic achievement has strong empirical support. Students high in self-efficacy are confident in their ability to learn successfully and to perform well on academic tasks (Schunk, 1991). This scholastic confidence translates to a willingness to work hard, and not give up, which leads to higher academic achievement (Bandura & Schunk, 1981; Pajares & Miller, 1994; Zimmerman, 2000), which in turn leads to higher self-efficacy. Higher self-efficacy has been found to be related to social and academic adjustment for international students attending an America university (Gong & Fan, 2006), as well as being correlated with high GPA (for example, Zimmerman & Kitsantas, 2005). Based on these findings, the strong positive predictive value of self-efficacy found in this study is not surprising.

More difficult to interpret, however, is the effect that self-efficacy has across all domains in the study. It is possible that the high correlations between scores in all academic domains (see Tables 16 to 21; correlations for all countries ranged between r = 0.77 and r = 0.92) are contributing to this effect; i.e., the academic domain scores are so highly correlated that a variable that affects one domain will affect all domains. While this situation may have had some smaller effect on the other motivation variables in the HLM models, the effect of self-efficacy is so strong that it appears for all domains (much like student morale at Level 2).

Another possible explanation is that in PISA, the self-efficacy items are not asking self-efficacy, but in fact test-taking self-efficacy. The students answering the questions are in a test situation, and they know that they will be asked to solve several types of mathematics problems, as well as other types of problems. Perhaps the way in which the students are interpreting or processing the self-efficacy items is in a more general sense of "How confident are you in solving *problems that will likely show up in this test-taking session*?". This possible explanation fits well with self-efficacy theory findings to date, in that in this situation, test-taking self-efficacy is task-specific for students who are writing the PISA test. Adding a set of test-taking efficacy items to future administrations of PISA is one way to test this possibility (although not a likely one, due to the financial and administrative constraints of adding items to PISA).

Despite the interpretation difficulties associated with the cross-domain effect of self-efficacy found in this study, self-efficacy does appear to be a motivation construct that is valid cross-culturally. Some research has begun that further supports this conclusion, such as the study by Bong (2008) that found that for students in South Korea, all relationships between perceptions of home and school characteristics, and academic achievement, were mediated by self-efficacy.

Level 2 variables (school-level variables)

Student morale

Higher student morale (as reported by school principals) was found to predict higher mean school scores (it was a significant predictor on the intercept) for all countries and all academic domains. As well, student morale had a significant effect on the self-efficacy slope for the United Kingdom and Hong Kong-China, where it acted to flatten the self-efficacy slope, reducing the positive relationship between self-efficacy and mean student scores. Finally, student morale also had a significant effect on the intrinsic motivation slope for mathematics, science, and reading in the United Kingdom, where it again flattened the slope, reducing the negative relationship between intrinsic motivation and mean student scores.

The items in the student morale (as reported by principals) index in PISA 2003 capture many of the elements that appear in the research literature on student belonging

(Anderman & Freeman, 2004; Goodenow, 1992, 1993; Goodenow & Grady, 1993). Goodenow (1992) found that perceived teacher support and general class belonging were significant in predicting motivation for students, although the positive effect of some classroom belonging features such as teacher support on student motivation decreased between 6th and 8th grade (Goodenow, 1993). Expanding on this research, Goodenow and Grady (1993) found that school belongingness also significantly predicted student motivation. Freeman, Anderman, and Jensen (2007) found that a sense of school belonging was associated with higher academic self-efficacy in university undergraduates. Pittman and Richmond (2007) found that, for first year university students, sense of school belonging at both high school and university was predictive of first year university grades. Additionally, and particularly relevant to this study, Gilman and Anderman (2006) conducted a study with high school students whose mean age was 15 years – a similar population to the students in the PISA sample. Gilman and Anderman (2006) found that a sense of school belonging was one of the variables associated with the "high motivation" group in their study.

Based on these research findings, the significant positive effect of student morale on mean school scores (the effect on the intercept) is not surprising. Further explanation of the effect of student morale on the slopes of the Level 1 motivation variables is needed, however. In the United Kingdom and Hong Kong-China, student morale lessened the effect of some significant Level 1 variables (self-efficacy and intrinsic motivation) by flattening the slopes of those variables. This means that for these two countries, student morale lessened the effect of the significant Level 1 predictors self-efficacy and intrinsic motivation. In the case of self-efficacy, for both the United Kingdom and Hong Kong-

China, student morale reduced the slope of the positive effect self-efficacy had on student scores in all academic domains. This does not mean that student morale lowered students' scores; rather, it means that as student morale in the school increases, the school becomes more equitable for all students by reducing the effect of self-efficacy on academic scores. A student with lower self-efficacy will be less adversely affected in a school where student morale is high. Further, for intrinsic motivation, which predicted lower scores in the United Kingdom models, the effect is lessened as student morale in the school increases.

This equalizing effect of student morale may be due to the fact that a sense of belonging in school is associated with more positive beliefs about learning and higher academic self-efficacy (Roeser, Midgley, & Urdan, 1996). This research found that the increase in positive beliefs was in turn related to better grades, so overall positive beliefs about school may be contributing over and above individual motivation elements (Roeser et al., 1996). Further, in schools where teachers showed concern for the emotional and social needs of their students, the relationship between low self-efficacy and the avoidance of help-seeking was minimized (Ryan, Pintrich, & Midgley, 2001).

The research discussed above that found a link between student morale and academic achievement was supported by the findings from this study; however, the research that found a link between student morale and motivation was not supported. The findings from this study did not show that increased student morale led to an increase in motivation, despite the fact that this finding would be expected based on previous research (cf. Anderman & Freeman, 2002).

Overall, the effect of student morale on mean school achievement scores was found to be consistent for all countries in this study. This suggests that the current literature on the effects of student morale on academic achievement applies cross-culturally, i.e., that both Western and Asian students can benefit from having high perceived student morale.

Teacher behaviour

Higher levels of teacher behaviours which positively influenced school morale (as reported by principals) were found to predict higher mean school scores (it was a significant predictor on the intercept) in all academic domains for the United Kingdom, and in science literacy for Canada, but no other countries. As well, these teacher behaviours had a significant effect on the intrinsic motivation slope for reading for Canada, where it acted to flatten the intrinsic motivation slope, reducing the negative relationship between intrinsic motivation and mean student scores.

The items which make up the teacher behaviour (principals' perceptions) index in PISA 2003 do not consistently reflect any one area of research. As well, these items are phrased in the questionnaire in the context of how the various teacher behaviours affect school morale, and all of the items were phrased negatively; for example, "*In your school, to what extent is the learning of students hindered by teacher absenteeism?*" . This variable was selected for this study with the expectation that it would be an indicator of schools in which there is openness to new instructional practices, good teacher-student relations, and high expectations of students, all of which have appeared in the primary research that links school climate to improved student attitudes and performance (Anderson, 1982; Haynes, Emmons, & Ben-Arie, 1997; Loukas & Robinson, 2004);

Roach & Kratchowill, 2004). Unfortunately, this variable did not appear to perform in this way. This is possibly the result of the way in which the items were phrased; principals may be hesitant to be too negative about these types of behaviours at their own schools. Phrasing these items in a positive way may give different results.

The findings in this study do have some support in the literature. Students in schools where the school climate emphasizes opportunities for all students to succeed are likely to demonstrate higher academic achievement and motivation (McEvoy & Walker, 2000). When teacher morale is low, teachers are more likely to have negative attitudes towards students and take more medical leave, among other consequences, which can be detrimental to student learning (Black, 2001), and can contribute to subsequent poor academic performance by students (Zigarelli, 1996). Conversely, when teachers are committed to their students' learning, there can be positive academic achievement outcomes for students (Kushman, 1992).

It is difficult to interpret the cross-cultural validity of this index. Although the teacher behaviours which positively influenced school morale index was a significant positive predictor of higher mean school scores for all academic domains in the United Kingdom, this does not necessarily mean that the individual teacher behaviours which make up this index are exclusively a United Kingdom phenomenon in their impact on student achievement. The index itself is problematic; making any general conclusions is inadvisable.

Teacher support

Higher perceived levels of teacher support in the school (as an aggregate of individual student reports) was found to predict higher mean school scores (it was a significant predictor on the intercept) for Japan in all academic domains. Aggregate teacher support was not a significant variable in any other HLM models for any of the countries in this study.

This finding – that teacher support was significant only in the models for Japan – is one of the least expected in this study. There is a large body of literature on the effects of teacher support on academic achievement. When students perceive their teachers as supportive, there are positive effects on student engagement and academic achievement (Voelkl, 1995), the valuing of mathematics after the transition from elementary to middle school (Midgley, Feldlaufer, & Eccles, 1989), and higher teacher support predicts effort and performance for both middle school and high school students (Goodenow, 1993; Murdock, 1999). The effect of teacher support on motivation and achievement is also seen at the university level (Freeman, Anderman, & Jensen, 2007).

One possible explanation of why teacher support was not significant in the models for the other countries is that it was an aggregate variable (Artelt, 2005). Teacher support was not measured at the school level so in order to examine it at the school level for this study, the student-level reports of teacher support were aggregated within each school to create a school-level measure of teacher support, which was then entered into the HLM equations as a school-level variable. The drawback to this method is that it is possible that within each school, the students writing the PISA assessment have different teachers, so the aggregate could be bringing together reports of positive teacher support (for one teacher)and negative teacher support (for another teacher). In creating this aggregate variable, the students with supportive teachers, who show concurrent improved academic performance, are blended with the students who do not have supportive teachers, and who may not have performed as well. As well, different students may have perceived the same teachers differently. In this way, it is possible that the student-level meaning of this variable was lost as it was aggregated to create a school-level variable. Future research could include analyzing the effect of student-reported teacher support at Level 1, to see the effect of teacher support on students' achievement scores. Although this would not be the same as examining how teacher support in the school affected overall student achievement (which was the intention behind using this variable in this study), using student-reported teacher support as a Level 1 variable would give information as to whether the positive effects of teacher support reported in the literature are consistent between Western and Asian countries.

A second possible explanation for this finding comes out of Hardre and colleagues' (2006) work with students in Taiwan. Hardre's research group found that teacher support was viewed differently depending on a student's need for cognition, or desire to know and learn a topic deeply. Students with a high need for cognition feel more able in the classroom, and report teachers and peers as more supportive. This finding may indicate a problem with how students self-report on the support they receive from teacher. If teachers are perceived as focusing on students who need extra help, and not giving as much support to the more able students, there may be a detrimental effect on the ways in which more able students report the level of teacher support in their classroom (a retaliatory effect if students feel overlooked).

Limitations of this research

There are several limitations to this research that must be kept in mind when interpreting the results. While none of these limitations negate the results presented here, they do allow the reader to put the findings into perspective while evaluating the merit of the conclusions presented in the final section of this paper.

The first and most important consideration is that this is a secondary data analysis study, which has some inherent drawbacks. The research questions here were exploratory, rather than confirmatory. The final results can be discussed in the context of previous research, but no intervention was performed, so while the analyses can be presented in the context of the predictive value of the variables that appeared in the HLM models, causality cannot be confirmed.

Another drawback of secondary data analysis is the fact that all of the variables used in this research were not collected for specifically examining the current research questions. While the student-level variables were based on primary research, and were derived from commonly used, validated research instruments, the school-level variables were not. Further, the items used for the student-level variables were not always the ones that would have been selected were this a primary research paper. For example, the performance orientation items, while they strongly resembled performance orientation items from a commonly used goal orientation instrument (the Patterns of Adaptive Learning Scales, Midgley et al., 1998; Table 5), were taken from a scale of preference for a competitive learning environment. Some information about each motivation construct may have been lost due to the need to use the existing indices in the dataset. The fact that the motivation variables were analyzed as indices, rather than at the individual item level, must also be considered when looking at the results of this study.

A final limitation that is specific to the fact that this was a secondary data analysis was the use of an aggregate variable at the school level. By aggregating the student reports of teacher support to derive a school-level variable, some of the meaning of the student-level student reports of teacher support may have been changed (Artelt, 2005).

A limitation of this study related to the secondary data analysis issue is the fact that the achievement data collected here are the products of a large-scale, "low-stakes" test. PISA has no effect on a student's individual grade, and so is considered a low-stakes test. Previous research has found that students do not necessarily perform at their maximum ability on these sorts of tests, nor are they motivated to do well (Wise & DeMars, 2005).

Finally, some variables that may have been valuable to examine were not included in this study. HLM models condition on the factors entered in the model; for this reason, things such as socio-economic status, immigration status, and sex could all change the final HLM models.

However, despite these drawbacks, the findings here do have validity and are of interest to educators and researchers. As a preliminary investigation into comparing the relationship of motivation and academic achievement across Western and Asian countries, this study gives important information on the similarities and differences between countries from these two cultures. Further, the results from this study can provide guidance to educators looking to choose which pedagogical approaches are likely to work best for all students in their classrooms.

Future research

In addition to the suggestions for future research mentioned in each of the individual variable sections above, the findings from this research reveal other areas which could be elucidated by further research.

The first of these areas is in conducting primary research with students in and from Asian countries. As detailed above in the individual variable discussions, some research has been carried out in this area. There is an indication that primary research with students in several Asian countries is being carried out; a search for motivation research articles (EBSCOhost) reveals several academic achievement motivation studies published in journals such as *Japanese Journal of Educational Psychology* and *Psychological Science (China)*. Unfortunately, these studies are not available in English, and so were not examined for their relevancy to the research reported here. They do need to be mentioned, however, to show that primary research on motivation in Asian students is being carried out.

Another area that bears examination is the relationship between motivation and the use of learning strategies. The majority of the studies cited in this discussion included explorations of the relationships between different motivation variables and how students use different learning strategies; books such as *The Handbook of Educational Psychology* (Alexander & Winne, 2006), *Motivation in Education* (Pintrich & Schunk, 2002), and *Motivating Students to Learn* (Brophy, 2004) detail the research that has been carried out in the field of how motivation and learning strategies interact. However, as with research that develops and extends motivation theories, research into the relationship between motivation and learning strategy use has been primarily carried out with Western students. There are student self-reports of the use of learning strategies in the PISA dataset (OECD, 2005). Examining how these strategies relate to motivation and academic achievement across several countries would give a clearer picture of whether the findings from primary research are valid cross-culturally.

Implications for educators

This study examined the relationship between motivation, environmental factors that are believed to affect motivation, and academic achievement across six countries, three Western and three Asian. The similarities and differences in those relationships were discussed, and the cross-cultural validity of each of the motivation variables was evaluated. This section addresses the following practical consideration: are instructional practice recommendations based on motivation theory useful and valid for all students, regardless of whether they come from Western or Asian backgrounds?

The short answer is: some instructional practice recommendations are valid, while some of them are not. The findings from this study suggest that pedagogical recommendations based on findings from achievement goal theory and self-efficacy theory will likely be beneficial to all students, while recommendations founded on research examining intrinsic and instrumental motivation may not be valuable for all students. Further, instructional practices which increase student morale in the school will likely both improve academic performance for all students, and act as a protective factor for students in the classroom who may be experiencing reduced levels of motivation.

In a practical sense, this suggests that such recommendations as setting challenging but achievable tasks [which leads to higher self-efficacy (Pintrich, 2003)], and minimizing the posting of grades and other tactics that inspire comparison and competition [which reduces mastery orientation and increases performance orientation (Dweck & Leggett, 1988; Stipek, 1993, 1996)] will be likely to be helpful for most students in the average North American classroom.

Conclusion

The findings from this study extend our understanding about the relationship between motivation and academic achievement, while revealing some areas where further research is needed. The vast majority of motivation research has been conducted primarily in Western countries, with Western students. By comparing the relationship between motivation and academic achievement across six countries, this study allowed for an examination of the generalizability of findings from motivation research to students from Asian countries. Overall, similarities and differences were found in the relationship between motivation and achievement between Western and Asian countries. No systematic differences were found between academic domains within countries, however, which did not follow some of the motivation theories, such as self-efficacy and instrumental motivation.

Some student-level motivation constructs performed similarly between Western and Asian countries. Self-efficacy and performance orientation were significant in the HLM models for both Western and Asian countries, and in all cases had the same effect on academic achievement (acting to increase academic achievement scores in the case of self-efficacy, and to decrease scores, in the case of performance orientation). These results support findings from previous research in achievement goal theory and self-efficacy theory, and lend support to the idea that these theories are generalizable across students from both Western and Asian backgrounds. While further primary research is advisable, the findings here suggest that instructional recommendations based on both achievement goal theory and self-efficacy theory will be applicable to most students in North American classrooms.

The other two motivation constructs examined, intrinsic motivation and instrumental motivation, did not show clear generalizability, in that they were having opposite effects depending on whether the countries were Western (intrinsic motivation was in all but one case a negative predictor) or Asian (intrinsic motivation was always a positive predictor), or were significant only in the models for Western countries (instrumental motivation). These findings suggest that further research is needed into how intrinsic and instrumental motivation relate to students in the classroom, and in the case of instrumental motivation, primary research with students in Asian countries is warranted.

At the school level, only principals' perception of the morale of students in their school was found to affect academic achievement in the same way in both Western and Asian countries. It is harder to make statements about the generalizability of the school-level variables, though, because the items that made up the indices used in this study were not based on instruments used in previous research (as were the student-level indices).

This study serves to extend motivational theory by showing that some motivation constructs whose empirical evidence comes primarily from Western cultures do not operate in the same way for students from different cultures. Concern about this topic has been expressed for the last few years (Pintrich, 2003), and some research has begun in this area (Bong, 2008; Hardre et al., 1996; Zusho, Pintrich, & Cortina, 2005). As educators, we need to be aware of the cultural differences in motivation of the students in our classrooms, if we are to design our teaching to best meet the needs of all of our students. As researchers, we need to be aware of the need to extend our research in motivation beyond Western students, because the typical North American classroom is no longer an exclusive domain of Western students. All motivation theories can benefit by examination in different cultural contexts.

Scientific knowledge is gained in small increments, and this study adds a little bit more to our understanding of the cross-cultural validity of motivation theories. This type of research benefits not only theory development, but, eventually, it is to the advantage of students and teachers as empirically-based instructional practices are developed that work for all students in a classroom.

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Appendix A: Ethics waiver

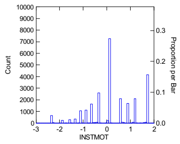
Please be advised that your Application for Ethics Approval Waiver entitled
'Motivation correlates of academic achievement: Exploring how motivation influences academic achievement in the PISA 2003 dataset' has been approved and assigned Protocol Number 07-002.

You may begin your research and will receive a Certificate of Approval via regular mail.

Good luck with your research.

Leah M. Potter | Human Research Ethics | University of Victoria | Technology
Enterprise Facility, Room 218 | Victoria, BC | Canada | Tel: 250-472-4545 |
FAX: 250-721-7836 | http://www.research.uvic.ca | E-mail: ethics@uvic.ca

Appendix B: Histograms for Level 1 and Level 2 independent variables



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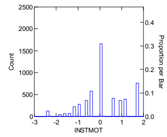

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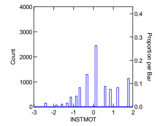

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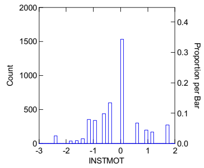

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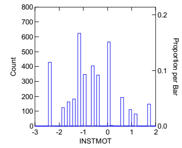

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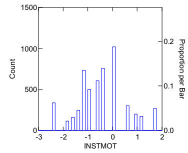
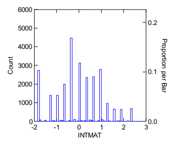


f. Korea

Figure B 1. Histograms for instrumental motivation for all countries.



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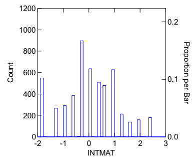

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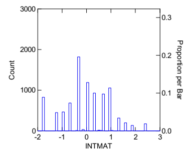

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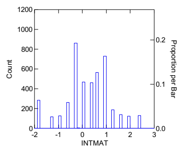
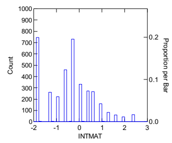
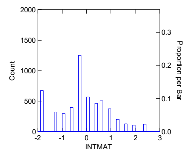


d. Hong Kong-China

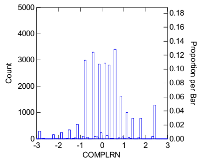


e. Japan



f. Korea

Figure B 2. Histograms for intrinsic motivation for all countries.



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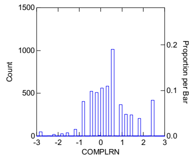

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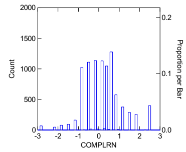

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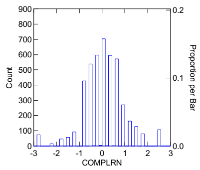

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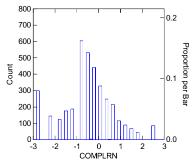

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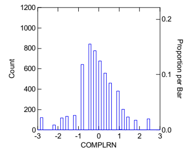
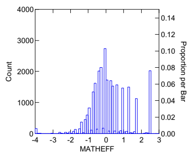


f. Korea

Figure B 3. Histograms for performance orientation for all countries.



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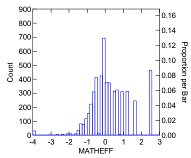

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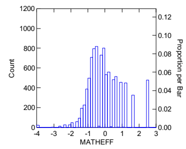

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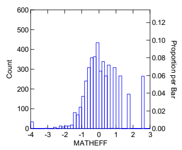

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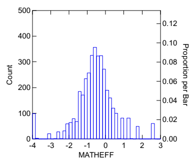

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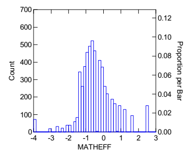
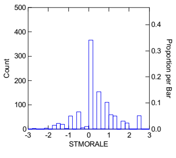


f. Korea

Figure B 4. Histograms for self-efficacy for all countries.



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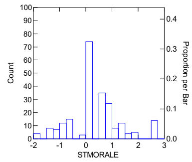

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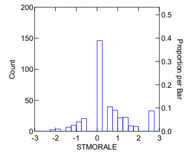

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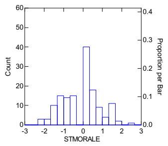
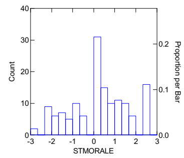
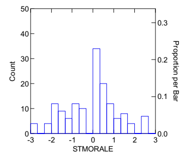


d. Hong Kong-China

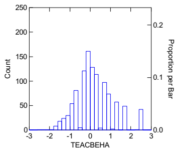


e. Japan

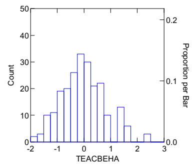


f. Korea

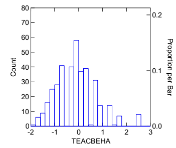
Figure B 5. Histograms for student morale and commitment for all countries.



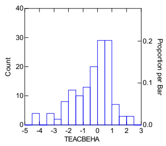
a. Canada



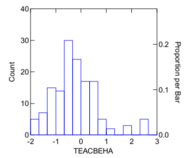
b. United States



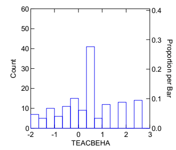
c. United Kingdom



d. Hong Kong-China

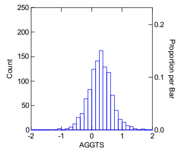


e. Japan

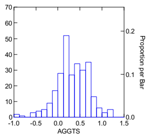


f. Korea

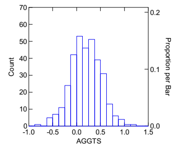
Figure B 6. Histograms for teacher factors affecting school climate for all countries.



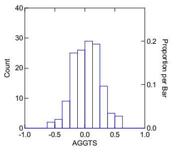
a. Canada



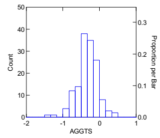
b. United States



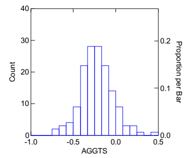
c. United Kingdom



d. Hong Kong-China



e. Japan



f. Korea

Figure B 7. Histograms for teacher support for all countries.

Appendix C: Descriptive statistics for plausible values for all domains and all countries.

Table C 1. *Descriptive statistics for general math ability scores for all countries.*

Country		Min.	Max.	Mean	SD	Skewness	Kurtosis
Canada	PV1math	160.34	859.28	521.63	87.95	-0.06	-0.17
	PV2math	83.14	866.83	521.14	87.39	-0.07	-0.13
	PV3math	123.96	856.47	521.55	87.48	-0.06	-0.14
	PV4math	119.75	853.28	521.25	87.86	-0.08	-0.14
	PV5math	191.03	844.48	521.42	87.87	-0.06	-0.14
The	PV1math	177.39	796.96	481.96	93.72	-0.03	-0.24
United	PV2math	181.99	749.99	480.81	93.23	-0.09	-0.28
States	PV3math	183.47	802.02	481.83	93.93	-0.04	-0.26
	PV4math	147.80	772.04	481.88	93.55	-0.03	-0.24
	PV5math	142.19	761.68	480.86	93.33	-0.06	-0.22
The	PV1math	155.59	809.19	514.36	90.93	-0.12	-0.14
United	PV2math	130.97	820.86	514.60	90.94	-0.10	-0.23
Kingdom	PV3math	155.12	804.52	514.68	91.18	-0.10	-0.15
	PV4math	168.36	821.89	514.25	91.29	-0.11	-0.20
	PV5math	123.96	788.00	514.32	91.41	-0.10	-0.22
Hong	PV1math	95.61	881.09	555.02	98.06	-0.46	0.31
Kong-	PV2math	159.87	870.96	555.28	96.83	-0.41	0.14
China	PV3math	174.20	877.19	556.83	97.46	-0.39	0.12
	PV4math	95.61	878.75	556.00	97.01	-0.42	0.19
	PV5math	159.87	893.78	556.18	97.90	-0.39	0.18
Japan	PV1math	140.40	839.80	529.63	98.70	-0.31	-0.02

	PV2math	119.36	828.12	530.61	99.24	-0.29	-0.01
	PV3math	152.86	831.63	530.85	99.61	-0.26	-0.15
	PV4math	162.21	816.98	529.77	99.49	-0.31	0.01
	PV5math	158.47	891.21	530.70	98.48	-0.23	-0.22
Korea	PV1math	197.57	849.62	540.07	92.17	-0.08	-0.08
	PV2math	169.61	842.14	540.23	92.51	-0.08	-0.14
	PV3math	192.04	855.38	541.03	92.44	-0.10	-0.05
	PV4math	189.39	848.61	541.19	92.89	-0.08	-0.10
	PV5math	181.60	888.41	540.50	92.64	-0.11	-0.05

Table C 2. *Descriptive statistics for science ability scores for all countries.*

Country		Min.	Max.	Mean	SD	Skewness	Kurtosis
Canada	PV1scie	83.35	892.02	508.50	99.34	-0.11	-0.13
	PV2scie	46.13	911.08	508.56	99.20	-0.09	-0.08
	PV3scie	89.70	862.24	508.83	99.14	-0.011	-0.11
	PV4scie	87.89	863.15	508.56	99.37	-0.012	-0.08
	PV5scie	113.30	903.82	508.83	99.98	-0.11	-0.08
The United States	PV1scie	111.49	812.95	490.01	100.44	-0.07	-0.26
	PV2scie	155.06	804.14	489.26	100.04	-0.08	-0.31
	PV3scie	158.51	823.21	490.46	100.73	-0.08	-0.30
	PV4scie	116.94	786.89	490.67	99.89	-0.09	-0.26
	PV5scie	99.69	812.95	489.67	100.07	-0.07	-0.18
The United	PV1scie	110.67	835.01	519.35	102.83	-0.12	-0.25
	PV2scie	133.28	834.83	519.64	102.18	-0.15	-0.18

Kingdom	PV3scie	113.40	886.75	519.45	102.62	-0.16	-0.20
	PV4scie	133.28	866.78	518.83	102.36	-0.15	-0.18
	PV5scie	113.39	891.29	519.62	103.24	-0.13	-0.18
Hong	PV1scie	127.92	814.86	544.37	92.56	-0.45	0.21
Kong-	PV2scie	183.93	786.71	544.33	91.16	-0.40	0.08
China	PV3scie	174.67	843.09	545.20	91.66	-0.38	0.07
	PV4scie	127.92	828.56	544.07	91.39	-0.42	0.08
	PV5scie	195.91	843.09	545.08	91.12	-0.42	0.16
Japan	PV1scie	90.34	898.55	544.68	108.79	-0.31	-0.05
	PV2scie	60.38	876.77	543.36	109.31	-0.29	-0.02
	PV3scie	69.46	866.78	544.28	108.75	-0.31	0.04
	PV4scie	84.25	835.92	543.73	107.79	-0.37	0.08
	PV5scie	96.06	895.83	543.97	106.43	-0.33	0.03
Korea	PV1scie	136.73	869.41	536.89	100.36	-0.22	0.04
	PV2scie	149.44	880.13	536.75	100.71	-0.25	0.08
	PV3scie	109.67	865.06	536.87	100.94	-0.120	-0.05
	PV4scie	144.08	907.63	537.41	100.82	-0.19	-0.04
	PV5scie	156.88	910.36	536.27	100.42	-0.24	-0.04

Table C 3. *Descriptive statistics for reading literacy scores for all countries.*

Country		Min.	Max.	Mean	SD	Skewness	Kurtosis
Canada	PV1read	100.30	818.67	516.09	90.74	-0.30	0.09
	PV2read	67.42	914.00	516.11	90.67	-0.29	0.05
	PV3read	98.38	817.24	516.22	90.26	-0.30	0.07

	PV4read	132.87	847.43	516.25	90.73	-0.30	0.07
	PV5read	131.26	914.00	516.21	90.81	-0.30	0.10
The United States	PV1read	54.10	799.12	493.77	99.86	-0.28	-0.02
	PV2read	108.64	766.15	493.16	100.01	-0.29	-0.07
	PV3read	138.96	812.47	494.22	100.12	-0.31	-0.04
	PV4read	86.82	780.06	495.56	99.32	-0.30	-0.04
	PV5read	18.01	804.53	493.74	100.10	-0.31	0.01
The United Kingdom	PV1read	137.68	800.39	512.05	92.91	-0.30	0.04
	PV2read	87.95	786.25	512.18	92.75	-0.31	0.08
	PV3read	110.41	807.10	512.91	93.67	-0.33	0.04
	PV4read	100.78	820.89	511.96	93.09	-0.128	0.08
	PV5read	97.58	831.54	512.08	93.47	-0.33	0.15
Hong Kong-China	PV1read	57.31	746.93	513.60	83.39	-0.72	1.06
	PV2read	98.22	735.41	514.07	81.72	-0.67	0.84
	PV3read	113.14	768.38	514.16	82.03	-0.68	0.96
	PV4read	105.92	750.11	513.96	82.15	-0.64	0.70
	PV5read	23.62	768.38	513.57	82.47	-0.69	1.05
Japan	PV1read	48.21	792.43	495.52	105.94	-0.47	0.22
	PV2read	-12.17	794.83	493.66	105.93	-0.48	0.36
	PV3read	25.17	780.64	494.91	105.59	-0.45	0.26
	PV4read	-63.81	790.26	494.12	104.70	-0.53	0.43
	PV5read	21.99	833.09	493.58	104.74	-0.50	0.29
Korea	PV1read	79.05	889.53	533.44	82.51	0.51	1.60
	PV2read	90.82	840.28	532.63	82.90	0.54	1.62

	PV3read	24.88	865.70	533.00	82.85	0.50	1.41
	PV4read	136.90	943.56	533.02	82.59	0.52	2.08
	PV5read	93.48	883.97	532.17	83.55	0.53	1.71

Table C 4. *Descriptive statistics for problem-solving ability scores for all countries.*

Country		Min.	Max.	Mean	SD	Skewness	Kurtosis
Canada	PV1prob	153.42	846.97	519.29	90.31	-0.16	-0.08
	PV2prob	8.58	907.65	518.88	89.94	-0.15	-0.06
	PV3prob	66.62	839.57	519.49	90.22	-0.017	-0.06
	PV4prob	114.10	915.75	519.19	90.14	-0.15	-0.04
	PV5prob	149.84	886.38	519.23	90.14	-0.16	-0.101
The	PV1prob	134.95	841.87	476.56	96.98	-0.10	-0.26
United	PV2prob	130.44	767.83	474.92	96.68	-0.16	-0.28
States	PV3prob	135.55	803.57	476.08	96.67	-0.12	-0.24
	PV4prob	50.28	795.06	476.55	96.60	-0.10	-0.21
	PV5prob	119.38	772.09	475.46	96.08	-0.13	-0.21
The	PV1prob	128.74	814.64	513.98	91.55	-0.18	-0.10
United	PV2prob	178.35	775.49	514.03	91.49	-0.17	-0.13
Kingdom	PV3prob	158.52	816.34	514.04	92.00	-0.19	-0.12
	PV4prob	177.24	814.47	512.97	91.92	-0.18	-0.11
	PV5prob	150.01	790.81	513.30	91.98	-0.20	-0.15
Hong	PV1prob	104.91	821.44	552.74	94.95	-0.50	0.34
Kong-	PV2prob	167.03	817.11	553.63	94.10	-0.50	0.28
China	PV3prob	114.27	846.12	553.40	93.91	-0.45	0.32

	PV4prob	92.14	821.44	552.70	94.51	-0.49	0.37
	PV5prob	118.53	853.19	552.92	94.46	-0.49	0.30
Japan	PV1prob	115.04	853.61	543.83	104.54	-0.41	-0.11
	PV2prob	33.43	850.38	544.52	103.68	-0.39	0.15
	PV3prob	138.01	815.49	544.33	103.64	-0.39	0.12
	PV4prob	75.89	815.32	542.67	104.16	-0.47	0.34
	PV5prob	76.83	882.72	543.20	102.44	-0.39	0.17
Korea	PV1prob	236.22	861.44	548.76	86.50	-0.17	0.09
	PV2prob	164.31	831.06	548.19	86.99	-0.21	0.12
	PV3prob	202.77	855.74	549.72	86.44	-0.21	0.14
	PV4prob	195.97	846.97	549.65	86.25	-0.19	0.13
	PV5prob	174.69	886.97	548.84	87.01	-0.21	0.17

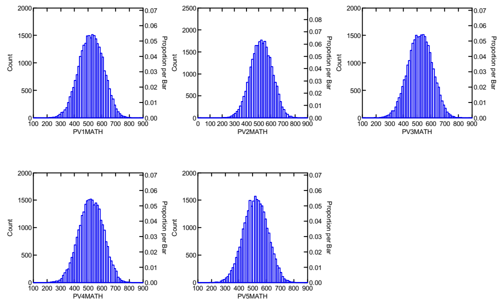


Figure C1 1. Histograms for the five plausible values for general math ability score for Canada.

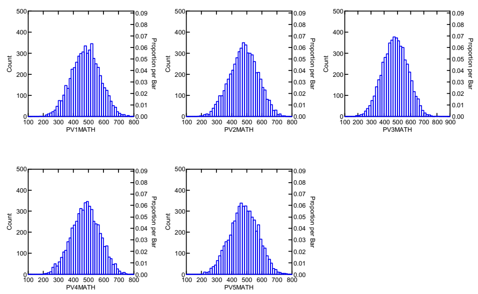


Figure C1 2. Histograms for the five plausible values for general math ability score for the United States.

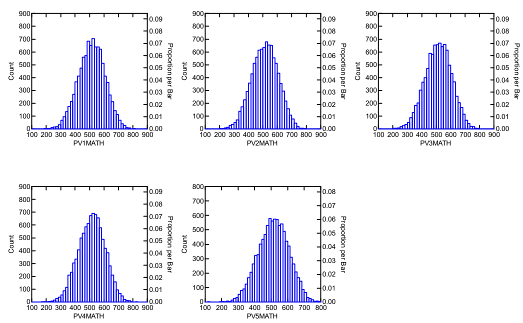


Figure C1 3. Histograms for the five plausible values for general math ability score for the United Kingdom.

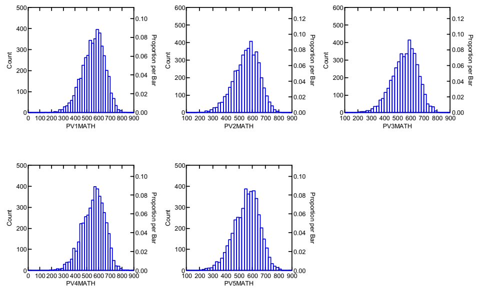


Figure C1 4. Histograms for the five plausible values for general math ability score for Hong Kong-China.

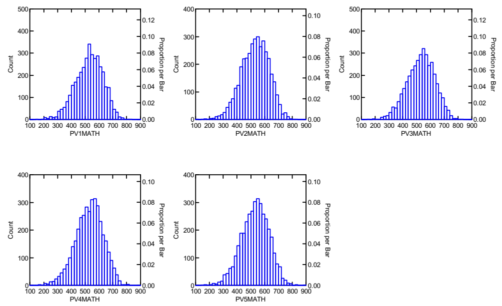


Figure C1 5. Histograms for the five plausible values for general math ability score for Japan.

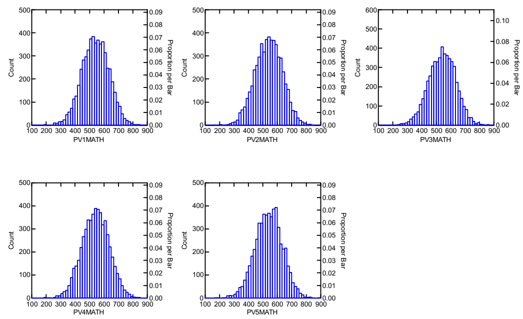


Figure C1 6. Histograms for the five plausible values for general math ability score for Korea.

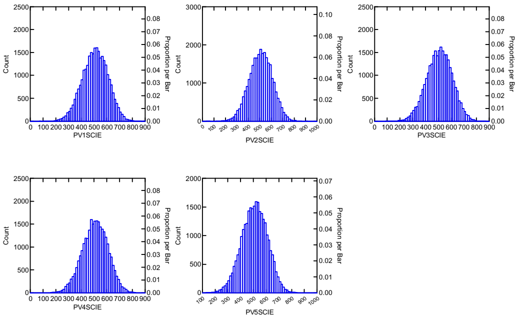


Figure C2 1. Histograms for the five plausible values for science literacy score for Canada.

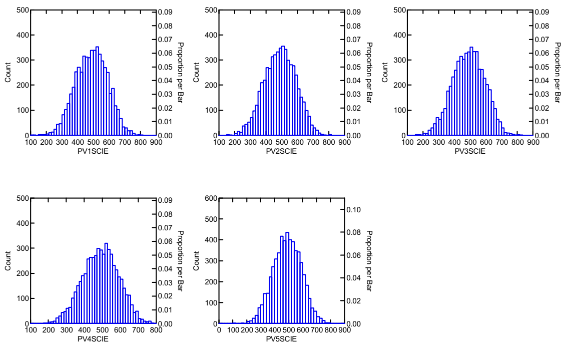


Figure C2 2. Histograms for the five plausible values for science literacy score for the United States.

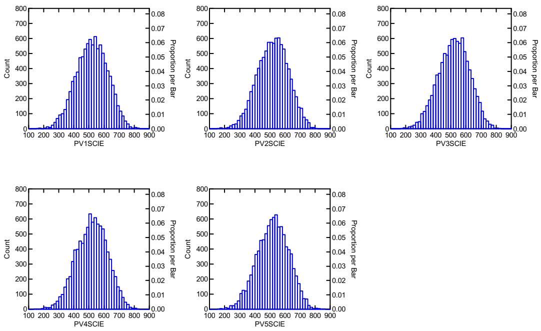


Figure C2 3. Histograms for the five plausible values for science literacy score for the United Kingdom.

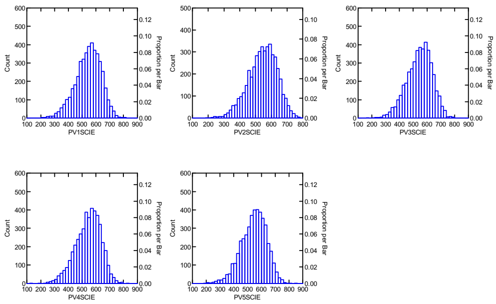


Figure C2 4. Histograms for the five plausible values for science literacy score for Hong Kong-China.

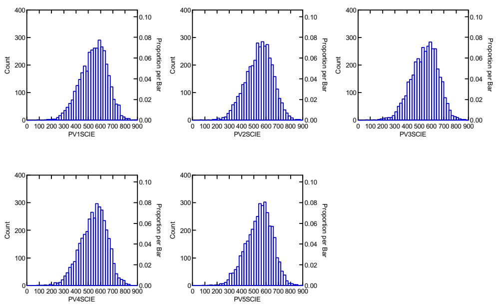


Figure C2 5. Histograms for the five plausible values for science literacy score for Japan.

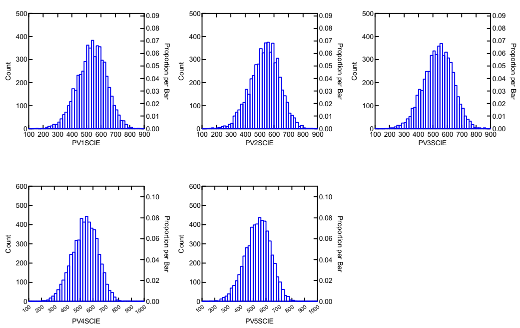


Figure C2 6. Histograms for the five plausible values for science literacy score for Korea.

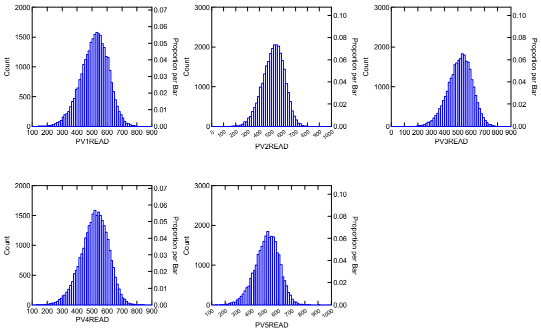


Figure C3 1. Histograms for the five plausible values for reading literacy score for Canada.

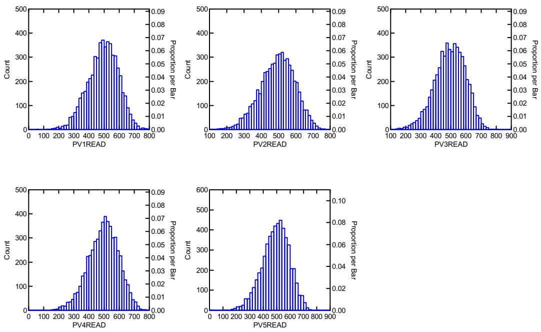


Figure C3 2. Histograms for the five plausible values for reading literacy score for the United States.

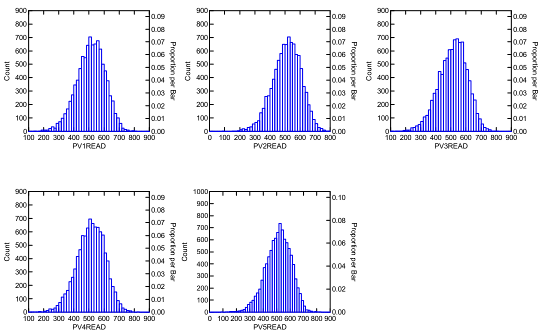


Figure C3 3. Histograms for the five plausible values for reading literacy score for the United Kingdom.

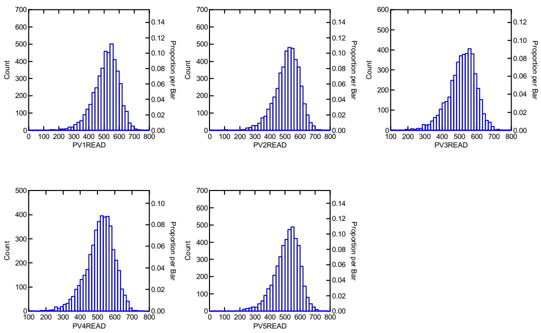


Figure C3 4. Histograms for the five plausible values for reading literacy score for Hong Kong-China.

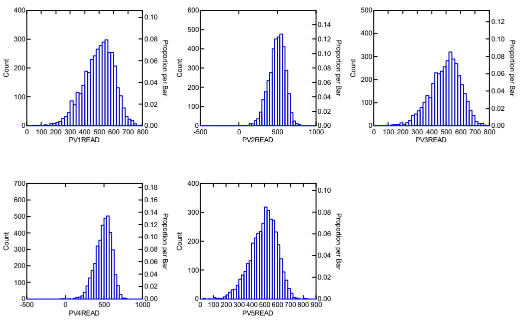


Figure C3 5. Histograms for the five plausible values for reading literacy score for Japan.

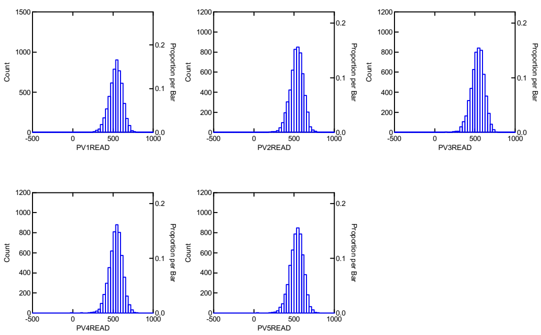


Figure C3 6. Histograms for the five plausible values for reading literacy score for Korea.

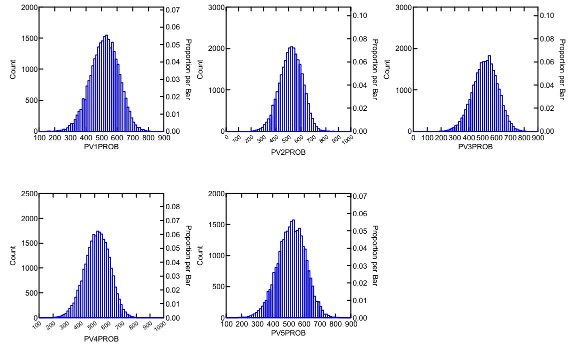


Figure C4 1. Histograms for the five plausible values for problem-solving ability score for Canada.

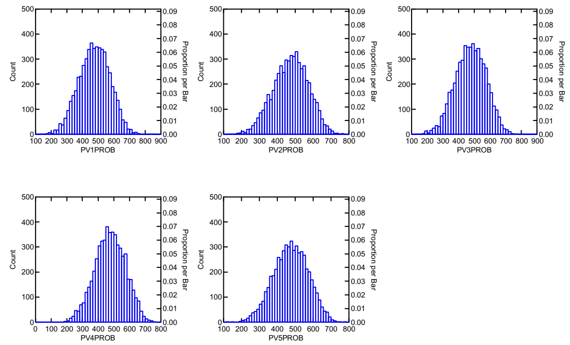


Figure C4 2. Histograms for the five plausible values for problem-solving ability score for the United States.

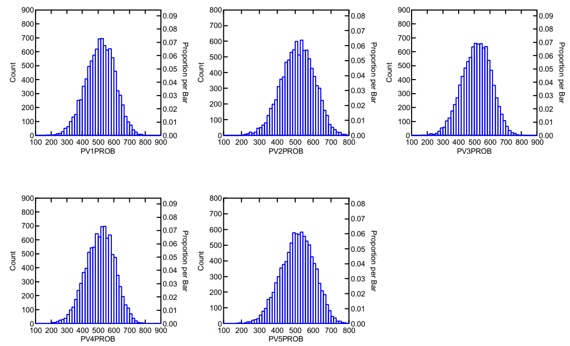


Figure C4 3. Histograms for the five plausible values for problem-solving ability score for the United Kingdom.

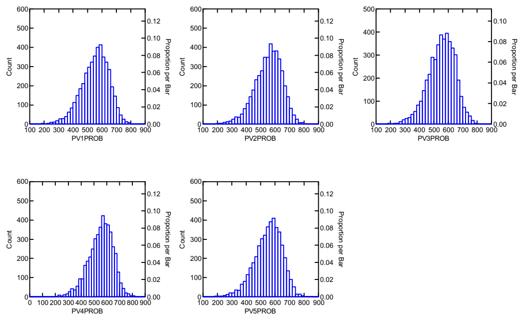


Figure C4 4. Histograms for the five plausible values for problem-solving ability score for Hong Kong-China.

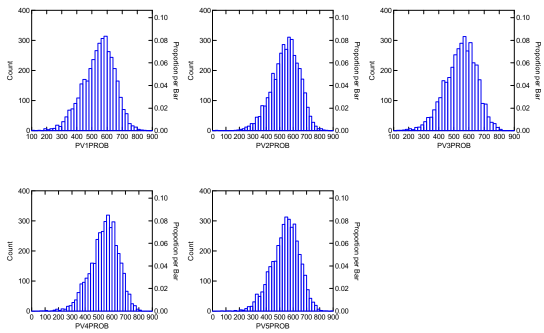


Figure C4 5. Histograms for the five plausible values for problem-solving ability score for Japan.

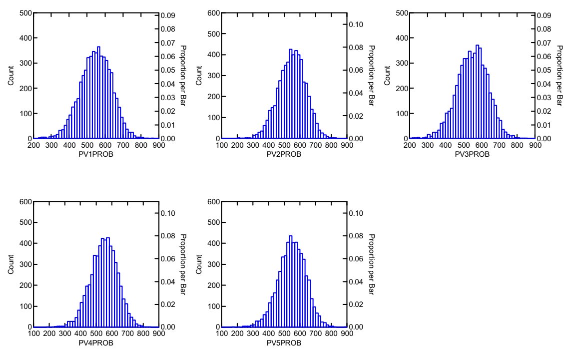


Figure C4 6. Histograms for the five plausible values for problem-solving ability score for Korea.

Appendix D: Hierarchical linear models

Table D 1. *Null models for general math ability scores.*

a. Canada

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
General Math Ability (Intercept, γ_{00})	519.54	1.35	385.24	1067	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	1532.40	39.15	6855.36	1067	0.000
School-Level Effect	6363.86	79.77			

Variance attributable to schools = $\frac{1532.4}{1532.4 + 6363.9}$ = 0.19

b. The United States

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
General Math Ability (Intercept, γ_{00})	482.36	3.37	142.94	224	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*

Student-Level Effect	2107.48	45.91	1542.17	224	0.000
School-Level Effect	6641.82	81.50			

Variance attributable to schools = $\frac{2107.5}{2107.5 + 6641.8}$ = 0.24

c. The United Kingdom

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
General Math Ability (Intercept, γ_{00})	511.79	2.84	179.90	312	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	2283.59	47.79	3393.95	312	0.000
School-Level Effect	6197.42	78.72			

Variance attributable to schools = $\frac{2283.59}{2283.59 + 6197.42}$ = 0.27

d. Hong Kong-China

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
General Math Ability	553.06	5.76	96.00	143	0.000

(Intercept, γ_{00})

Random Effects	Variance Component	SD	χ^2	df	p
Student-Level Effect	4532.41	67.32	4010.70	143	0.000
School-Level Effect	5079.45	71.27			

Variance attributable to schools = $\frac{4532.4}{4532.4 + 5079.4}$ = 0.47

e. Japan

Variables	Parameters Estimate			df	p
	Coefficient	SE	t		
Fixed Effects					
General Math Ability (Intercept, γ_{00})	526.83	6.83	77.08	115	0.000

Random Effects	Variance Component	SD	χ^2	df	p
Student-Level Effect	5266.37	72.57	4158.37	115	0.000
School-Level Effect	4735.27	68.81			

Variance attributable to schools = $\frac{5266.4}{5526.4 + 4735.3}$ = 0.53

f. Korea

Variables	Parameters Estimate			df	p
	Coefficient	SE	t		

Fixed Effects					
General Math Ability (Intercept, γ_{00})	539.00	5.09	105.95	147	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	3655.42	60.46	4025.20	147	0.000
School -Level Effect	5000.24	70.71			

Variance attributable to schools = $\frac{3655.4}{3655.4 + 5000.2}$ = 0.42

Table D 2. *Null models for science ability scores.*

a. Canada

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Science Ability (Intercept, γ_{00})	506.72	1.48	342.58	1067	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	1799.91	42.42	6365.92	1067	0.000
School -Level Effect	8292.02	91.06			

Variance attributable to schools = $\frac{1800}{1800 + 8292}$ = 0.18

b. The United States

Variables	Parameters Estimate			df	p
	Coefficient	SE	t		
Fixed Effects					
Science Ability (Intercept, γ_{00})	491.77	3.43	143.29	224	0.000
Random Effects	Variance Component	SD	χ^2	df	p
Student-Level Effect	2077.00	45.57	1307.90	224	0.000
School -Level Effect	7932.54	89.06			

Variance attributable to schools = $\frac{2077}{2077+7932.5}$ = 0.21

c. The United Kingdom

Variables	Parameters Estimate			df	p
	Coefficient	SE	t		
Fixed Effects					
Science Ability (Intercept, γ_{00})	518.30	3.12	165.94	312	0.000
Random Effects	Variance Component	SD	χ^2	df	p
Student-Level Effect	2711.28	52.07	3182.88	312	0.000
School -Level Effect	8000.56	89.44			

Variance attributable to schools = $\frac{2711.3}{2711.3+8000.6}$ = 0.25

d. Hong Kong-China

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Science Ability (Intercept, γ_{00})	541.93	5.31	102.03	143	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	3880.16	62.29	3773.30	143	0.000
School -Level Effect	4621.02	67.98			

Variance attributable to schools = $\frac{3880.1}{3880.1 + 4621} = 0.46$

e. Japan

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Science Ability (Intercept, γ_{00})	540.67	6.98	77.41	115	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	5458.51	73.88	3218.00	115	0.000
School -Level Effect	6417.95	80.11			

Variance attributable to schools = $\frac{5458.5}{5458.5 + 6417.9}$ = 0.46

f. Korea

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Science Ability (Intercept, γ_{00})	534.92	5.30	100.89	147	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	3923.67	62.64	3471.20	147	0.000
School -Level Effect	6290.24	79.31			

Variance attributable to schools = $\frac{3923.7}{3923.7 + 6290.2}$ = 0.38

Table D 3. *Null models for reading literacy scores.*

a. Canada

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Reading literacy (Intercept, γ_{00})	514.95	1.31	391.48	1067	0.000

Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	1448.90	38.06	6216.19	1067	0.000
School -Level Effect	6919.87	83.19			

Variance attributable to schools = $\frac{1448.9}{1448.9 + 6919.9}$ = 0.17

b. The United States

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Reading literacy (Intercept, γ_{00})	495.69	3.59	137.94	224	0.000

Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	2234.85	47.27	1418.05	224	0.000
School -Level Effect	7633.55	87.37			

Variance attributable to schools = $\frac{2234.8}{2234.8 + 7633.5}$ = 0.23

c. The United Kingdom

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Reading literacy (Intercept, γ_{00})	510.37	2.92	174.80	312	0.000

Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	2343.05	48.40	3280.00	312	0.000
School -Level Effect	6581.03	81.12			

Variance attributable to schools = $\frac{2343.1}{2343.1+6581} = 0.26$

d. Hong Kong-China

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Reading literacy (Intercept, γ_{00})	511.54	4.60	111.13	143	0.000

Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	2929.17	54.12	3350.72	143	0.000
School -Level Effect	3946.50	62.82			

Variance attributable to schools = $\frac{2929.1}{2929.1+3946.5} = 0.43$

e. Japan

Variables	Parameters Estimate	Standard		Approx. *df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					

Reading literacy (Intercept, γ_{00})	490.97	6.85	71.70	115	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	5174.45	71.93	3176.52	115	0.000
School -Level Effect	6124.21	78.26			

Variance attributable to schools = $\frac{5174.4}{5174.4 + 6124.2}$ = 0.46

f. Korea

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Reading literacy (Intercept, γ_{00})	530.92	4.26	124.64	147	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	2502.44	50.02	3082.57	147	0.000
School -Level Effect	4464.11	66.81			

Variance attributable to schools = $\frac{2502.4}{2502.4 + 4464.1}$ = 0.36

Table D 4. *Null models for problem-solving ability scores.*

a. Canada

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		

Fixed Effects					
Problem-solving Ability (Intercept, γ_{00})	518.04	1.33	389.20	649	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	1388.42	37.26	6018.02	1067	0.000
School -Level Effect	6894.45	83.03			

Variance attributable to schools = $\frac{1388.4}{1388.4 + 6894.5}$ = 0.17

b. The United States

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Problem-solving Ability (Intercept, γ_{00})	476.78	3.44	138.42	224	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	2098.05	45.80	1410.07	224	0.000
School -Level Effect	7238.41	85.08			

Variance attributable to schools = $\frac{2098}{2098 + 7238.4}$ = 0.22

c. The United Kingdom

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Problem-solving Ability (Intercept, γ_{00})	510.83	2.77	184.13	312	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	2039.35	45.16	2874.84	312	0.000
School -Level Effect	6565.62	81.03			

Variance attributable to schools = $\frac{2039.4}{2039.4 + 6565.6}$ = 0.24

d. Hong Kong-China

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Problem-solving Ability (Intercept, γ_{00})	550.56	5.13	107.22	143	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	3608.66	60.07	3039.23	143	0.000

School -Level Effect	5396.27	73.46			

Variance attributable to schools = $\frac{3608.7}{3608.7+5396.3}$ = 0.40

e. Japan

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Problem-solving Ability (Intercept, γ_{00})	540.15	6.82	79.15	115	0.000
Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	5184.10	72.00	3342.92	115	0.000
School -Level Effect	5790.21	76.09			

Variance attributable to schools = $\frac{5184.1}{5184.1+5790.2}$ = 0.47

f. Korea

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Problem-solving Ability (Intercept, γ_{00})	547.12	4.55	120.30	147	0.000

Random Effects	Variance Component	*SD*	χ^2	*df*	*p*
Student-Level Effect	2875.41	53.62	3404.99	147	0.000
School -Level Effect	4694.84	68.52			

Variance attributable to schools = $\frac{2875.4}{2875.4+4694.8}$ = 0.38

a. Canada

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{PERFORT}) + \beta_{2j}(\text{INSTMOT}) + \beta_{3j}(\text{INTMAT}) + \beta_{4j}(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{STMORALE}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20}$

$\beta_{3j} = \gamma_{30} + u_{3j}$

$\beta_{4j} = \gamma_{40} + u_{4j}$

b. United States

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{PERFORT}) + \beta_{2j}(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{STMORALE}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20} + u_{2j}$

c. United Kingdom

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{PERFORT}) + \beta_{2j}(\text{INTMAT}) + \beta_{3j}(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{STMORALE}) + \gamma_{02}(\text{TEACBEHA}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20} + \gamma_{21}(\text{STMORALE})$

$\beta_{3j} = \gamma_{30} + \gamma_{31}(\text{STMORALE}) + u_{3j}$

d. Hong Kong-China

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{PERFORT}) + \beta_{2j}(\text{INTMAT}) + \beta_{3j}(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{STMORALE}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20}$

$\beta_{3j} = \gamma_{30} + \gamma_{31}(\text{STMORALE})$

e. Japan

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{INTMAT}) + \beta_{2j}(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{STMORALE}) + \gamma_{02}(\text{AGGTS}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20}$

f. Korea

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{INTMAT}) + \beta_{2j}(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{STMORALE}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20} + u_{2j}$

Figure D 1. Final models for general mathematics ability achievement for all countries.

a. Canada

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{PERFORT}) + \beta_{2j}(\text{INSTMOT}) + \beta_{3j}(\text{MATHEFF}) + r_{ij}$
$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{STMORALE}) + \gamma_{02}(\text{TEACBEHA}) + u_{0j}$
$\beta_{1j} = \gamma_{10}$
$\beta_{2j} = \gamma_{20} + u_{2j}$
$\beta_{3j} = \gamma_{30} + u_{3j}$

b. United States

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{PERFORT}) + \beta_{2j}(\text{INSTMOT}) + \beta_{3j}(\text{INTMAT}) + \beta_{4j}(\text{MATHEFF}) + r_{ij}$
$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{STMORALE}) + u_{0j}$
$\beta_{1j} = \gamma_{10}$
$\beta_{2j} = \gamma_{20}$
$\beta_{3j} = \gamma_{30}$
$\beta_{4j} = \gamma_{40} + u_{4j}$

c. United Kingdom

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{PERFORT}) + \beta_{2j}(\text{INTMAT}) + \beta_{3j}(\text{MATHEFF}) + r_{ij}$
$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{STMORALE}) + \gamma_{02}(\text{TEACBEHA}) + u_{0j}$
$\beta_{1j} = \gamma_{10}$
$\beta_{2j} = \gamma_{20} + \gamma_{02}(\text{STMORALE})$
$\beta_{3j} = \gamma_{30} + \gamma_{03}(\text{STMORALE}) + u_{3j}$

d. Hong Kong-China

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{PERFORT}) + \beta_{2j}(\text{INTMAT}) + \beta_{3j}(\text{MATHEFF}) + r_{ij}$
$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{STMORALE}) + u_{0j}$
$\beta_{1j} = \gamma_{10}$
$\beta_{2j} = \gamma_{20}$
$\beta_{3j} = \gamma_{30} + \gamma_{03}(\text{STMORALE})$

e. Japan

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{PERFORT}) + \beta_{2j}(\text{MATHEFF}) + r_{ij}$
$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{STMORALE}) + \gamma_{02}(\text{AGGTS}) + u_{0j}$
$\beta_{1j} = \gamma_{10}$
$\beta_{2j} = \gamma_{20}$

f. Korea

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{MATHEFF}) + r_{ij}$
$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{STMORALE}) + u_{0j}$
$\beta_{1j} = \gamma_{10} + u_{1j}$

Figure D 2. Final models for science achievement for all countries.

a. Canada

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{PERFORT}) + \beta_{2j}\,(\text{INSTMOT}) + \beta_{3j}\,(\text{INTMAT}) + \beta_{4j}\,(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{STMORALE}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20}$

$\beta_{3j} = \gamma_{30} + \gamma_{31}\,(\text{TEACBEHA}) + u_{3j}$

$\beta_{4j} = \gamma_{40} + u_{4j}$

b. United States

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{PERFORT}) + \beta_{2j}\,(\text{INSTMOT}) + \beta_{3j}\,(\text{INTMAT}) + \beta_{4j}\,(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{STMORALE}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20}$

$\beta_{3j} = \gamma_{30}$

$\beta_{4j} = \gamma_{40} + u_{4j}$

c. United Kingdom

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{PERFORT}) + \beta_{2j}\,(\text{INTMAT}) + \beta_{3j}(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{STMORALE}) + \gamma_{02}\,(\text{TEACBEHA}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20} + \gamma_{02}\,(\text{STMORALE})$

$\beta_{3j} = \gamma_{30} + \gamma_{03}\,(\text{STMORALE}) + u_{3j}$

d. Hong Kong-China

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{PERFORT}) + \beta_{2j}(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{STMORALE}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20} + \gamma_{02}\,(\text{STMORALE})$

e. Japan

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{PERFORT}) + \beta_{2j}\,(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{STMORALE}) + \gamma_{02}\,(\text{AGGTS}) + u_{0j}$

$\beta_{1j} = \gamma_{10} + u_{1j}$

$\beta_{2j} = \gamma_{20}$

f. Korea

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{STMORALE}) + u_{0j}$

$\beta_{1j} = \gamma_{10} + u_{1j}$

Figure D 3. Final models for reading literacy achievement for all countries.

a. Canada

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{PERFORT}) + \beta_{2j}\,(\text{INSTMOT}) + \beta_{3j}\,(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{STMORALE}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20}$

$\beta_{3j} = \gamma_{30} + u_{3j}$

b. United States

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{PERFORT}) + \beta_{2j}\,(\text{INSTMOT}) + \beta_{3j}\,(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{STMORALE}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20}$

$\beta_{3j} = \gamma_{30} + u_{3j}$

c. United Kingdom

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{PERFORT}) + \beta_{2j}\,(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{STMORALE}) + \gamma_{02}\,(\text{TEACBEHA}) + u_{0j}$

$\beta_{1j} = \gamma_{10} + u_{1j}$

$\beta_{2j} = \gamma_{20} + \gamma_{02}\,(\text{STMORALE}) + u_{2j}$

d. Hong Kong-China

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{PERFORT}) + \beta_{2j}\,(\text{INTMAT}) + \beta_{3j}(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{STMORALE}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20}$

$\beta_{3j} = \gamma_{30} + \gamma_{03}\,(\text{STMORALE})$

e. Japan

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{PERFORT}) + \beta_{2j}\,(\text{INTMAT}) + \beta_{3j}(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{STMORALE}) + \gamma_{02}\,(\text{AGGTS}) + u_{0j}$

$\beta_{1j} = \gamma_{10} + u_{1j}$

$\beta_{2j} = \gamma_{20}$

$\beta_{3j} = \gamma_{30}$

f. Korea

$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{INTMAT}) + \beta_{2j}\,(\text{MATHEFF}) + r_{ij}$

$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{STMORALE}) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20} + u_{2j}$

Figure D 4. Final models for problem-solving ability achievement for all countries.