Enlightening Science:

Addressing the Cognitive and Non-Cognitive Aspects of Science Learning

Munirah Shaik Kadir

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Institute for Positive Psychology and Education, Australian Catholic University

Principal Supervisor:	Professor Alexander S. Yeung
Co-Supervisor:	Professor Richard M. Ryan
Assistant Supervisor:	Dr. Anne Forbes

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This thesis is dedicated to my precious son,

Adam Rayan Dula,

who, was born during my PhD journey and became my greatest source of strength.

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Prior to embarking on my PhD journey, I was seconded to the National Institute of Education / Nanyang Technological University, where I worked as a lecturer and research associate with the Centre for Research in Pedagogy and Practice in Singapore. It was this four-year stint which nurtured my love for educational research, curriculum design, and science teacher training. I am very grateful for the wonderful opportunities given to me and the research experiences in the projects I managed under the leadership of Professor Foong See Kit and Professor Paul Lee. It was them who encouraged me to pursue a doctorate in science education and supported me in my PhD applications with their letters of recommendation. They have played important roles which contributed to the success of my PhD journey and I will be forever grateful. “Thank you for everything that you have done for me, Prof Foong and Prof Lee!”

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STATEMENT OF AUTHORSHIP AND SOURCES

This thesis contains no material that has been extracted in whole or in part from a thesis that I have submitted towards the award of any other degree or diploma in any other tertiary institution.

No other person's work has been used without due acknowledgment in the main text of the thesis.

All research procedures reported in the thesis received the approval of the relevant Ethics/Safety Committees (where required).

Munirah Shaik Kadir

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STATEMENT OF CONTRIBUTION OF OTHERS

Statement of Contribution of Chapter 2: Literature Review (Section A)

Chapter 2.A. - “Element Interactivity in Secondary School Mathematics and Science Education” has been published in a book - *Progress in Education*.

I, Munirah Shaik Kadir, wrote the book chapter and acknowledge that my contribution to the above work is 80%.

Signature:

This book chapter was co-written by Dr Bing H. Ngu and Professor Alexander S. Yeung. They contributed their expertise to this chapter substantively and methodologically. Thus, the contribution of each co-author to the above work is 10%.

Signature of co-authors:

Dr. Bing H. Ngu:

Professor Alexander S. Yeung:

Statement of Contribution of Chapter 2: Literature Review (Section B)

Chapter 2.B. - “Academic Self-Concept” has been published in a book - *Encyclopedia of Personality and Individual Differences*.

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Signature of co-author:

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Study 1 - "Simultaneous Testing of Four Decades of Academic Self-Concept Models" has been published in a top-tier peer-reviewed journal – *Contemporary Educational Psychology*.

I, Munirah Shaik Kadir, conducted this study and acknowledge that my contribution to the above work is 80%.

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This study was supervised by Professor Alexander S. Yeung and Dr. Thierno M.O. Diallo. They contributed their expertise to this journal paper substantively and methodologically. Thus, the contribution of each co-author to the above work is 10%.

Signature of co-authors:

Professor Alexander S. Yeung:

Dr. Thierno M.O. Diallo:

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ASC	Academic Self-Concept
BFLPE	Big-Fish-Little-Pond Effect
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CI	Confidence Interval
CL	Cognitive Load
CLT	Cognitive Load Theory
DCT	Dimensional Comparison Theory
DFE	Department for Education
EI	Element Interactivity
FIML	Full Information Maximum Likelihood
I/E	Internal/External Frame of Reference
LTM	Long-term Memory
OECD	Organisation for Economic Co-operation and Development
PSLE	Primary School Leaving Examination
RMSEA	Root Mean Square Error Approximation
REM	Reciprocal Effects Model
RI/EM	Reciprocal Internal/External Frame of Reference Model
SDT	Self-Determination Theory
SEM	Structural Equation Modeling
SOED	Scottish Office Education Department
STEM	Science, Technology, Engineering, and Mathematics
TIMSS	Trends in International Mathematics and Science Studies
TLI	Tucker-Lewis Index
WM	Working Memory

THESIS ABSTRACT

Physical science (or physics) is known to be one of the least popular school curriculum domains, mainly because of its complexity. When students encounter seemingly insurmountable difficulties when learning something, they lose the motivation to continue. It has been suggested that both the cognitive (e.g., students' conceptual understanding and achievement) and non-cognitive (e.g., psychological aspects such as academic self-concept and motivation) factors of learning are essential for helping students achieve their optimal best in a curriculum domain. However, there has not been much research, if any, which uses a dual approach to investigate both aspects of science learning. Most research focused on either the cognitive or non-cognitive aspect. Research on cognitive aspects of learning suggests that element interactivity is a useful construct with which to examine students' cognitive processes and the complexity of learning materials. However, there has been no illustration on how an analysis of interacting elements in science learning tasks may improve learning. Studies on the effects of reducing element interactivity on students' achievement and motivation are also scarce. Research on non-cognitive aspects of learning suggests that motivation is necessary to sustain students' engagement in learning. However, if the complexity of learning tasks is so high that students experience repeated failures, their motivation is not sustained. Therefore, both cognitive and non-cognitive factors play a crucial role in students' learning and both must be present to ensure an optimal learning environment.

The overarching aim of this thesis is to investigate the cognitive (i.e., students' achievement and cognitive processes in terms of element interactivity) and non-cognitive aspects (i.e., self-concept and other motivational factors) of students' learning of science. The thesis includes five studies. The first study showed that the five main findings from past self-concept research were applicable to the Grade 7 students from Singapore selected for the study. Students' sense of competence in a curriculum domain enhanced their future achievement in that domain only, except for physics and math, which showed interrelatedness (i.e., the enhancement was transferable from one domain to the other). The findings showed a strong interplay between academic self-concept and achievement and highlighted the important role that academic self-concept plays in determining students' learning outcomes. Therefore, strategies to enhance students' self-concept should be implemented in schools.

The results of the second study showed strong positive correlations between students' achievement and their motivation within a school year. Students' Grade 6 (final primary school year) achievement did not strongly contribute to their motivation in Grade 7, indicating the importance of providing an optimal learning environment in Grade 7 for a positive start to their secondary school education.

The third study showed how the interactions between the elements (i.e., element interactivity) in problem solving tasks reflect their level of complexity and how the number of operational lines that students used to solve problems could indicate their level of expertise in problem solving in that domain. This study highlighted the role of element interactivity as a planning tool for learning tasks and how teachers may use it to gain insights into students' cognitive processes.

The fourth study involved an intervention, which reduced element interactivity during science instruction, and the results revealed that students' achievement improved, and their science self-concept was maintained. The results and implications of the first four studies were used to design a dual-approach instruction to facilitate both cognitive and non-cognitive aspects of students' learning in the fifth and final study.

The results of the final intervention study indicated that the dual-approach instruction was beneficial. The experimental group of students outperformed the comparison group in both cognitive and non-cognitive factors. Results from multiple regression analyses revealed that those who experienced the intervention not only had higher achievement than those in the comparison group in the complex problem tasks, but also had higher motivation (i.e., self-regulation, task goal, inquiry, and educational and career aspirations) and higher academic self-concept (i.e., sense of competence).

This thesis demonstrates that there are strong associations and a significant interplay between students' achievement and motivation levels (i.e., cognitive and non-cognitive aspects of learning). The analysis of learning tasks and instruction in terms of element interactivity enables the scaffolding of complex learning tasks to suit students' cognitive levels, leading to higher achievement. Higher achievement contributes to higher motivation levels, including students' academic self-concept. When learning environments attend to basic psychological needs (i.e., a sense of competence, autonomy, and relatedness), students' motivation is enhanced and when motivated students experience learning that is within their ability and cognitive load capacities, their self-beliefs and motivation in the learning domain are sustained. Attention to both cognitive and non-cognitive factors in learning situations maximizes students' learning potential and should therefore be strongly considered by educators and curriculum planners.

CHAPTER 1: INTRODUCTION AND OVERVIEW

1.1. Background

Science education, especially in physics, is in crisis. In recent years, the number of students enrolled in science-related courses at the tertiary level has entered a spiral of decline in many countries around the world (National Science Board, 2014, 2015). This has led to a recursive shortage of science-related professionals such as qualified science teachers, scientists (Office of the Chief Scientist, 2012) as well as scientifically literate citizens. Physics knowledge and understanding lay the foundations for technology and engineering and therefore underpin a knowledge-based economy with engagement in science-related issues, global competitiveness, and national security (Oon & Subramaniam, 2010). It is therefore crucial to research and understand why school students do not choose to study physics and to hopefully reverse the trend to an upward cycle.

Similar to other science instruction, physics instruction in school generally focuses on problem solving. Thus, the main aim of teachers is to have students: (1) acquire information, concepts, and knowledge (conceptual) and (2) develop problem-solving skills (procedural). However, more than any other subject in the school curriculum, students describe physics as a "difficult subject with a high workload" (Angell, Guttersrud, Henriksen, & Isnes, 2004, p. 6). Current practices in physics classes focus on teacher-centered lectures to deliver the conceptual information, and drill-and-practice sessions to train students to follow procedures to solve physics problems. According to Wieman (2007), the problems that arise with these methods are that students: (1) understand only 10% of what was delivered in the lectures, (2) are unable to transfer (apply) their learning to solve related physics problems, and (3) even when they are able to solve physics problems, they may not actually understand the conceptual underpinnings of their problem solving procedures.

CHAPTER 1: Introduction and Overview

Treagust and Chandrasegaran (2007) emphasize that the success of science programs at the university level is dependent on the foundational improvements in science education in primary and secondary schools. Hence, improvements of science lessons at primary and secondary schools are critical. There is an urgent need to move away from the traditional approach of instruction in the science classrooms of young students in schools which are deductive and teacher-led (Andres, Steffen, & Ben, 2010). This traditional approach has been criticized for being ineffective in the teaching of science (Wieman, 2007), in terms of conceptual understanding and motivation, and has been known to be ineffective as early as the beginning of the 20th century. For example, Armstrong (1910) argued that science cannot be taught by means of lectures and demonstrations alone, where scientific ideas were transmitted as a series of unchanging facts from teachers to students, with students expected to memorize them. Instead, science should be presented to students in ways that would kindle their curiosity, encourage them to use their eyes and hands to discover knowledge by their own efforts, and stimulate their thinking (Armstrong, 1910).

There have been numerous research and intervention studies conducted with an attempt to solve the issue of educators using ineffective traditional pedagogies (e.g., Hardy, Jonen, Möller, & Stern, 2006; Kearney, 2016). However, most of these studies are segmented and either focus on the cognitive (i.e., achievement and learning processes) *or* the non-cognitive aspect (i.e., psychological factors such as motivation) of learning. To improve science education in secondary schools, there is a need for educators to incorporate *both* the cognitive and non-cognitive aspects where their strong interplay results in students' optimal learning (Forbes, Kadir, & Yeung, 2017; Kuppan, Munirah, Foong, & Yeung, 2010; Phan, Ngu, & Yeung, 2016). In this thesis, *both* the cognitive and non-cognitive aspects of science learning were addressed, their relations investigated, and the findings used to design an intervention addressing both cognitive and non-cognitive outcomes, which were then were measured.

1.2. Choice of Participants

Early adolescence is a vulnerable period when students go through vast changes in terms of their motivational attitudes towards learning as well as their achievement beliefs (Eccles & Midgley, 1989). For some of these students, the changes they experience as they leave their childhood (e.g., increased self-reflection, self-identity, self-concept, autonomy) lead to new academic goals, interests, attitudes towards learning such as increased self-regulated learning and a commitment to school learning (Goodenow, 1993). However, for many students in this age group, a decline in academic self-concept and autonomous motivation is salient (Ryan & Patrick, 2001). These students may have self-doubts about their academic abilities, are not committed to completing their schoolwork, question the value of learning, and do not put in much effort in their schoolwork and academic learning in general (Eccles, Wigfield, Harold, & Blumenfeld, 1993; Schunk, Pintrich, & Meece, 2008). “Autonomous motivation comprises both intrinsic motivation and the types of extrinsic motivation in which students have identified with an activity’s value and ideally will have integrated it into their sense of self” (Deci & Ryan, 2008, p. 182). Autonomous motivation predicts many important outcomes such as psychological health and well-being, effective performance, creative problem solving, deep or conceptual learning, and greater long-term persistence, for example, maintained change toward healthier behaviors (Ryan & Deci, 2017). When students are autonomously motivated, “they experience volition, or a self-endorsement of their actions” (Deci & Ryan, 2008, p. 182). Therefore, it is important to study the autonomous motivation of students, so that an intervention could be designed and administered to steer student learning experiences and motivation in a positive direction.

The critical components of science education include the learning processes, which then contribute to student achievement and form the cognitive aspect, and motivational and other psychosocial factors, which form the non-cognitive aspect. If young students in schools have positive learning experience with science – in both cognitive and non-cognitive aspects – they may be more likely to enroll in science-related courses in their senior secondary school years, and even beyond. Hence, for successful science education, lessons need to include these critical components (i.e., cognitive and non-cognitive) in parallel to each other. Since my research is focusing on the physics component of science, the student sample was selected from a school in Singapore, which offered Physics as a 'stand-alone' subject in the first year of secondary school (Grade 7 or Secondary 1).

1.3. Thesis Aim

The overarching aim of this thesis was to further the understanding of the relations between the cognitive and non-cognitive aspects of science learning by examining students' learning processes, achievement, and their motivation and self-concept towards science learning. In order to meet this aim, a series of five studies was conducted. The studies included exploration of the relations between cognitive and motivational aspects of learning with the findings contributing to the design and assessment of an instruction intervention that addressed both aspects of learning. The aim was not to create a 'bull's eye' shot to solve all problems related to science education, but to identify a network of cognitive and motivational determinants of science education and intervention practices in dealing with both the cognitive and non-cognitive issues of science education. The ultimate goal is to enlighten science to become a manageable, interesting, and popular domain.

1.4. Studies within the Thesis

The thesis includes five studies, each contributing to the overarching research aim of exploring the relations between the cognitive and non-cognitive aspects of science learning. Study 1 was a review of four decades of research on academic self-concept, a well-documented determinant of academic success. The study investigated whether the five main findings from past self-concept research were applicable to the sample of Secondary 1 (i.e., Grade 7) students from Singapore selected for the study, and to study any associations between students' achievement and their academic self-concept. In Study 2, associations between students' achievement and motivation were investigated using a wider range of motivational factors (e.g., self-efficacy, engagement, and educational aspiration). Study 3 explored the cognitive processes that contributed to student achievement. It focused on the role of element interactivity as a construct for (1) the analysis of science learning tasks, (2) for exploring students' cognitive processes, and (3) assessing students' expertise in the tasks. In Study 4, the effects of reducing element interactivity during science instruction on students' science achievement and science self-concept were investigated. Finally, the findings and implications of research from studies 1 to 4 were used to guide the design and implementation of a *dual-approach instruction* (i.e., sequencing element interactivity and enhancing motivation) in Study 5. In the dual-approach instruction, the 'isolated elements strategy' from cognitive load theory (Ayres, 2013) was used to sequence the element interactivity of the science materials. The learning environment was designed to nurture students' motivation by adding features which could fulfil students' basic psychological needs (i.e., sense of relatedness, autonomy, and competence), as suggested by self-determination theory (Ryan & Deci, 2017). The effects of the intervention on students' cognitive (i.e., performance in easy and complex tasks), and non-cognitive (motivation and academic self-concept) aspects of learning were examined.

1.5. Thesis Structure

This thesis is structured in the form of publishable papers. Due to specific requirements of publishers, the spelling and formatting may vary across chapters. Where there is co-authorship, the word "we" is used to reflect collaborative effort. This chapter (Chapter 1) provides the background to the research journey and explains how the five studies presented in this thesis contribute to the overarching research aim. The literature review (Chapter 2) presents the theoretical background for the five studies and positions the studies within their broader research context. Chapter 2 comprises four sections: Sections A to D. Sections A and B present two literature reviews which have been published as book chapters. Section C presents a review of literature which has not been discussed in Sections A and B. Section D presents the research questions and hypotheses guiding the five studies. Chapters 3 to 7 present the five studies, reported in the form of journal articles. Chapters 2 to 7 begin with a preface explaining the chapter's rationale and its role in answering the overarching research questions. Chapter 8 concludes this thesis with a general discussion of implications for future research and educational practice.

CHAPTER 2: LITERATURE REVIEW

2.1. Preface

This literature review sets the overall context for this thesis by explaining the cognitive and non-cognitive aspects in the field of science education (focusing on the branch of physics) and identifies the gaps in understanding. It provides an overview of the recent developments and syntheses of the studies in cognitive load theory and self-concept theory, as well as other theories of motivation such as self-determination theory, and science education in general. This literature review chapter has four main sections. Section A focuses on the cognitive aspects of learning: the learning processes (i.e., human cognitive architecture), and element interactivity as proposed by cognitive load theory. Section B focuses on the non-cognitive aspects of learning: students' academic self-concept. Sections A and B have been published as book chapters by Nova and Springer, respectively. Section C provides a juxtaposition of the cognitive and non-cognitive aspects of learning, highlighting relevant literature not covered in Section A and Section B. Section D provides an overview of this thesis, including specific research objectives for each of the five studies, an outline of the remaining chapters, and the overall significance of this research.

Section A:

The Cognitive Aspects of Learning –

Human Cognitive Processes and Element Interactivity

"Without the knowledge of human cognitive processes, instructional design is blind"

(Sweller, Ayres, & Kalyuga, 2011, p. v)

Note. This section has been published as a book chapter in the publication Progress in Education, edited by Roberta V. Nata. Permission to present the published version of this study in this thesis has been obtained from the publisher – Nova Science Publishers, Inc.

Kadir, M. S., Ngu, B. H., & Yeung, A. S. (2015). Element interactivity in secondary school mathematics and science education. In R. V. Nata (Ed.), *Progress in education* (Vol. 34, pp. 71-98). New York, NY: Nova.

2.A. Element Interactivity in Secondary School Mathematics and Science Education

2.A.1. Preface

The cognitive issue of physics instruction is its complex nature (van Merriënboer & Sweller, 2005). Clark and Elen (2006) suggest that the complexity of a learning task is related to the degree to which its mastery requires the learner to consciously and deliberately process numerous elements which interact in multiple ways. This is particularly so if the multiple elements or relationships are changing over time as is frequently the case in physics. The perceived complexity is increased when the learners are novices, so physics is generally considered to be very challenging to learn for secondary school students (van Merriënboer & Sweller, 2005), since it is newly introduced to them at that stage (i.e., Grade 7). Before effective instructional methods are designed to overcome these issues, knowledge about the human cognitive processes is necessary. When educators know how the brain works and understand the constraints and limitations of the brain and the learning processes, the instruction they design will be more effective in dealing with the cognitive challenges that students face. Section A of this literature review elaborates on the cognitive processes involved in learning and problem solving. Since physics instruction involves applying science conceptual knowledge in the form of equations (which forms part of the procedural knowledge to solve physics problems), there is also a component that looks into mathematical problem solving using equations.

2.A.2. Abstract

Learning mathematics and science entails learning the relations among multiple interacting elements, especially when solving problems. Assimilating multiple interacting elements simultaneously in the limited working memory capacity would incur cognitive load. Unless the instructions provide a mechanism to manage the high cognitive load involved, learning effectiveness may be compromised. Researchers have investigated instructional efficiency across diverse domains from the perspective of cognitive load theory. Progress in educational theory has enabled a better understanding of three types of cognitive load that students experience during the learning process: intrinsic, extraneous, and germane cognitive load. Processing the intrinsic nature of a task constitutes intrinsic cognitive load (e.g., complexity of elements). Sub-optimal instruction requiring unnecessary processing of elements constitutes extraneous cognitive load. Investing mental effort in multiple practices constitutes germane cognitive load. Recent advance in cognitive load theory highlights element interactivity (i.e., the interaction among elements to be processed) as a common thread among different types of cognitive load. However, despite progress in cognitive load research, little is known about the effects of element interactivity in secondary school mathematics and science education. Using element interactivity as a point of reference, this article reviews the design features of different approaches to teaching linear equations in mathematics and the topic of density in science. Evidence seems to point to the practical benefit of using instructional approaches that address the issue of multiple elements interacting with each other to facilitate learning. As such, the conceptualization of cognitive load in terms of element interactivity will bring further progress in the research on cognitive load in mathematics and science learning.

2.A.3. Introduction

The purpose of this chapter is to revisit the conceptualization of cognitive load in terms of element interactivity in mathematics and science learning in secondary schools. By defining and analyzing various types of cognitive loads (i.e., intrinsic, extraneous, and germane) in terms of element interactivity, it would be possible to analyze almost any learning material that may present a challenge to the learners. This approach will enable us to tailor instructions to suit students' knowledge levels and progress in mathematics and science education to a new level.

Many students perceive mathematics and science as difficult subjects to learn (Shen, 2001, 2002, 2006; Shen & Pedulla, 2000), most probably due to the complex nature of the concepts involved. Complexity in the learning materials is primarily due to the need to simultaneously process multiple elements of information, creating a burden on the limited working memory. This issue is particularly salient in problem solving situations in mathematics and science education, where students need to concurrently manage both conceptual and procedural knowledge. By understanding the issues caused by the interaction of various elements in mathematics and science learning materials, educators will be in a better position to choose appropriate instructional designs and methods to help students learn mathematics and science more effectively.

2.A.4. Cognitive Load as a Learning Issue

When students engage in a cognitive task, such as mathematics and science problem solving, the information required to complete the task must first be processed through the working memory (WM) of the brain system (Baddeley, 1986, 1992, 1998). The WM, a cognitive structure where current mental activity takes place (Simon, 1974), is limited in its capacity and duration (Peterson & Peterson, 1959). Cognitive load arises when WM resources are used to engage in a mental activity (e.g., Paas, Renkl, & Sweller, 2003, 2004). Clark and

Elen (2006) suggest that the complexity of a learning task is related to the degree to which its mastery requires the learner to consciously and deliberately process numerous elements which interact in multiple ways. Processing interacting elements impose a cognitive load on the WM (Sweller, 1994). If the cognitive load involved in the mental processing of the element interactivity exceeds the capacity of the WM, some of the information will be lost and problem solving success will be hindered (Ayres, 2006; Paas & Ayres, 2014). Evidence points to cognitive load issues related to the interacting elements of conceptual and procedural knowledge in mathematics and science problem solving tasks, and they form the focus of the present chapter.

2.A.5. Conceptual and Procedural Knowledge

The literature on problem solving has illustrated the importance of the mastery of concepts and problem solving procedures, because conceptual knowledge makes it possible to effectively use procedural knowledge to solve problems (Glaser, 1984). Policy documents such as the *National curriculum for science* for England and Wales (DFE, 1995) and *Environmental studies 5–14* for Scotland (SOED, 1993), also emphasize the integrated acquisition of conceptual and procedural knowledge. The simultaneous processing of conceptual and procedural knowledge creates issues in mental processing of information during mathematics and science problem solving, due to the limitations of the WM in dealing with such high cognitive load.

As simply stated by Ryle (1976), conceptual knowledge is ‘knowing that’ and procedural knowledge is ‘knowing how’. Education researchers in mathematics and science have defined and explained these two types of knowledge further. In mathematics, conceptual knowledge is “an integrated and functional grasp of mathematical ideas” (Kilpatrick, Swafford, & Findell, 2001, p. 118) and procedural knowledge is the “ability to execute action sequences to solve problems, including the ability to adapt known procedures to novel problems” (Rittle-

Johnson, & Star, 2007, p. 562). In Science, conceptual knowledge is “the factors and mechanisms which underpin key events” and procedural knowledge is “the controlled manipulation of factors, the prediction and observation of outcomes, and the utilization of observations to draw conclusions” (Howe, Tolmie, Duchak-Tanner, & Rattray, 2000, p. 362; also see DFE, 1995; SOED, 1993).

In this chapter focusing on mathematics and science problem solving, we refer to conceptual knowledge as understanding the “meaning” behind the learning task and procedural knowledge as the ability to carry out the “steps” and “processes” to solve the problem in the task. When the interacting elements in problem solving are effectively managed, students will develop well-linked schemas and gain both conceptual and procedural knowledge which is flexible and generalizable to other similar problem situations.

2.A.6. Cognitive Processes in Problem Solving

An understanding of the cognitive processes that underlie mathematics and science problem solving is critical for learning more about how students deal with element interactivity that constitute cognitive load during problem solving (Carlson, Chandler, & Sweller, 2003; Chinnappan & Chandler, 2010). Figure 2.1 illustrates a model of human memory structures and the processing of information, more commonly known as the human cognitive architecture. This model identifies the main cognitive structures and processes of how students learn mathematics and science. It is based on the components of working memory (WM) advanced by Baddeley and Hitch (2000), which was illustrated by Chinnappan and Chandler (2010).

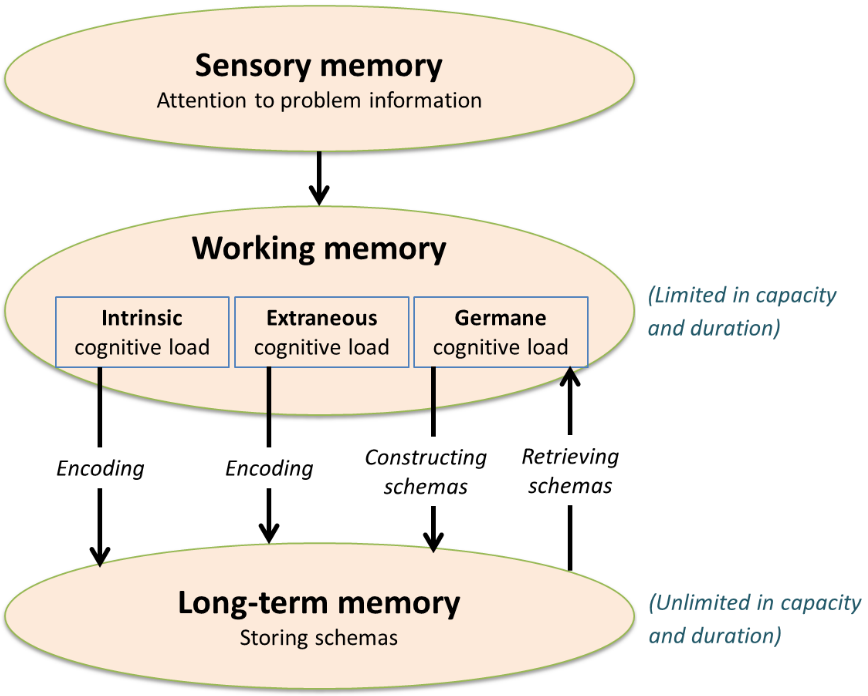

Figure 2.1. Human cognitive architecture.

The model shows that sensory memory first registers the incoming visual and auditory signals and then the relevant information is processed within the WM. During mathematics and science instruction, when students pay attention to a problem solving task, the input from sensory memory becomes relevant. As students process the new mathematical and scientific information, the process imposes cognitive load on WM, which has limited capacity and duration. The cognitive load involved in the process can be categorized as intrinsic, extraneous, and germane (Sweller, Ayres, & Kalyuga, 2011). Basically, the interacting elements in the learning material will impose intrinsic cognitive load and the sub-optimal instruction will impose extraneous cognitive load on the WM. If the instruction is optimal, the extraneous cognitive load will be minimal and there will be enough WM resources to deal with the interacting elements in the learning material. The mathematical and scientific knowledge will then be effectively processed, encoded, and organized as schemas and stored in long-term memory (LTM). LTM has unlimited capacity (Landauer, 1986) and is able to store unlimited schemas (Newell & Simon, 1972) such as mathematics and science concepts, theorems, and procedural rules. These schemas can be retrieved from LTM to interact with new elements in the WM to make sense of new incoming information to develop new mathematical and scientific concepts to be again stored in the LTM as new schemas (Figure 2.1). This cycle of schema construction and retrieval imposes germane cognitive load on WM and requires WM resources, but is essential for schema construction and retrieval, which facilitates learning. Successful learning is characterized by the automation of the retrieval of stored information for the acquisition of new knowledge, which will increase students' mathematical and scientific conceptual knowledge base and expertise in problem solving procedures. The following segments explain the main components of the model in more detail.

2.A.6.1. Working Memory

Working memory (WM) refers to the brain system that is used during learning and completing cognitive tasks such as problem solving (Baddeley, 1986, 1992). WM functions as a thinking mechanism, processing the instructional information with its cognitive resources, within the limitations of its capacity and duration (Peterson & Peterson, 1959). Because of its limited capacity and duration, researchers have tried to find ways to address the limitations. One suggestion is to organize large amounts of discrete information elements into smaller "chunks" and to sequence the chunks in a meaningful way (Miller, 1956). Remembering information elements in chunks extends the information processing ability of WM (Gobet et al., 2001). For example, remembering a number with 9 elements like 123488888 as 2 chunks (i.e., chunk 1: four consecutive numbers starting with 1; followed by chunk 2: five repeated numbers of 8), instead of 9 separate digits, reduces the processing load on WM (Clark, Nguyen, & Sweller, 2006). In mathematics and science, when dealing with problems with many interacting elements, it has been estimated that only about two to four of these chunks can be simultaneously processed by the WM (Cowan, 2001). This is because the interactions of the elements in these chunks would also use up limited WM resources.

When instructional materials are successfully processed through WM, the information is stored in LTM in the form of schemas. Recent studies in cognitive load theory have indicated that the limitations of the WM may be the single most critical factor that needs to be considered when designing instruction (Jeung, Chandler, & Sweller, 1997; Mayer, 2001; Sweller, 1999, Sweller, van Merriënboer, & Paas, 1998; Tindall-Ford, Chandler, & Sweller, 1997). This is because the failure to process necessary information effectively in WM leads to failed schema construction, which is detrimental to learning.

2.A.6.2. Long-Term Memory

While WM has limited capacity and duration, long-term memory (LTM) has unlimited capacity (Landauer, 1986) and is viewed as the central structure of human cognition. It is able to store a vast amount of knowledge that has been processed (Newell & Simon, 1972) by WM. The knowledge stored in LTM can be described as schemas that have been indexed and categorized for easy retrieval (Valcke, 2002) whenever WM is actively processing a task that is related to what has been stored in LTM. These schemas may be retrieved from LTM when required, to process with relevant new information in WM (Ericsson & Kintsch, 1995) to form new multi-dimensional mental webs of interconnected information (Chi, Glaser, & Rees, 1982; Gick & Holyoak, 1983), resulting in higher-level schemas related to the domain.

2.A.6.3. Schemas

Schemas are stored, organized, and interconnected knowledge that has been processed by the WM and transferred to LTM. A schema summarizes the common elements of related information, categorizes them and provides a generic characterization of the knowledge acquired (Anderson, Spiro, & Anderson, 1978). Because schemas in LTM are hierarchically organized, they allow us to categorize different problem states and decide upon the most appropriate solution strategies (Paas, van Gog, & Sweller, 2010). That is, for solving mathematics and science problems, how different chunks of information are organized as schemas in LTM will determine the quality of students' mathematics and science knowledge, which will influence the deployment of that knowledge during problem solving attempts (Chinnappan & Chandler, 2010).

The interconnectedness of schemas plays a crucial role in making a student an expert in problem solving tasks. If knowledge is organized in schemas that allow the learner to categorize multiple interacting elements of information as a single element (Pawley, Ayres, Cooper, & Sweller, 2005), the burden on WM is much reduced when processing new information. Well-organized schemas enable the learner to retrieve relevant knowledge from LTM with less conscious effort (Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977). The increased automatic processing is a crucial factor in learning, as it removes the burden on WM, allowing cognitive resources to be directed to more important learning processes.

A beginning learner (i.e., a novice) will initially construct simple, low-level schemas in the domain and store them in LTM. As more related materials are learned, the schema is recalled as a single element to facilitate the construction of more complex schemas by combining elements consisting of lower level schemas into higher-level schemas as the learner becomes more skilled (Paas et al., 2004). Research indicates that it is the existence of such domain-specific schemas that determines one's problem solving expertise (Chi et al., 1982; Larkin, McDermott, Simon, & Simon, 1980). As complex problem solving involves a high level of element interactivity, recalling knowledge as schemas will reduce the level of element interactivity managed by WM at any one time, preventing the WM from being overloaded.

Indeed, the success of the equation approach highlighting a two-part learning process for the percentage problems relies on the recall of the acquired lower-level schema (Ngu, Yeung, & Tobias, 2014). Consider a percentage problem: "*Find the new cost of an iPod if the* *advertised price of \$250 is marked up by 12%".* Part 1 involves the review of pre-existing knowledge such as percentage quantity (i.e., \$250 ×12%). Part 2 involves the sum of the original amount (\$250) plus the percentage quantity (\$250 ×12%), which is the solution. The recall of the lower-level schema of percentage quantity (\$250 ×12%) in Part 1 reduces the degree of element interactivity in Part 2 because the learners can treat the percentage quantity as a single element.

From an instructional design perspective, it follows that the goal of instruction should be to facilitate the construction, development and automation of schemas, so that complex schemas can be constructed to develop students' expertise in the domain (Ericsson, 2006a). Automated schemas provide the structure for LTM and allow students to effortlessly process information through limited WM (Carlson et al., 2003), and thus optimizing learning. This is critical for problem solving transfer and applying learned knowledge in new contexts (Cooper & Sweller, 1987; Kotovsky, Hayes, & Simon, 1985). For example, Kirschner (2002) revealed that mathematical knowledge bases that are effectively organized in the form of schemas will facilitate more effective application of conceptual knowledge during problem solving. This will in turn benefit problem solving in science which relies on conceptual and procedural knowledge.

However, it is a challenging process which requires numerous practice and repetitions (Ericsson, 2005; 2006b). Also, for this to work effectively, it requires the initiation of attention on the students' part. Hence student motivation is also necessary in order for learning tasks to be completed and for learning to occur. On the other hand, even if students are motivated and focused on the learning tasks, schema acquisition will still not take place if the element interactivity of a learning task is so high that it exceeds the capacity of WM. It is therefore crucial that learning materials are analyzed in terms of interacting elements to ensure that the cognitive load does not exceed students' WM capacity. Otherwise it will hinder schema acquisition (learning will be adversely affected) and schema automation will not occur (adversely affecting future learning of the similar domain) to solve similar problems.

This chapter will look to element interactivity in cognitive load theory to guide the review of instructional approaches in mathematics and science problem solving. Our stand is that if element interactivity is effectively managed for secondary school students, it will facilitate the construction, development and automation of schemas to solve complex problems in mathematics and science.

2.A.7. Cognitive Load Theory

To address the cognitive issues on the basis of the information processing model of human cognition described above, researchers have developed cognitive load theory (CLT) to examine instructional designs and to improve learning (Mayer, 1992; Sweller, 2012; Sweller et al., 2011). Cognitive load theory (CLT; Paas et al., 2003; Sweller, 1988, 1999) is mainly concerned with the learning of complex cognitive tasks, where learners are often overwhelmed by the number of information elements and their interactions that need to be processed simultaneously before meaningful learning can begin. Instructional control of this excessively high load, in order to attain meaningful learning in complex cognitive domains, has become the focus of CLT. A major purpose is to make the cognitive load involved in the mental processing of instructional materials manageable (Yeung, 1999). CLT deals with complexity using a single construct, element interactivity (Sweller, 1994, 2006; van Merriënboer & Sweller, 2005). As mathematics and science learning is often regarded as complex, we use CLT to analyze a number of mathematics and science problems in terms of element interactivity.

2.A.8. Element Interactivity

Element interactivity is the major source of WM load for all the three types of cognitive load identified by CLT – intrinsic, extraneous and germane (Sweller, 2010). Sweller defines an element as “anything that needs to be or has been learned, such as a concept or a procedure” (p.

124). In most cases of problem solving that require the application of conceptual knowledge and mathematical procedures, essential elements of information required to solve the problems are often interrelated and need to be dealt with simultaneously. This inevitably results in element interactivity. According to Sweller (2010), if an element is to be learned in isolation, with minimal reference to other elements, there is low element interactivity in the learning material. In contrast, if the new material consists of elements that heavily interact and cannot be learned in isolation, then it is considered to have high element interactivity.

Element interactivity is at the epicenter of mathematics and science education. The learning of mathematics and science not only involves the understanding of concepts and procedures, but also the relations among multiple elements and manipulating them to solve problems. Most word problems in mathematics and science require the students to find a value, for example, “calculate the density of the wood”. Many students, being novices, will use a means-ends analysis strategy to handle the problem (Newell & Simon, 1972; Sweller, 1988) and consider: (1) the current problem state (e.g., values and information given in the problem), (2) the goal state (e.g., value to be found), (3) the differences between the two states, (4) the problem solving operators that can be used to reduce the differences (e.g., algebraic rules or scientific formula that can be used to find the value), and (5) any sub-goals that have been established. Each process involves several elements and when considered simultaneously, would result in a high number of interacting elements within each and across multiple processes. The high level of element interactivity makes learning mathematics and science difficult for a novice learner who has low pre-existing knowledge of the new learning material (van Merriënboer & Sweller, 2005).

The cognitive load imposed on students during mathematics and science problem solving is proportionate to the extent to which the various elements interact (Ngu, Chung, & Yeung, 2015). Therefore, it is the element interactivity that primarily determines the level of complexity of the problem solving task, not just the number of elements involved in the mental process (Carlson et al., 2003; Leahy & Sweller, 2005; Pollock, Chandler, & Sweller, 2002). For example, even if a problem involves only a few elements, it will be a complex problem to solve if these elements are so highly interacting with one another that the WM is overloaded. For secondary school students learning mathematics and science, the many interactive elements including the application of rules, following procedures, the manipulation of symbols and values, as well as applying relevant conceptual knowledge, may incur a high cognitive load within their limited WM space.

In this chapter, we illustrate how element interactivity may be estimated based on secondary school students' knowledge levels. A few assumptions need to be stated to make sense of our estimates. First, the following analysis assumes that the learners are novices, learning to solve the word problems for the first time. They are assumed to have a good understanding of the language in the problem statement (so the words in the problem text are considered as one "chunk" of element) and of carrying out basic mathematical procedures (so an operation such as multiplication is considered as one element). The element interactivity in word problems that lead to the three types of cognitive load is analyzed below.

2.A.8.1. Intrinsic Cognitive Load

Intrinsic cognitive load is imposed by the basic structure of the learning material (Sweller et al., 2011). The level of intrinsic cognitive load is assumed to be determined by the level of "interactivity" among essential elements of information (Sweller, 2010, p. 124). For example, learning individual symbols in the formula of the area of a circle ($A = \pi r^2$) in isolation by role would involve limited understanding, and incur low element interactivity. The learner can learn the symbol 'A' (area), 'π' (a number), and 'r' (radius) independent of each other. In contrast, learning the relation between the elements in that the left side, A (area), equals to the right side, $\pi \times r^2$, could constitute a high element interactivity task. The learner is required to process the relations between five elements (A, =, π, $\times$, r^2) simultaneously to understand area (A) in the context of a circle. In essence, intrinsic cognitive load can be estimated by examining the number of elements and the interactions among them that are necessary for solving the problem successfully.

However, while element interactivity levels may be estimated in terms of the interacting elements (Sweller & Chandler, 1994; Tindall-Ford et al., 1997), the effects of the cognitive load involved may be quite different for different learners depending on their knowledge level (Sweller, 2010; Kalyuga, Ayres, Chandler, & Sweller, 2003; Yeung, Jin, & Sweller, 1998). For example, for a mathematics expert (e.g., mathematics teacher), the formula of the area of a circle **($\mathbf{A} = \pi r^2$)** that constitutes one element (recalled as a schema) may instead constitute several interacting elements for a secondary school student who is still a novice in mathematics for whom such schemas do not yet exist. Nevertheless, a full assessment of the elements and their interactivity involved in problem solving irrespective of prior learner expertise is a reasonable starting point for estimating the intrinsic cognitive load involved in the process.

2.A.8.2. Extraneous Cognitive Load

Instructional procedures such as lesson delivery and structures of instructional information (i.e., pedagogy) that are less than optimal can also impose a cognitive load on the WM, in a way that may not contribute to learning (Sweller, 2010). This “unnecessary to learning” load is called “extraneous cognitive load”. Extraneous cognitive load takes up available cognitive resources that can otherwise be used for schema development and acquisition, which enhances learning. Math and science can be taught in various ways and each way may generate its own extraneous cognitive load, depending on how the interacting elements in text, audio and visual inputs are organized by teachers to teach students a new concept or procedure.

Much research has been conducted to show the various sources of extraneous cognitive load such as those that lead to different effects including goal-specific (Sweller, Mawer, & Ward, 1983), split-attention (Sweller, Chandler, Tierney, & Cooper, 1990), and redundancy effects (Chandler & Sweller, 1991). In all of the experiments that showed these effects, student learning improved when either the elements or their interactions were reduced in the instructional procedures. Therefore, reducing the element interactivity in extraneous cognitive load will free up WM resources for germane cognitive load which are crucial to learning. In other words, extraneous cognitive load is often "avoidable" by improving "sub-optimal instructional designs" (Beckmann, 2010, p. 253). That is, if teachers are able to reduce the element interactivity in a learning task without altering what is learned, then the extraneous cognitive load can be reduced or eliminated. Students carrying out a problem solving task will also experience extraneous cognitive load during the problem solving task itself, due to their lack of problem-type schemas as a result of sub-optimal instruction. The element interactivity due to students' choice of sub-optimal methods to solve a word problem will impose extraneous cognitive load on the WM. More examples on element interactivity resulting in extraneous cognitive load will be described later in the chapter.

2.A.8.3. Germane Cognitive Load

WM resources that the learner allocates to dealing with intrinsic cognitive load which are relevant to learning a material can be referred to as germane cognitive load (Sweller et al., 2011). Cognitive load imposed by learning activities is considered germane in nature when it directly relates and contributes to schema development and automation (Chinnappan & Chandler, 2010) which brings about meaningful learning (van Gog, Paas, & van Merriënboer, 2006). Germane cognitive load does not constitute an independent source of cognitive load. It merely refers to the WM resources available to deal with the element interactivity associated with intrinsic cognitive load (Sweller, 2010).

According to Sweller (2010), germane cognitive load is "purely a function of the working memory resources devoted to the interacting elements that determine intrinsic cognitive load" and by assuming constant levels of motivation, "the learner has no control over germane cognitive load" (Sweller, 2010, p. 126). As germane cognitive load is concerned with knowledge acquisition, it has been an important facet of CLT for some time but has been least explored and explained in terms of element interactivity. As schema formation occurs through the retrieval of existing schemas and encoding of new information, involving interacting elements from WM and LTM, germane cognitive load should be seen as a result of element interactivity and associated cognitive behaviors (Beckmann, 2010). For example, if students are asked to find the area of a circle (after prior optimal instruction), they would be able to recall the formula of the area of a circle ($A = \pi r^2$) as a single element (i.e., schema) from LTM. Retrieving the formula as a schema to interact with the magnitude of the radius of the circle given in the problem, r, in WM, together with other elements such as the conceptual and procedural knowledge of problem solving, involves element interactivity that constitutes germane cognitive load.

In the following segments, we will illustrate how element interactivity in these cognitive loads affects students' problem solving in mathematics and science. By analyzing the cognitive load in terms of element interactivity, we can look into areas where element interactivity can be reduced for instructional information to be more effective.

2.A.9. Element Interactivity and Solving Mathematical Equations

Figure 2.2 shows a widespread problem on solving equation as illustrated by Ngu et al. (2014). In their study, they explained how the element interactivity involved in solving equations such as this would impose cognitive load on a secondary school student, although they did not specifically describe element interactivity in terms of each type of cognitive load.

Find the unknown a in the following equation:

$$\frac{(5+a)}{2} = 1$$

Figure 2.2. A mathematical problem.

Solution using the balance method			Solution using the inverse method		
Line 1	$\frac{(5+a)}{2} = 1$	x2 *on both sides*	Line 1	$\frac{(5+a)}{2} = 1$	2 *becomes* x2
Line 2	x2 x2		Line 2	(5+a) = 1 x2	*remove bracket*
Line 3	(5+a) = 2	*remove bracket*	Line 3	5 + a = 2	+5 *becomes* -5
Line 4	5 + a = 2	-5 *on both sides*	Line 4	a = 2 - 5	
Line 5	-5 -5		Line 5	a = -3	
Line 6	a = -3				

Figure 2.3. Two approaches to solving a mathematical problem.

In an experiment, Ngu et al. (2014) examined two methods of teaching students to solve equations – the balance method and the inverse method. They illustrated how solving the same equation (i.e., keeping intrinsic cognitive load of the equation constant) using different methods would alter element interactivity, which would in turn affect student learning. Figure 2.3 shows the two procedures used in each method (Ngu et al., 2014, p. 5).

2.A.9.1. Intrinsic Cognitive Load

As intrinsic cognitive load is imposed by the complexity of the problem itself, the intrinsic cognitive load of the equation presented here is the same for both methods. There are four elements (5, *a*, 2 and 1) in the equation with three operations (+, ÷ and =). The problem involves four concepts: (1) '*a*' represents an unknown number, (2) interprets the two elements (5 and *a*) within a bracket as one entity, (3) the = sign describes a relation between the left and right sides so that they are equal, and (4) to isolate '*a*' and find its value. The elements and concepts need to be processed simultaneously in order to solve the problem and cannot be altered by the instructional method. Both the balance and inverse methods need to address all the interacting elements that constitute intrinsic cognitive load of the equation.

2.A.9.2. Extraneous Cognitive Load

Changing the way elements interact without altering the intrinsic nature of the problem is a way to modify the extraneous cognitive load during instruction. The balance and inverse methods as described by Ngu et al. (2014) have different levels of element interactivity, imposing different levels of extraneous cognitive load on the student (Figure 2.3). The inverse method has apparently less interacting elements than the balance method in the procedure, and therefore, tends to impose less extraneous cognitive load on the students solving the equation.

To illustrate the element interactivity involved in solving the equation in Figure 2.3, Ngu et al. (2014) used relational and operational lines to describe the solution procedure. A relational line describes a relation between elements (i.e., values, pronumeral) whereby the left side equals the right side (e.g., Line 1 of balance and inverse methods, Figure 2.3). An operational line shows the application of an operation to change the problem state of the equation and yet at the same time to preserve the equality of the equation (e.g., Line 2 of balance and inverse methods, Figure 2.3). The main difference between the balance and inverse method lies in the operational line (e.g., -5 on both sides vs. +5 becomes -5), where the interaction between elements occurs on both sides of the equation for the balance method, but only on one side for the inverse method. Consequently, the learners need to invest more cognitive effort to manage the increased element interactivity arising from the operational line of the balance method.

The results of the experimental study by Ngu et al. (2014) supported the above hypothesis. In their study, they found that the group of students using the ‘inverse method’ outperformed the balance group for equations that involved high element interactivity. The students in the inverse method group also reported less mental effort than those in the balance method. Hence, when the degree of element interactivity is reduced, as is the case of the inverse method, students have more WM capacity to deal with the interacting elements in the equation solving task. This, in turn, will increase the students' problem solving efficiency over time, as schema construction and automation processes are supported.

The merit of the balance method (Rittle-Johnson & Star, 2007, 2009; Star & Rittle-Johnson, 2008; Star & Seifert, 2006) is that it generates meaningful learning by focusing on the conceptual aspect of the "balanced" feature of a mathematical equation. Nonetheless, students who are novices in equation solving may not have enough WM resources to deal with the high level of element interactivity introduced by the balance method across the operational lines in the solution procedure. When there are insufficient cognitive resources for coding to occur (Figure 2.1), schema construction for problem solving will be hindered, and students will not be able to solve similar problems in the future, as schema automation will not occur. Hence, to promote learning, there should be a reduction in element interactivity in order to increase the transfer of information from WM to LTM for schema construction.

2.A.9.3. Germane Cognitive Load

The element interactivity of conceptual and procedural knowledge during problem solving constitutes germane cognitive load. For an equation, the element interactivity in conceptual and procedural knowledge is embedded in the operational and relational lines in the solution procedure. For $(5+a)/2 = 1$ (Figure 2.3), the balance method requires the learner to perform the same operation such as ×2 on both sides in order to balance the equation (procedural knowledge). An understanding of $(5+a)/2 = 1$ is the same as $(5+a)/2×2 = 1×2$ implies the grasp of the relation between elements whereby the left side equals to the right side of the equation (conceptual knowledge). The inverse method described by Ngu et al. (2014) requires the learner to treat, for example, division as inverse to multiplication (Cai, Lew, Morris, Moyer, Ng, & Schmittau, 2005), and then move ÷2 from the left side to become ×2 on the right side in order to balance the equation (procedural knowledge). If the learner is able to judge $(5+a)/2 = 1$ and $(5+a) = 1\times2$ as being equivalent, he or she must have understood the relation between elements where the left side equals to the right side of the equation (conceptual knowledge).

For experts with adequate prior procedural and conceptual knowledge to solve the equation with either the balance or the inverse methods, there will be enough room in their WM to deal with the element interactivity and to make a choice between the balance or the inverse method. However, for students who are novices at solving such problems, using a method with high element interactivity may constitute a high extraneous cognitive load that will take up so much cognitive resources that there will be no room for germane cognitive load. In such a case, schema construction will be impeded and learning will be hindered. Repeatedly solving similar problems using a method suitable to the learner during the process continually activates the newly acquired schema to reinforce it. Essentially, the germane cognitive load generated from practice has the function of optimizing learning by consolidating the concept, the procedure, and the connection of both. This enables the learner to transform from a novice to an expert in solving that specific type of problems due to the automation of schemas. For this particular example where the balance method has the advantage of establishing the 'balance' concept (conceptual knowledge) while the inverse method reduces the burden of element interactivity during the solution procedure (procedural knowledge), both methods need to be introduced at suitable stages of instruction. Nevertheless, teachers' judgment on the appropriate timing for introducing either of the methods is crucial because after all, the effects of element interactivity due to instructional approaches depend also on learner expertise (Yeung, 1999).

2.A.10. Element Interactivity and Science Problem Solving

The learning of science, especially in the branch of physics, requires the students to solve problems mathematically, applying formulae that represent the relationships among quantities which have been derived from concepts that have been theoretically proven. To apply the formulae effectively, students require procedural knowledge in equation solving and conceptual knowledge in the scientific domain. Most students find such a learning task difficult because it requires the students to manipulate multiple interacting elements simultaneously. As explained by Carlson et al. (2003) and Leahy and Sweller (2005), the processing of interacting elements that cannot be separated from each other constitutes high cognitive load and makes the learning task difficult. Like in solving mathematics problems, the high degree of element interactivity in solving problems in science arises from the combination of relational and operational processes (important procedural steps), as well as the simultaneous application of mathematics and science conceptual and procedural knowledge, which need to be processed altogether. To illustrate the element interactivity involved in solving typical science problems, we will first look at how solving a science problem on density (Figure 2.4) would impose cognitive load on a secondary school student.

The mass of a copper rod is 60 g. What is its density if it has a volume of 15 cm^3?
Solution:
Density = mass / volume
= 60 g / 15 cm^3
= 4.0 g/cm^3

Figure 2.4. Science problem on density.

2.A.10.1. Intrinsic Cognitive Load

The words, numbers and units that exist in the information of the problem text are considered as elements and need to be simultaneously processed in the learner's WM for the problem to be understood and solved. This constitutes intrinsic cognitive load and for this problem on density (see Figure 2.4), there are two chunks of elements that need to be processed simultaneously - words and magnitudes (i.e., 60 g and 15 cm^3) - imposing a low intrinsic cognitive load on WM, assuming that the students have a good understanding of the language and are familiar with magnitudes.

While this problem may be simple to an expert, it may not be so for a novice who is newly introduced to solving such word problems. The two lines of information in the problem may not contain many elements of information, but the interaction of these elements, together with interacting elements for the conceptual and procedural processes of science and mathematics may impose a substantial amount of cognitive load on the students. The conceptual process will involve the knowledge of the relation between density, mass, and volume. The procedural process will involve the manipulation of the algebraic transformation of density = mass / volume, where the solution can be density, mass, or volume, depending on the problem situation. This cognitive load, however, could be reduced with practice, which supports schema construction and automation, as students' pre-existing knowledge in the domain increases.

2.A.10.2. Extraneous Cognitive Load

Extraneous cognitive load is the result of engaging in activities that are not directed at schema acquisition (Sweller, 1994). Such activities include finding, relating, or integrating elements of information within the instructional materials. These activities could be considered as elements and result in element interactivity when experienced by students concurrently. Problem solving search (Simon & Kadane, 1975), where the goal is to reach a solution to a problem, and a search technique commonly experienced by novices during problem solving, known as the means-ends analysis (Sweller, 1988), can impose extraneous cognitive load on the students, who are mostly novices at problem solving. Sweller (1988) stated that novices carry out this search in their attempts to reduce the differences between the problem state encountered (e.g., finding the unknown density given two magnitudes of mass and volume) and the goal state (e.g., finding density), using operators such as the rules of algebra and the density formula.

Part of the problem solving search also includes decision making processes where students decide on appropriate moves to undertake in order to complete each step of the problem solving process. For this problem (Figure 2.4), students will need to identify the task features of the problem and search for a method to calculate density, given the two magnitudes of mass and volume in the problem. This search technique is categorized as extraneous cognitive load as it is not intrinsic to the problem itself, but is instead a process adopted by the novice in an attempt to solve the problem. Experts would have existing problem-type schemas (Gick & Holyoak, 1983; Reed, 1993) that they could easily retrieve from their LTM to instantiate with the information in the problem to execute a solution (van Lehn, 1989), with procedural moves that are mostly automated within each step of problem solving.

For students who are mostly novices, the problem solving search processes interact with each other to create a substantial extraneous cognitive load. However, with effective instruction and more practice sessions, such problem solving processes can become automated as a consequence of repeatedly recalling information as schemas, reducing the cognitive load to a manageable level (Yeung, 1999). Extraneous cognitive load manifested in the form of such search processes involve element interactivity, which uses up limited WM resources that could otherwise be devoted to learning. Omitting crucial information, or not relating the formula to scientific reasoning during acquisition, results in students not being able to retrieve the formula as a schema and thus would not be able to solve the problem like experts, who would begin problem solving by choosing a suitable equation formula for the problem, eliminating the backward-working phase (Larkin et al., 1980; Simon & Simon, 1978). An effort to just memorize the formula without understanding the concept could worsen the problem solving search process and could lead to a wrong recall of information, dampening the success of recalling the correct formula (e.g., is it *volume / mass* or *mass* x *volume* or *mass / volume*?) to effectively solve the problem. Element interactivity in extraneous cognitive load will be discussed in greater detail later when we compare two methods of solving the same problem.

2.A.10.3. Germane Cognitive Load

The process of solving the problem (Figure 2.4) involves several interacting elements: (1) the formula of density = mass / volume indicates a relation in that the density is equal to a specific quantity of mass in g, divided by a specific quantity of volume in cm^3, and the density is expressed in g per cm^3, (2) mass and volume each is associated with a value and respective units, (3) matching of a variable and values in a formula (i.e., symbolic representation of relations), and (4) mathematical procedure involving interacting elements such as values and a variable. After analyzing the problem (intrinsic cognitive load), the students with relevant pre-existing knowledge would be able to use the formula density = mass / volume as a single element (schema) and apply it to solve the problem mathematically.

The purpose of instruction in problem solving is to facilitate schema construction and consolidate it so that it is retrievable. Practice is therefore essential for establishing the link between the conceptual and procedural elements of problem solving in various forms and combinations. Practice inevitably introduces cognitive load, which may be intrinsic or extraneous, or both. However, the cognitive load involved in practice is somewhat different from the cognitive load during the acquisition stage when neither the concept nor the procedure was well established. During acquisition, students are given the formula: Density = mass /

volume; whereas during practices, the formula is assumed to have become part of the students' schema and is therefore not given. The cognitive load involved in practice is therefore primarily due to the need to retrieve the formula from LTM before working out the solution using their procedural knowledge. After substituting the values into the formula, the students need to apply their mathematical skills to compute the division. The whole process constitutes germane cognitive load which involves not only the five interacting elements (60, its unit g, division operation, 15 and its unit cm^3 to come up with the final answer, 4.0 g/cm^3), but an interaction between these and the newly formed problem-based schema of density = mass / volume.

In essence, retrieving this essential information from the schema (probably not stable at initial stages of new learning) to interact with all other elements constitutes germane load because the practice consolidates and automates the mental process, which facilitates the construction and automation of schemas. With more practice, schema construction and automation will be enhanced, reinforcing students' pre-existing knowledge. Intrinsic cognitive load, and in turn, germane cognitive load will be subsequently reduced, as less WM resources are required to deal with the interacting elements when automation of conceptual and procedural schemas related to solving such problems are developed. As students progress in their lessons on density, the science curriculum will typically challenge them to do higher-level density problems.

2.A.11. Element Interactivity of Complex Science Problem

Figure 2.5 shows an example of a higher-level complex density problem (Lau, Foong, Kadir, & Wong, 2011) commonly found as a science assessment task for secondary 1 students in Singapore. Solving such a complex problem requires students to simultaneously process many interacting elements (see Figure 2.6). The following segment explains the element interactivity in the three forms of cognitive load within the secondary school students' problem solving experience.

> A piece of copper has a mass of 639 g and a density of 9.0 g/cm^3. A piece of tin has a mass of 150 g and density of 6.0 g/cm^3. The 2 metals are melted, mixed together and cooled to form an alloy. Find the density of the alloy.

Figure 2.5. Complex problem on density *(secondary* 1 science curriculum in Singapore).

2.A.11.1. Intrinsic Cognitive Load of Complex Problem

Similar to the density problem discussed earlier, to solve this word problem, students need to understand its objective by reading the words and studying the magnitudes (numbers and units) involved. The element interactivity in dealing with the words and magnitudes in the problem simultaneously constitutes intrinsic cognitive load. In addition to that, mathematical knowledge, as well as students' pre-existing knowledge and understanding of the science concept of density and the term "alloy" need to be strong as well, in order to first decide what to do to solve the problem.

For example, firstly, students' schema of the formula, density = mass / volume, needs to be applied to calculate the density of alloy, but both the mass and volume of the alloy are not given in the problem and have to be derived from the other quantities. In other words, the sub-goals of the problem involve the calculation of the volume of copper and the volume of tin separately. This increases the level of element interactivity in the problem, imposing a high intrinsic cognitive load.

Like the problem in Figure 2.4, there are three main elements interacting with one another simultaneously: words, numbers, and units. However, for this problem, there are two different types of units belonging to four different quantities that need to be processed simultaneously. As the information given in the problem cannot be directly substituted into the density formula, there is a need to complete some algebraic manipulation at various stages in order to complete the problem. Therefore, this problem on density can be categorized as complex, especially to a novice learner, because of the high number of interacting elements that need to be processed concurrently, imposing a high intrinsic cognitive load. If the number of interacting elements exceeds the capacity of the students' WM, the students will not be able to solve the problem correctly. Figure 2.6 shows two different ways to solve the problem.

2.A.11.2. Extraneous Cognitive Load of Complex Problem: Methods 1 and 2

Method 1 comprises five steps while Method 2 combines the five steps into two steps to solve the problem. Even though Method 1 comprises 5 steps, every step in the solution involves not more than two elements undergoing just one operation between them (i.e., *either* addition or division). Thus, each step, when considered in isolation, constitutes a low element interactivity task.

In contrast, Method 2 comprises two steps with high element interactivity within each step, involving three to four elements undergoing at least two operations (i.e., *both* addition and division) among the elements. Much WM resources are required to execute these two steps successfully, resulting in high cognitive load. For example, to complete step 1 in Method 2, students have to first apply the algebraic manipulation of the density = mass / volume formula, making volume the subject (i.e., volume = mass / density), after which they have to substitute the respective quantities for each formula for copper and tin (e.g., volume of copper = mass of copper / density of copper). This step alone has high element interactivity (i.e., at least six interacting elements of quantities and operations), as students need to concurrently apply both their mathematics and science conceptual and procedural knowledge.

Step 2 in Method 2 has slightly fewer interacting elements but the cognitive load is still high (i.e., at least five interacting elements of quantities and operations within one solution step). To complete this step, students have to apply the formula for density by first doing a sum of the two masses of copper and tin to find the total mass of the alloy and then dividing this sum by the volume of the alloy found in Step 1.

While Method 2 apparently incurs higher element interactivity compared to Method 1, the solution procedure of Method 2 involves fewer steps. If the steps in the solution procedure were to be considered as 'elements' as well, then the reduced number of steps in Method 2 may be considered as a reduction of element interactivity. The two solution steps in Method 2 is likened to a typical solution procedure used by an expert in the domain, who tends to choose fewer solution steps when solving a problem (Star & Newton, 2009). However, to benefit novices, teachers should probably first introduce Method 1 and progress to introducing Method 2 only after sufficient practice to establish pre-existing knowledge. In fact, teachers can even consider introducing an intermediate stage to bridge the element interactivity gap between the two methods. The intermediate stage could be one that comprises three solution steps: volume of copper = 69 g ÷ 9.0 g/cm^3 = 71 cm^3 (step 1), volume of tin = 150 g ÷ 6.0 g/cm^3 = 25 cm^3 (step 2), and the density of alloy = (639 + 150) g ÷ (71 + 25) cm^3. In terms of the element interactivity, the first two steps are identical to steps 2 and 3 in Method 1 and thus each constitutes a lower element interactivity task. The third step involves four elements and a mathematical operation; hence, it incurs higher element interactivity than the first and second steps.

We can envisage that only problem solvers with a strong conceptual and mathematical foundation will be able to solve the problem using Method 2. Problem solvers with an established schema will be able to retrieve the 'density' formula as well as the relevant mathematical and scientific procedures from LTM, greatly reducing the number of interacting elements within each step. Method 2 will not pose a challenge for mathematics teachers, for example, who are experts in the domain because they can treat the density concept, formula and the mathematical procedures as a single unit or element. Without established schemas, the high element interactivity within each step will overload the students' WM, hindering the success of problem solving. On the other hand, as students' expertise in solving such density problems increases, Method 1 could even cause an expertise reversal effect (Kalyuga et al., 2003), making Method 2 a more effective approach to solve the problem. Expertise reversal effect comes about when instructional methods which are effective for novice learners become ineffective as learners gain expertise in the domain, and contributes to extraneous cognitive load for the experts (Kalyuga, 2007). In sum, the interacting elements at every stage of the problem solving process have to be manageable for the students.

<table>
<tr><td colspan="4">To effectively solve this problem, students need to apply this formula:
Density of alloy = total mass of alloy / total volume of alloy</td></tr>
<tr><td colspan="2">Method 1 using the step by step method</td><td colspan="2">Method 2 using the combined method</td></tr>
<tr><td>Step 1</td><td>Total mass of alloy
= mass of copper + mass of tin
= 639 g + 150 g
= 789 g</td><td>Step 1</td><td>Total volume of alloy
= Total volume of copper and tin
= (639 g / 9.0 g/cm^3) + (150 g / 6.0 g/cm^3)
= 96 cm^3</td></tr>
<tr><td>Step 2</td><td>Volume of copper
= mass / density
= 639 g / 9.0 g/cm^3
= 71 cm^3</td><td>Step 2</td><td>Total density of alloy
= total mass / total volume
= (639 g + 150 g) / 96 cm^3
= 8.2 g/cm^3</td></tr>
<tr><td>Step 3</td><td>Volume of tin
= mass / density
= 150 g / 6.0 g/cm^3
= 25 cm^3</td><td></td><td></td></tr>
<tr><td>Step 4</td><td>Total volume of alloy
= volume of copper + volume of tin
= 71 cm^3 + 25 cm^3
= 96 cm^3</td><td></td><td></td></tr>
<tr><td>Step 5</td><td>Total density of alloy
= mass of alloy/volume of alloy
= 789 g / 96 cm^3
= 8.2 g/cm^3</td><td></td><td></td></tr>
</table>

Figure 2.6. Two ways to solve a science problem.

2.A.11.3. Germane Cognitive Load of Complex Problem

The process of solving this problem involves four interacting elements: (1) the concept of density = mass / volume, (2) mass and volume for each metal: copper, tin and alloy, (3) matching of variable and value in a formula (i.e., symbolic representation of relations), and (4) mathematical procedure involving interacting values.

After instruction thus far, the student would have learned 1 above (concept) and also 2, 3, and 4 (problem solving procedure). Retrieving 1 from the schema (probably not stable at initial stages of new learning) to interact with 2, 3, and 4 constitutes germane load because the practice consolidates and automates the mental process. If students have had much practice before, they would know how to apply the density formula and process the multiple interacting elements in the problem to solve the problems correctly (i.e., apply scientific concept, recall related formula, use mathematical skills to solve problem). These basic concepts would be recalled as schemas. However, for this problem, there are several magnitudes given and they are not easily substituted into the density formula directly. Those schemas need to interact with the new elements in the problem contributing to a high level of element interactivity during problem solving.

Since there are two different values of mass and two different values of volume given in the problem, students with a good understanding of the concept of density and alloy will make the correct decision as to how to use the density formula to solve the problem, applying the concept that density is mass per unit volume. Students lacking in understanding the density concept will not know how to manage the different elements of information provided in the problem. In addition to that, students' pre-existing knowledge of mathematical skills such as algebra needs to be good as well, since the quantity of volume is not given and needs to be derived from the density formula (i.e., density = mass / volume) by the manipulation of quantities (i.e., volume = mass / density) using their algebraic skills. For example, WM resources are required for the high element interactivity involved in the process of executing two operations of division and addition involving four magnitudes within a single operational line in step 1, Method 2. If students have superior mathematical skills and chose Method 2 to complete the problem, they would retrieve the mathematical procedural knowledge as schemas, freeing up WM resources to deal with the interacting elements of the science concepts imposing germane load that is within the capacity of WM.

2.A.12. Discussion

From the examples discussed in this chapter, we have illustrated the various types of cognitive load involved in learning mathematics and science problem solving in terms of element interactivity. Problems that appear ‘simple’ due to few elements in the problem statement may not be simple to secondary school students who are mostly novice problem solvers, due to the high element interactivity among the conceptual and procedural knowledge and processes required to solve the problem. Table 2.1 summarizes the issues of element interactivity in the three types of cognitive load during conceptual and procedural knowledge acquisition.

2.A.12.1. Theoretical Implications

The examples in this chapter provide a new theoretical perspective for cognitive load theory (CLT), and in particular, the critical role of element interactivity in the understanding and learning of mathematics and science. In problem solving, some materials can only be understood if multiple elements are considered simultaneously in WM rather than serially (Carlson et al., 2003). Materials that require the concurrent processing of several elements constitute high element interactivity. Materials or learning tasks with high element interactivity contribute to a high intrinsic cognitive load. This is because the multiple learning elements and their relations (i.e., procedural and conceptual knowledge) need to be processed together through a very limited WM. Under these conditions, choosing the instructional methods and procedures that reduce element interactivity for secondary school learners will reduce the total cognitive load in the WM, which is likely to aid learning and understanding of mathematics and science. Once students have had experience with the learning tasks and developed domain-specific schemas, other methods involving higher cognitive load can be introduced, as the schemas will reduce the element interactivity and not overwhelm the WM.

Table 2.1
Summary of Element Interactivity

Knowledge	Intrinsic CL	Extraneous CL	Germane CL
Conceptual	Understanding the context of the problem by: ▪ Reading and processing the words, variables and magnitudes which interact in the problem context and ▪ Matching these with the major concepts.	Working towards the goal of finding a solution to the problem, involving interacting elements embedded in *problem solving search* processes such as ▪ Finding, relating, and integrating pieces of information in the problem	Connecting the existing problem context with pre-existing knowledge by: ▪ Applying the relevant equation to solve the problem ▪ Integrating separate conceptual elements into a whole concept
Procedural	Identifying the mathematical strategies required to solve the problem by: ▪ Analyzing the words, variables and magnitudes which interact as chunks during problem analysis and ▪ Assessing the problem state and solution state by processing the interacting elements in the problem	Means-ends analysis: ▪ Making decisions towards the choice of problem solving moves to complete each solution step	Schema construction and automation by recalling existing problem-type schemas and applying conceptual knowledge and mathematical strategies by: ▪ Recognizing relevant problem states and associated procedural moves and ▪ Carrying out the mathematical procedure

2.A.12.2. Practical Implications for Mathematics and Science Education

Secondary school students who are new to a learning task are considered as novice learners due to their lack of pre-existing knowledge (thus lack of schemas) in that learning domain. Unless mathematics and science instruction has a mechanism to reduce the degree of element interactivity for complex learning tasks, problem solving will remain difficult for secondary school students. This is because when element interactivity is high, students' cognitive resources will be overloaded and when the WM capacity is exceeded, learning will not occur (Kalyuga et al., 2003). Therefore, instruction for novices has to start with a simple problem with few interacting elements, as the elements may need individual attention before interactions between the elements can be understood (Cook, 2006). For example, if students are not able to assimilate both conceptual and procedural knowledge concurrently, teachers should focus on one, and introduce the other at a later stage when students have acquired the relevant schema for the specific concept. Reducing element interactivity at the initial stages and gradually increasing it as schemas in the domain that are more established will make learning more effective for the students.

High intrinsic cognitive load can be modified by isolating the interacting elements, where possible, to provide a simpler learning task (Ayres, 2006, 2013). This modification will allow novices to construct lower-level schemas to gradually progress to higher-level schemas for the highly interactive materials (Ayres, 2006, 2013; Gerjets et al., 2004; Pollock et al., 2002). When students have had more practice and knowledge, their schematic mental webs intensify and by recalling conceptual and procedural knowledge as schemas, they will be able to process materials which may constitute a higher cognitive load for other students who have not had sufficient practice (e.g., Method 1 vs. Method 2). As problem solving is a common feature in secondary school mathematics and science education, it is important that they are analyzed in terms of element interactivity to ensure that instruction is geared towards complexity levels appropriate for the students' knowledge base in the domain.

2.A.12.3. Recommendations

To improve learning effectiveness and efficiency, teachers should capitalize on CLT in recent progresses in mathematics and science education. We recommend that teachers consider:

1) Analyzing and identifying the element interactivity of instructional materials to estimate the cognitive load students may experience in the learning process.
2) Element interactivity as a basis for determining the complexity of mathematics and science materials.
3) Element interactivity as the starting point for designing appropriate instructions to suit learners who exhibit varying levels of mathematics and science abilities.
4) Identifying the additional cognitive load involved in the process of acquiring conceptual and procedural knowledge in solving problems. The intrinsic number of elements together with the procedure involved in problem solving may interact to introduce unduly high extraneous cognitive load. By delineating the element interactivity and devising effective instruction to counter the element interactivity, we will be able to facilitate more efficient learning.
5) Building upon conceptual understanding and progressing to efficient procedures with an emphasis on schema construction and maintenance.
6) Using challenging problems for transfer and extension of existing knowledge. Practice does not always make perfect, but effectively progressed practice does. The purpose is to generate an appropriate level of germane cognitive load to facilitate schema building and retrieval.

2.A.13. Conclusion

Learning to solve problems in mathematics and science entails challenges to our limited working memory capacity. The cognitive load involved in learning may be due to the intrinsic nature of the learning material or the nature of the instruction causing extraneous cognitive load, whereas germane cognitive load is, nevertheless, necessary and beneficial for building schemas. Progress in educational theory has enabled us to understand the nature and consequence of each type of cognitive load. By conceptualizing cognitive load in terms of issues of element interactivity manifested in the learning material (intrinsic cognitive load), or the instruction (extraneous cognitive load), or the facilitation of schema construction and retrieval (germane cognitive load), educators will be able to devise optimal instruction to facilitate learning. Our analysis of secondary mathematics and science problems points to the practical benefit of using instructional approaches that address the issue of multiple interacting elements to facilitate learning. The conceptualization of cognitive load in terms of element interactivity has the potential of bringing further progress in the research on cognitive load not only in mathematics and science, but perhaps also in other areas of learning.

Section B:

The Non-Cognitive Aspects of Learning –

Academic Self-Concept

"Self-concept is a hot variable that makes good things happen, facilitating the realization of full human potential in a range of settings"

(Marsh & Craven, 2006, p. 134)

Note. This section has been accepted for publication as a book chapter in the Encyclopedia of Personality and Individual Differences, edited by Virgil Zeigler-Hill and Todd K. Shackelford. Permission to present the published version of this work in this thesis has been obtained from the publisher – Springer.

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2.B. Academic Self-Concept

2.B.1. Preface

A vast number of studies conducted on academic self-concept over the past four decades have highlighted the benefits of high academic self-concept on academic outcomes such as classroom behaviors, school achievement, educational and career aspirations, and academic choices. There remain, however, questions concerning whether the operationalization of academic self-concept as a single factor explains these positive outcomes or whether certain components of academic self-concept are responsible for specific academic outcomes. Researchers who have looked into the internal structure of academic self-concept have recently differentiated it into cognitive and affective components. While some studies have attended to both of these highly related but distinct components of academic self-concept, most studies have focused mainly on the competency (cognitive) component. The purpose of this chapter is to provide some insights into the two distinct components of self-concept (i.e., competency and affect) and their associations with academic outcomes. This chapter also discusses four other major theoretical advances in academic self-concept research, namely, domain specificity, reciprocal effects, frame of reference, and interrelatedness among academic domains. Awareness of the special characteristics of each component of academic self-concept, as well as its role in contributing to different educational outcomes, can help educators provide learners with the best learning environment to optimize their potential.

2.B.2. Definition

In a general sense, academic self-concept (ASC) can be defined as one's academic self-perceptions or one's perception of one's general ability in school (Shavelson, Hubner, & Stanton, 1976). This conceptualization of ASC was part of the multidimensional and hierarchical self-concept model for students proposed by Shavelson et al. (1976) and later modified by Marsh and Shavelson (1985). The model puts global self-concept at the apex of the self-concept hierarchy which then branches into two separate facets: (1) ASC and (2) non-ASC, each of which further branches out into specific domains (see Shavelson et al., 1976, p. 413).

2.B.3. Introduction

Academic self-concept (ASC) has been widely researched, with studies spanning over four decades. The prominence of this research is due to the associations found between ASC and a wide range of educational and behavioral outcomes (Marsh & Craven, 2006). These outcomes include achievement (e.g., Kadir, Yeung, & Barker, 2012; Marsh & Yeung, 1997), motivation (e.g., Yeung, Craven, & Kaur, 2012), effort, (e.g., Yeung, 2011), educational aspirations (e.g., Yeung, Kuppan, Foong et al., 2010), course choices (e.g., Guo, Parker, Marsh, & Morin, 2015) and career aspirations (e.g., Yeung, Kuppan, Kadir, & Foong, 2010). On one hand, these findings reinforce Marsh and Craven's (2006) claim that "self-concept is a hot variable that makes good things happen, facilitating the realization of full human potential in a range of settings" (p. 134). On the other hand, findings suggesting that self-concepts do good things for everyone in every way may lead to questions about whether further self-concept research is needed at all. This chapter attempts to summarize the major findings in self-concept theory (Marsh, 1986) and identify directions for applications and further research.

Between a global ASC and distinct ASC in specific domains, Marsh and Shavelson (1985) advocate focusing on the latter. This is because global academic ASC masks the important distinctions that individuals make when evaluating their ability in various domains (Shavelson et al., 1976). Marsh and Shavelson (1985) argued that self-concept cannot be adequately understood if only a global component is considered. This argument is particularly compelling in the light of evidence showing that ASCs in verbal and math domains are often non-positively correlated (Marsh, 1986). In essence, a global ASC may not be particularly useful as it cannot adequately represent two major ASCs that are not positively related to each other. Following this argument, most studies today have focused on domain-specific ASCs.

Studies with a domain-specific focus have contributed to the conceptualization and identification of various ASC facets, such as the separation of cognitive and affective components of academic self-concepts (e.g., Marsh, Craven, & Debus, 1999); the domain specificity of self-concept (e.g., Yeung, Kuppan, Foong et al., 2010); the reciprocal effects between self-concept and outcomes (Marsh & Craven, 2006); and the frame of reference model (Marsh, 1986), which also looked into the interrelatedness of academic domains (Xu et al., 2013). The purpose of this chapter is to provide some insights into the conceptualization and measurement of ASC, and how ASC is related to important educational outcomes. Implications for advancing theory, research, and practice will also be discussed.

2.B.4. Measurement of Academic Self-Concept

Given the subjective nature of ASC, the most appropriate and most popular method of measuring ASC is self-reports. The self-report questionnaires given to students generally comprise items to which the students respond on a Likert scale, to show the extent of their belief in what each item states. There are many instruments that measure ASC. For example, the Perception of Ability Scale for Students (PAAS) (Boersma & Chapman, 1992) has been used to measure students' perceptions of their ability in spelling, reading, writing, math, and the language arts and has been shown to have good psychometric properties (Marsh & Yeung, 1997). Other instruments that have subscales to measure ASC include the

Multidimensional Self-Concept Scale (MSCS) (Bracken, 1992), the Piers-Harris Self-Concept Scale (Piers & Harris, 1969), and the Tennessee Self-Concept Scale, Second Edition (TSCS:2) (Fitts & Warren, 1996). However, two of the most popular instruments to measure ASC are: (1) the Self-Description Questionnaire series including SDQI, SDQII, and SDQIII designed for use on preadolescent, adolescent, and late adolescent samples, respectively (see Marsh & Yeung, 1997), as well as the *Academic Self-Description Questionnaire* (ASDQ); and (2) Self-Perception Profile for Children/for Adolescents (SPP-C and SPP-A) by Harter (1985).

2.B.4.1. Academic Self-Description Questionnaires

Because of its academic focus, the ASDQ has been extensively used in academically focused studies. The ASDQ is multidimensional as it differentiates multiple academic domains (e.g., English, math, science, history), in addition to measuring an overall ASC. The ASDQ items focus on students' cognitive perceptions of their domain-specific ability (i.e., a sense of competence). The SDQI, SDQII, and SDQIII instruments cover various domains including academic, such as verbal and math domains. These scales cover both cognitive perceptions and affective-motivational (e.g., interest, values) responses to the specific domains. Although the original design of the scale treated these as a combined representation of a unified construct, recent research has emphasized the distinctiveness of the cognitive and affective-motivational components of ASC (Arens, Yeung, Craven, & Hasselhorn, 2011; Yeung, 2011; Yeung, Kuppan, Foong et al., 2010). Self-perceived competency was defined by items asking students how competent they feel they are in a specific subject domain. Affect was defined by items asking the extent they are interested in that domain. Over the years, ASC instruments have extended to include additional academic domains (e.g., art, music) and scales in different languages (e.g., Chinese and German).

2.B.4.2. Self-Perception Profile for Adolescents and Children

Another commonly-used series of self-report instruments for measuring ASC is the Self-Perception Profile for Adolescents (SPP-A) and Self-Perception Profile for Children (SPP-C) developed by Harter (1985). In contrast to the ASDQ, the SPP-A/C is not domain-specific as it does not address students' ASC in academic domains (e.g., math; science). Examples of the items used in the SPP-A/C instruments are, "Some kids do very well at their class work but other kids don't do well at their class work" and "Some kids have trouble figuring out the answers in school but other kids can almost always figure out the answers." The standard items of the SPP-A/C measure students' general attitudes towards school, which is primarily a global measure of ASC. However, researchers (e.g., Bouchey & Harter, 2005) have modified the five academic subscale items of the SPP-A (Harter, 1985) to measure the domain-specific ASC (i.e., self-perceived competency) of students in academic domains such as math and science. Examples of the items are, "I am pretty slow at finishing work in science" and "I am smart for my age in math." This measurement seems to work pretty well.

2.B.5. Important Findings and Advances in ASC Research

Studies on ASC, which span four decades and several continents, have led to important findings. These findings may lead to practical implications in the education sector.

2.B.5.1. Competency and Affective Components

Marsh et al. (1999) tested the possibility of separating the self-concept construct into competency and affect components, based on research that provided a strong theoretical rationale for the separation of expectancy and task value in an individual's learning motivation (e.g., Eccles, Wigfield, Harold, & Blumenfeld, 1993). Marsh et al. (1999) conducted confirmatory factor analyses (CFAs) and found a competency and an affect factor which were highly correlated, but distinguishable, from each other. The separation of the two ASC factors was also supported by other ASC researchers (e.g., Arens et al., 2011; Yeung, 2011). Essentially, they demonstrated that CFA models assuming two factors (with items about competency forming one factor and items about affect forming another) was better than a single factor solution (assuming a global factor incorporating both competency and affect items).

Arens et al. (2011) reinforced the theoretical underpinning of the competency-affect differentiation and further highlighted its importance for better understanding of students' individual differences. Other studies have shown that ASC, when separated into its cognitive and affective components, predicts different educational outcomes (e.g., Yeung et al., 2012). A study by Yeung et al. (2012) showed that competency was a better predictor of academic achievement than was affect. Other studies have also shown the differential functions of the ASC components, supporting the differential prediction hypothesis (e.g., Yeung, Kuppan, Foong et al., 2010). Essentially, the competency component of ASC is highly related to students' school achievement (Arens et al., 2011; Kadir et al., 2012) whereas the affective component of ASC tends to be associated with students' behavior in school, including school engagement, effort expended on learning tasks, and educational aspirations (e.g., Yeung, 2011; Yeung, Kuppan, Foong et al., 2010).

2.B.5.2. Domain Specificity

The domain specificity of the effects of ASC means that students can clearly differentiate their self-concepts in various academic domains (e.g., math, verbal, science). ASC research in the last four decades has repeatedly demonstrated the domain-specific nature of ASC (e.g., Marsh & Craven, 2006; Yeung, Kuppan, Foong et al., 2010). Studies investigating math and verbal ASC have found them to be uncorrelated (e.g., Marsh, 1986). Over the years, many researchers have extended this research to show the domain specificity of ASC in other academic domains such as science (e.g., Yeung, Kuppan, Foong et al., 2010) and other verbal domains such as German (e.g., Arens, et al., 2011) and Chinese (e.g., Xu et al., 2013). A prevalent area of ASC research examines the relations between ASC and achievement, which is also domain specific. This research demonstrates that students' ASC in a specific academic domain (e.g., math) only influences achievement in the respective domain (i.e., math) but not any other domain (e.g., English).

2.B.5.3. Reciprocal Effects

To determine the causal ordering between ASC and academic achievement, Marsh and Craven (2006) proposed the reciprocal effects model (REM) in which ASC predicts subsequent achievement, and achievement predicts subsequent ASC. Their multi-wave longitudinal panel data displayed the expected reciprocal causal relations between ASC and academic achievement; that is, it demonstrated a mutually reinforcing relationship between them. Hence, ASC is both an outcome and an antecedent of achievement. Subsequent studies conducted with students of different age groups across different countries showed similar results, that academic self-concept and academic achievement share a mutually reinforcing relationship, each leading to gains in the other.

This demonstration of the REM has profound implications for education practices as reciprocity means sustainability. The potential of sustainability has been further illustrated in subsequent research. Consistent with REM predictions, ASC was found to be the best predictor of long-term educational attainment – better than socioeconomic status, academic ability, grade point average, or global self-esteem (Marsh, Xu, & Martin, 2012). However, it is important to note that the reciprocal effects of ASC and achievement only operate within specific domains. For example, a positive math ASC predicts subsequent high achievement in math, and high math achievement in turn predicts a subsequent increase in ASC in math, but not in other unrelated academic domains such as English.

2.B.5.4. Frame of Reference

Across academic domains, students may use both an internal and an external frame of reference to form their ASC (Marsh, 1986). According to Marsh (1986), tests of a frame of reference hypothesis started because of a consistent pattern found with student samples showing a non-positive (often near-zero) correlation between students' verbal and math ASC but a positive correlation between verbal and math achievement scores. This pattern of results implies that even though students may do well in both academic domains, their ASC in those domains may differ. Marsh (1986) proposed the internal/external frame of reference (i.e., I/E) model to explain such a phenomenon. The model posits students' simultaneous comparisons of their perceived competency relative to: (1) the rest of their academic domains (i.e., internal comparison), and (2) their peers (i.e., external comparison). For example, if students perceive that their English ability is better than their peers (external comparison), they are likely to have a higher English ASC. However, this higher ASC in English may suppress their ASC in other non-related academic domains such as math and science (internal comparison). This is because students with a high verbal ASC may perceive themselves as a 'language expert' instead of a 'math or science expert'. The combined operation of both the internal and external counterbalancing comparison processes would explain the low, near-zero, or even negative correlations between the ASCs (i.e., sense of competency) of the math and verbal domains (Marsh, 1986; Marsh et al., 2012). This pattern of results has been shown in studies involving different age groups of students in a variety of countries, and using different methodologies, such as meta-analysis, experimental, longitudinal, and cross-cultural studies (e.g., Xu et al., 2013).

2.B.5.5. Interrelatedness

As studies involving more domains were conducted, the I/E model underwent serious scrutiny. Some researchers found that the I/E model does not hold as strongly for some interrelated domains. Unlike the negative correlation observed between English ASC and math achievement or math ASC and English achievement, positive correlations were found between other pairs of academic domains such as math and physics (e.g., Marsh et al., 2015), or English and Chinese (Xu et. al, 2013). Möller and Marsh (2013) extended the I/E model into what they called *dimensional comparison theory* (DCT), which posits that negative cross-domain predictive paths between achievement in one domain and ASC in a contrasting domain (e.g., math and verbal) will diminish and even become positive for domains that share similar features (i.e., interrelatedness). Extending DCT, Marsh et al. (2014) showed that the more dissimilar the academic domains, the more negative the cross-domain paths from achievement to ASC (e.g., math and verbal domains) become, whereas cross-domain paths from achievement to ASC for more similar domains (e.g., Dutch and English) are much less negative and at times, positive. Research by Marsh et al. (2015) considered biology, physics, and math as near domains on the ASC continuum and found positive cross-domain effects of achievement on ASC in these three domains, controlling for matching achievement.

2.B.5.6. Gender and Age Differences

Gender and age are important determinants of ASC, as research demonstrates that there are differences in the ASC of male and female students and that ASC varies with age (e.g., Marsh, 1989; Yeung, 2011). Females have generally lower global ASC ratings than males even if they are performing equivalently or better than males academically (e.g., Marsh, 1989). However, studies involving large sample sizes have shown that the gender differences for global ASC tend to be small (around d = 0.20) or trivial ($d \leq 0.10$) (e.g., Hyde, 2014). Most of the differences that exist are in domain-specific ASC that are explained primarily in terms of gender stereotypes. For example, males have higher ASC in curriculum domains such as science and mathematics while females have higher ASC in verbal domains such as reading (e.g., Marsh, 1989).

Age differences in ASC can be seen in Marsh's (1989) study of the self-concepts of adolescent students using the SDQ instruments for different age groups. He found a decline in students' ASC from preadolescence to early and middle adolescence until about Grade 8 or 9 at which point it levels out; then students' ASC increases in Grades 10 and 11 and continues to increase during late adolescence and early adulthood. Yeung (2011) had similar results showing lower student ASC in higher grade levels. This overall trend is similar for both male and female students, and is reasonably consistent across different dimensions of self-concept. As students grow older, they incorporate more information about their actual skills and abilities (based on their performance), performance feedback from others, as well as other external criteria (like comparing their abilities with those of others) into their self-concepts in different domains, making their ASCs more stable, reliable and realistic (Marsh et al., 1999). They are also better able to make distinctions between their cognitive and affective components of ASC (Marsh et al., 1999; Yeung, 2011).

2.B.5.7. Big-Fish-Little-Pond Effect (BFLPE)

The BFLPE is a theoretical model based on research findings showing that students who are in high-ability learning environments (e.g., selective class or school settings) have lower ASC than their equally able counterparts educated in low- and average-ability environments. The BFLPE model posits that although individual ability is positively related to ASC, average ability within one's school is negatively associated with ASC (Marsh, 1987). According to this model, one's ASC partly depends on one's own ability and partly on the ability of other students in one's school. If an average student is placed in a high-ability class, social comparisons can make the student feel less adequate, resulting in a low ASC. In contrast, if placed in a lower-ability class, the student may hold a higher ASC. This is in line with the

I/E frame of reference model (Marsh, 1986) and the claim that students' ASC is developed through their interaction with the environment and with other students (Shavelson et al., 1976).

Since BFLPE was first introduced by Marsh (1987), there has been a growing body of research demonstrating the detrimental effects of ability grouping in education systems (e.g., Seaton, Marsh, & Craven, 2009). BFLPE appears to be evident across cultures and nations (Seaton et al., 2009), so it should be seriously considered when choosing a suitable learning environment for a student. Choosing a learning environment that is too competitive for students may lead to lowered ASC, which has detrimental effects on future achievement and other academic and non-academic outcomes.

2.B.6. Conclusion

ASC refers to students' self-views in school curriculum domains. This chapter has discussed the conceptualization of ASC and the major instruments used to measure ASC. It has also synthesized some important findings from four decades of self-concept research, most of which have profound practical implications for theory and practice in education. Although many researchers still operationalize ASC as perceived competency, many researchers now differentiate between cognitive (competency) and affective (interest) components of ASC. Students' ASC is also domain specific. Students with a high ASC in math may not have a high ASC in English. The effects of an intervention in math are unlikely to transfer to unrelated domains such as history.

ASC and academic achievement are mutually reinforcing (i.e., REM), and such reciprocal relations are also domain specific. By improving students' math ASC, we may improve their subsequent achievement in math, but not in unrelated domains such as English. Apart from their own achievement, students' ASC is also influenced by their perceptions of peers' achievement. Internal and external comparisons work simultaneously to shape students' ASC in a particular domain. Hence, students who perceive their ability in math to be superior to their peers' ability are likely to be high in math ASC, but their high math ASC may lower their ASC is an unrelated academic domain such as English. I/E comparison patterns may vary depending on how closely the domains in question are related. For domains sharing similar characteristics or requisite skills, it is likely that achievement in one domain will be positively related to ASC in the other domain. As math and physics are highly interrelated, by increasing achievement in math, we may predict subsequently increased ASC in physics.

Social comparisons not only lead to I/E predictions but also BFLPE. If students compare themselves with high-ability peers who thrive in every academic domain, they are likely to feel that they are academically inadequate, resulting in a low ASC. Educators need to be aware of the detrimental effects of such social comparison especially in highly selective educational environments such as gifted and talented settings, selective schools, etc. Students in such settings may need special guidance and counseling.

2.B.6.1. Recommendations for the Application of ASC Theory and Research

A positive ASC has been associated with higher occupational and educational aspirations, university attendance, course selection, and achievement as well as educational attainment levels (e.g., Marsh & Craven, 2006), and should therefore be promoted. Based on ASC research findings and recent advances in research, we would like to make the following recommendations.

(1) **Theory-based measurement.** To assess students' ASC, it is essential to use a validated measuring instrument with a sound theoretical underpinning. Depending on the purpose of the measurement, measurement may be focused on the students' sense of competency or affect toward learning.

(2) **Competency and affect.** Educators need to identify the focus of intervention and choose to target competency as the focus, if the target is to improve achievement and performance outcomes. For long-term outcomes, affect should be the focus. A focus on both

is naturally ideal, but not always feasible given constraints in resources and time. A focus on one at a time for achieving specific educational outcomes would be more cost-effective.

(3) **Domain specificity**. Educators need to identify the focus of intervention and choose the targeted domain to develop specific strategies for best effects. For example, if a school wants to improve students' academic achievement in math, then the intervention should target students' ASC in math, and not in other unrelated domains.

(4) **Reciprocal effects**. The reciprocal effects found between ASC and achievement imply that if schools want to improve either students' ASC or academic achievement in a domain, both ASC and achievement have to be simultaneously targeted in any intervention.

(5) **I/E model**. Practitioners in schools (including teachers and counselors) need to be aware of the social comparisons affecting students' development of ASC. This awareness needs to be extended to parents and caregivers, who can provide useful feedback and guidance to students to help them develop realistic ASC based on their individual talents instead of social comparisons. Emphasis should be placed on enhancing students' positive view about themselves.

(6) **Interrelatedness.** Teachers in a specific domain may make use of students' ASC in another domain to optimize learning. For example, by enhancing students' ASC and achievement in math, students' are more likely to benefit also in a related domain such as physics in higher school grade levels. Strategically promoting verbal ASC and achievement will positively impact the ASC of interrelated subject areas such as history and geography.

(7) **BFLPE.** Social comparisons not only lead to I/E predictions but also BFLPE. Students in competitive schooling environments are affected by the BFLPE as a consequence of comparing with others. Students in a high-ability environment should be

made to be aware of and to appreciate their own strengths and their peers' and be guided to build on these strengths instead of feeling crushed by the success of their peers.

2.B.6.2. Further Research

Despite the extensive studies on ASC, there are still gaps that need to be further addressed. For example, even though recent research has shown the distinctiveness of the cognitive and affective components of ASC, the majority of studies on ASC simply assessed the cognitive component of ASC instead of both. Drawing conclusions on ASC based on the competency component only will limit the contribution of ASC to educational outcomes. Future research should include the affective component of ASC to gain more knowledge about its role in contributing to a variety of outcomes. For the few existing studies that also investigated the affective component, they did not include a wide range of educational outcomes beyond achievement and educational choices, to better test the predictability of the affective component. Including a wider range of educational outcomes, academic and non-academic, will better inform practice. Another major gap is that the major findings on ASC have been derived from separate studies. Research is needed to test and replicate all these major findings altogether on specific groups of students to ascertain that the theory holds true when all hypotheses are tested in the same study. Such research will reinforce the claim of replicability of ASC studies.

All in all, the findings in ASC research have shown that promoting positive ASC for both its competence and affect components is crucial to maximizing educational outcomes. Educational policy makers and practitioners should endorse and promote students' positive ASC to help them gain optimal benefits from their learning environment.

Section C:

The Juxtaposition of Cognitive and Non-Cognitive Aspects of Learning – Innovative Cognitive Practices and Motivational Factors

"Orientation of motivation concerns the underlying attitudes and goals that give rise to action—that is, it concerns the why of actions"

(Ryan & Deci, 2000, p. 54)

2.C.1. Innovative Cognitive Practices

Most science lessons around the world are still being delivered in the traditional teacher-centered talk-down approach (Andres, Steffen, & Ben, 2010). As research has pointed to the ineffectiveness of such traditional pedagogy (Wieman, 2007), there have been attempts to innovate science learning. Recent innovation in science instruction tends to focus on authentic learning tasks (Merrill, 2002; van Merriënboer & Kirschner, 2001) using minimally guided approaches such as inquiry learning (McDermott, Shaffer, & Rosenquist, 1996; Riga, Winterbottom, Harris, & Newby, 2017; Van Booven, 2015), discovery learning (e.g., Anthony, 1973), experiential learning (Boud, Keogh, & Walker, 1985), problem-based learning (e.g., Schmidt, 1983), and constructivist learning (Duit, 1996). Researchers have suggested that such instruction helps students to: integrate the scientific knowledge, science experimental skills, and develop scientific attitudes necessary for optimal science performance; provide opportunities to develop and coordinate essential skills that are required for optimal science performance; and eventually enable knowledge transfer to everyday life or work situations (Riga et al., 2017). Learning science through such instruction is exciting but risky to young students who lack pre-existing knowledge in the domain, as they may become overwhelmed by the complexity of the learning tasks, and experience cognitive overload resulting in impaired learning (Kirschner, Sweller, & Clark, 2006). If students are unable to understand the underlying concepts in the science learning tasks, then motivation could be lost (Palmer, 2005). As stated by Niemiec and Ryan (2009), “students will only engage and personally value activities they can actually understand and master” (p. 139). When students repeatedly encounter difficulties in tasks due to cognitive overload and subsequently experience failure, it lowers their sense of competence in that domain (Yeung, Kuppan, Foong et al., 2010). Therefore, it is critical that students’ learning be scaffolded at the initial stages to ensure that learning tasks are within students’ capabilities and level of pre-existing knowledge (Kadir, Ngu, & Yeung, 2015; Riga et al., 2017). When instruction is within the capacity of the working memory, students are able to construct schemas and learn more easily (Sweller et al., 2011). This results in higher academic success, which in turn, builds up students’ sense of competence (Marsh & Craven, 2006) and motivation (Ryan & Patrick, 2001), which can be further enhanced in a learning environment which also fulfills students’ basic psychological needs of competence, autonomy, and relatedness (Deci & Ryan, 2000). Figure 2.7 illustrates this phenomenon.

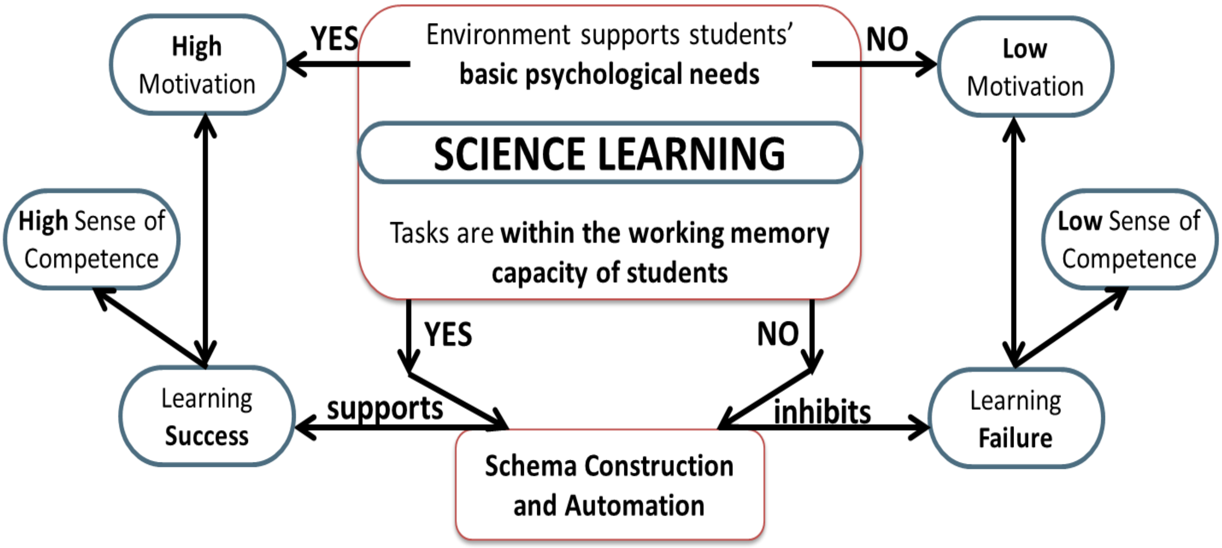

Figure 2.7. *An illustration of students' science learning environment.*

2.C.2. Non-cognitive aspects of learning

Students' academic behavior and achievement are often found to be closely associated with their motivation in schoolwork (e.g., McInerney & Ali, 2006). Pintrich, Marx, and Boyle (1993) emphasize that instructional models focusing only on cognition tend to neglect the inclusion of factors such as an individual's goals, intentions, purposes, expectations, and needs. Schwedes (1973, as cited in Laukenmann et al., 2003) argued quite similarly when she criticized physics teaching for not sufficiently taking into consideration that students are 'young persons with a variety of interests, desires, experiences and feelings' (p. 489). Hence, non-cognitive motivational factors such as basic psychological needs, academic self-concept, task goals, self-regulation, education, and career aspirations were also considered and measured in the research studies. Researchers have demonstrated that students' motivation and self-beliefs can significantly influence essential academic outcomes (e.g., McInerney, Yeung, & McInerney, 2001). These findings were based on research from various perspectives and theories, including expectancy-value theory (Wigfield & Eccles, 2000), goal theory (McInerney & Ali, 2006), and self-related frameworks such as self-concept (Marsh & Craven, 2006) and self-determination theory (Ryan & Deci, 2000, 2017).

2.C.2.1. Basic Psychological Needs in Self-Determination Theory

The concept of basic psychological needs is central to self-determination theory (SDT; Deci & Ryan, 1985; Ryan & Deci, 2017). SDT is a macro-theory of human motivation, emotion, and personality developed by Edward Deci and Richard Ryan and has been widely used to explain motivational behaviors for the past 40 years. Basic psychological needs theory, a sub-theory of self-determination theory, proposes that everyone has three innate basic psychological needs: competence, autonomy, and relatedness, which are collectively the driving force behind motivated behaviors (Vansteenkiste, Niemiec, & Soenens, 2010) and nutriments for optimal functioning (Deci & Ryan, 2000). Competence is the feeling of being capable and effective rather than feeling inadequate in one's actions (Niemiec & Ryan, 2009). Autonomy is the feeling of doing something because one chooses to, such that one's action is self-determined and volitional (Deci & Ryan, 1985), as opposed to feeling pressured or coerced to do so (Ryan & Deci, 2016). Relatedness is the feeling of being connected to others and having meaningful relationships, rather than feeling ostracized or left out (Deci & Ryan, 2000). In the educational context, the support of students' basic psychological needs is associated with positive motivational and educational outcomes such as intrinsic motivation and autonomous types of extrinsic motivation, academic engagement and better learning. In contrast, and the thwart of students' basic needs is associated with negative motivational and educational outcomes such as academic disengagement and poorer learning (Ryan & Deci, 2017). "SDT maintains that, when students' basic psychological needs for autonomy, competence, and relatedness are supported in the classroom, they are more likely to internalize their motivation to learn and to be more autonomously engaged in their learning" (Niemiec & Ryan, 2009, p. 139). Therefore, it is essential to create a learning environment which allows students to satisfy their basic psychological needs in order to enhance their motivation and optimize their learning.

2.C.2.2. Motivation

Motivation research in the last few decades has generated a number of theories (e.g., self-determination theory, expectancy-value theory, goal theory, socio-educational theory, etc). In this thesis, I mainly focus on self-concept research and self-determination theory (SDT; Deci & Ryan, 1985; Ryan & Deci, 2017) to explain student motivation.

"To be motivated means to be moved to do something" (Ryan & Deci, 2000, p. 54). As established by numerous motivational studies including those in SDT, individuals vary not only in the level or amount of motivation, but also in the orientation of that motivation (i.e., motivation type) (Ryan & Deci, 2000). According to SDT, types of motivation can be broadly categorized as autonomous or controlled, both of which energize and direct behaviors in different ways (Deci & Ryan, 2008). When individuals are autonomously motivated, they experience volition, or a self-endorsement of their actions (Ryan & Deci, 2016). In contrast, those who experience controlled motivation are compelled to think, feel, or behave in specific ways (Deci & Ryan, 2008). Each category of motivation can be subdivided into various forms of motivation and expressed on a continuum of relative autonomy (Figure 2.8, adapted from Ryan & Deci, 2000). In this continuum *intrinsic motivation* (i.e., most self-determined behavior) is placed at one end of the continuum and *amotivation* (i.e., lack of motivation and intention) is at the opposite end (Ryan & Deci, 2000). Intrinsic motivation (the most autonomous form of motivation) is associated with activities that individuals personally choose to participate in (in the absence of external stimulus), because they find the activities interesting and enjoyable (Ryan & Deci, 2016). Next on the continuum is extrinsic motivation, which is subdivided into various forms of regulation beginning from more autonomous to more controlled motivation. Integrated and identified regulations are forms of extrinsic motivation which are considered autonomous because individuals have identified with an activity's value and ideally will have integrated it into their sense of self (Ryan & Deci, 2016). Simply put, they do something willingly because they see the value in doing it. Introjected and external regulations are forms of extrinsic motivation which are identified as controlled (Ryan & Deci, 2000). Individuals who experience introjected regulation have partially internalized their behavior but are mostly energized by factors such as ego-involvements, approval motive, and avoidance of shame (Deci & Ryan, 2008). Those who experience external regulation do something because of "external contingencies of reward or punishment" (Deci & Ryan, 2008, p. 182).

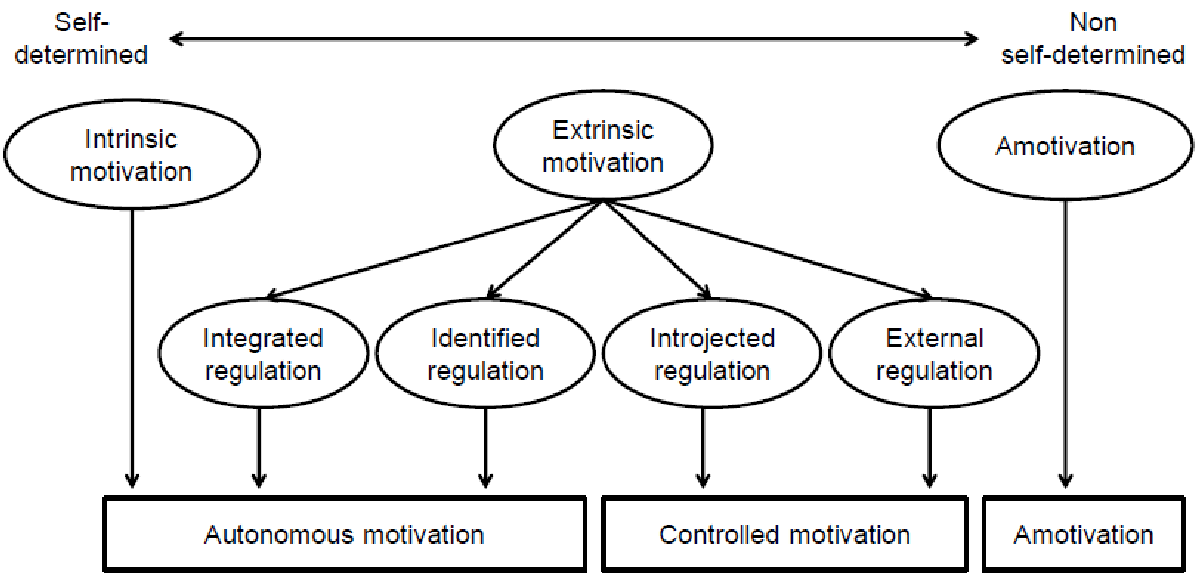

Figure 2.8. The continuum of human motivation types, adapted from Ryan & Deci (2000).

As shown by Deci, Koestner, and Ryan (1999), both basic psychological needs for competence and autonomy need to be satisfied in order to sustain intrinsic motivation in individuals. Competent students believe they can meet the challenges in their learning tasks and autonomous students willingly devote their time, energy and effort into their learning (Niemiec & Ryan, 2009). Relatedness is not always necessary for intrinsic motivation as students are able to engage in intrinsically motivating tasks on their own without the need of a support group. However, relatedness is a prerequisite of internalization. Students who feel a sense of relatedness to a group are more likely to internalize the values and beliefs of that group (Gagne & Deci, 2005; Vansteenkiste et al., 2010). Nevertheless, the interpersonal support received from the group has to be autonomy-supportive in order for the need of relatedness to be satisfied; otherwise it is not considered as self-determined. In sum, competence and relatedness are important to the internalization process but autonomy-support is the key to fully autonomous behavior. In Study 5 of this thesis, I will demonstrate a learning environment to support students' basic psychological needs using strategies suggested by Niemiec and Ryan (2009):

(1) Competence was enhanced by: teachers providing positive feedback that was constructive and providing optimally challenging tasks which were within students' cognitive abilities;

(2) Autonomy was enhanced by: providing students with an autonomy-supportive learning environment – by giving them opportunities to make decisions in their learning process, explaining the rationales behind the learning tasks, acknowledging students' feelings about their learning experiences, and minimizing control and stress during learning; and

(3) Relatedness was enhanced by: teachers conveying care, concern, and respect to students, and closely monitoring the students during teamwork to ensure that team members treated each other the same positive way as they were treated by the teachers.

The extent to which the learning environment encourages autonomous motivation in students depends on the extent to which it satisfies students' basic psychological needs. In order to measure the extent to which students' basic psychological needs were met, different types of motivation related to science were measured as outcomes, namely interest (intrinsic regulation), educational and career aspirations (integrated regulation), task goal (identified regulation), and ego (introjected regulation). Other outcomes of motivation measured were self-regulation, and sense of competence in science.

2.C.2.3. Motivational outcomes

As motivation is a multi-dimensional construct, a range of motivational outcomes were selected to measure student motivation. These outcomes were selected on the basis of past research on student motivation and covered several types of motivation from autonomous to controlled. The following section provides an overview of the variables used in the studies of this thesis. More details are given in the respective chapters where these variables were measured.

2.C.2.3.1. Self-efficacy

According to social cognitive theory, self-efficacy is defined as “people's beliefs about their capabilities to produce designated levels of performance that exercise influence over events that affect their lives” (Bandura, 1994, p.71). Bandura, Barbaranelli, Caprara, and Pastorelli (2001) theorized that students’ self-efficacy may influence their achievement goals, educational aspirations, as well as career aspirations. This is in line with Elliot’s (1999) ‘hierarchical model of achievement motivation’ where he suggested that students’ self-efficacy could exert a direct effect on students’ achievement goals, which in turn influence students’ learning processes and outcomes.

2.C.2.3.2. Self-regulation

Numerous studies have examined the cognitive and motivational outcomes associated with self-regulated learning (e.g., Ryan & Deci, 2008). Students who reported high levels of self-regulation in a learning domain: (1) were rated by their teachers as being high on academic achievement (Grolnick, Ryan, & Deci, 1991), and (2) reported high levels of perceived competence and interest, as well as lower anxiety levels in the learning domain (Black & Deci, 2000). There are many variations and definitions of self-regulation in student learning. In this thesis, I have focused on the cognitive strategies that students use to learn and monitor their understanding of the learning materials (Zimmerman & Pons, 1986). Self-regulation is an important motivational outcome since students who are motivated will use several strategies to self-regulate their learning and monitor their understanding of the concepts.

2.C.2.3.3. Engagement

Cognitive engagement is a form of motivated behavior (Pintrich, Smith, García, & McKeachie, 1993). Research has shown that students who are cognitively engaged in their learning will persist in using a variety of cognitive strategies to complete learning tasks and develop skills for knowledge transfer (Pintrich et al., 1993). Engagement is thus a vital contributor towards quality learning and academic success (Skinner, Furrer, Marchand, & Kindermann, 2008). The engagement factor used in this thesis focused on the behavioral aspect of engagement as an outcome measure, defined in terms of students' attention and participation in learning tasks and classroom activities during science lessons.

2.C.2.3.4. Task goal orientation

Achievement goal theory (Urdan & Maehr, 1995) defines goals as cognitive representations of the different purposes students may adopt for their learning in achievement situations (Ford & Nichols, 1991). Mastery goal orientations are believed to influence a range of cognitive, affective, and behavioral outcomes for children (Barker, McInerney, & Dowson, 2002; Pintrich & Schunk, 1996; Robins & Pals, 2002). These mastery goal orientations may be conceptualized as task and effort goals separately (Yeung & McInerney, 2005). In this thesis, the focus is on task goal. Students with a high task goal orientation tend to focus on learning, solving problems and developing their skills (Elliot & Dweck, 1988; Nicholls, 1989).

2.C.2.3.5. Aspiration

According to SDT, the degree to which students' basic needs for competence, relatedness, and autonomy are satisfied in a domain influenced their aspirations in that domain (Deci & Ryan, 2008). Students' educational and career aspirations in physics are two important outcomes for measuring the success of science instruction. If instruction increases students' desires to further their studies in physics and possibly choose a physics-related job, then the cognitive and non-cognitive theoretical underpinnings of the instruction processes could be applied to other areas of physics instruction in order to solve the declining enrolment and other issues surrounding physics education.

2.C.2.3.6. Ego involvement

Ego refers to one's self-esteem being dependent on one's performance, and in SDT, it is considered a type of introjected regulation (Ryan, 1982). When ego is involved, a student feels an internal pressure to perform in learning tasks so as to feel worthy or to avoid shame (Niemiec, Ryan, & Brown, 2008). Since this motivation emanates from outside the self, such behavioral regulation is a form of extrinsic motivation, which is more controlled than autonomous (Niemiec & Ryan, 2009). In this thesis, the focus is on students' ego in relation to their peers' performance.

2.C.3. Summary

The main cognitive issues in physics education are the high levels of element interactivity during instruction that easily overload students' working memory, while the main non-cognitive issues are the lack of motivation to learn physics and students' lack of self-concept. Figure 2.9 illustrates these issues. One way to overcome these issues is to address them simultaneously by merging strategies from both cognitive and motivational studies in education (i.e., implementing them in the same learning environment).

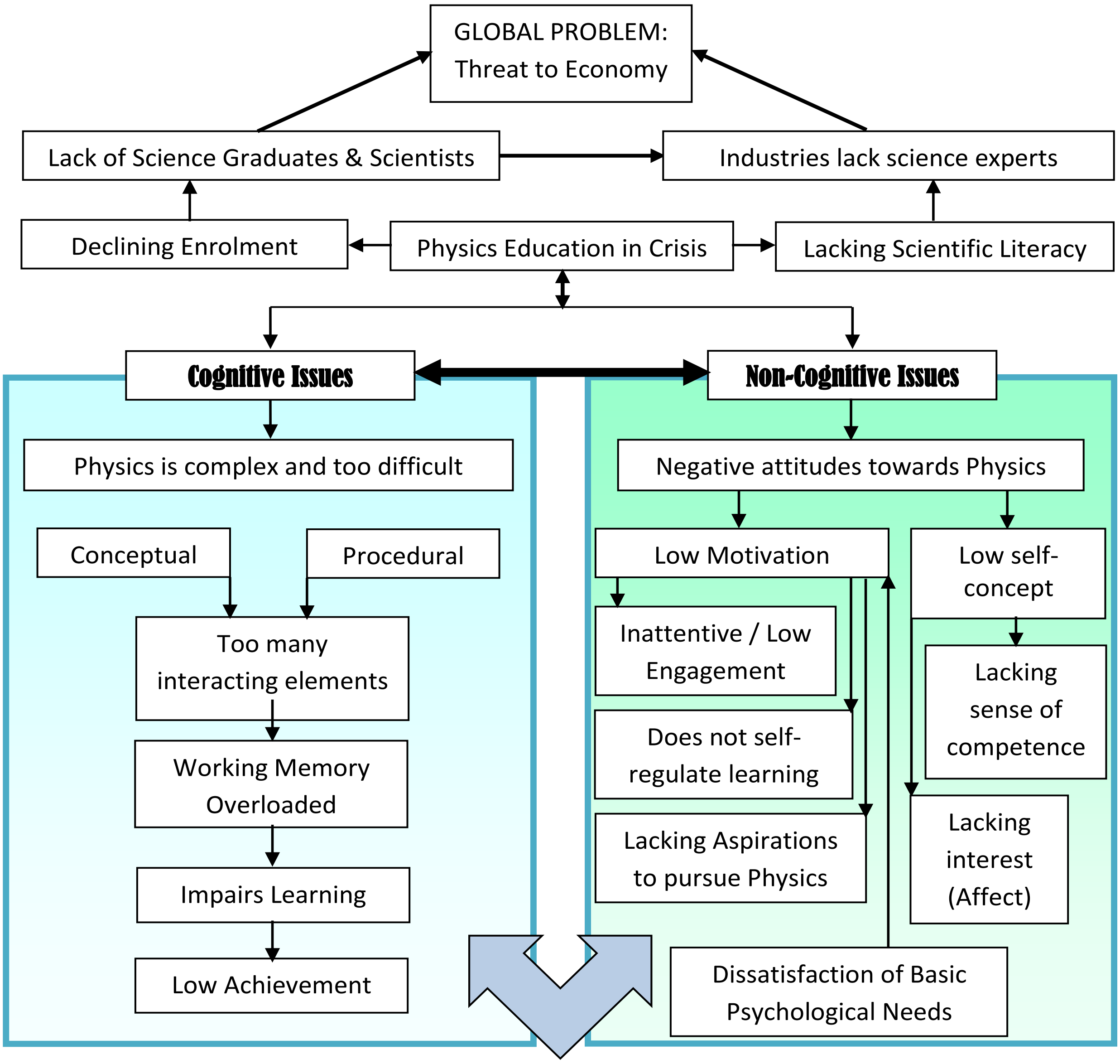

Figure 2.9. Overview of the main cognitive and non-cognitive issues in science education addressed in the thesis.

Section D:
Overview of Thesis

"… complex learning is a lengthy process requiring learners'

motivational states and levels of expertise development to be taken into account"

(van Merriënboer & Sweller, 2005, p. 147)

2.D.1. Thesis Aim

The overarching aim of the research is to: (1) investigate the relations between the cognitive and non-cognitive factors of science education; and (2) design and implement an intervention to improve both the cognitive and non-cognitive learning outcomes of a physics instruction for Grade 7 students. To achieve this objective, five studies were carried out and a number of specific research objectives were met.

2.D.2. Specific Research Objectives

Study 1: Simultaneous Testing of Four Decades of Academic Self-Concept Models

1. Review the evidence and form hypotheses from self-concept studies on the relationships between academic self-concept and achievement,
2. Identify knowledge gaps in the studies and include these in the hypotheses, and
3. Test hypotheses on a sample of Grade 7 students using structural equation modelling and identify the relations between student achievement and their academic self-concept.

Study 2: School Achievement and Science Motivation during the Primary-Secondary School Transition

1. Evaluate the psychometric properties of the psychological constructs to demonstrate that the instrument used is a valid and robust measure of the constructs under investigation, and
2. Investigate the relations between student achievement and motivatinal attitudes before and after transition from primary to secondary school (i.e., Grade 6 to 7) to see if there is an association between Grade 6 achievement and Grade 7 motivation.

Study 3: Element Interactivity as a Construct for the Analysis of Science Problem Solving Processes

1. Analyze science word problem in terms of element interactivity to determine the level of complexity,
2. Analyze students' science problem solving processes in terms of operational lines to deduce the element interactivity and infer students' level of expertise in science problem solving, and
3. Investigate the relations between element interactivity and student achievement.

Study 4: Effects of Managing Element Interactivity on Student Achievement and their Academic Self-Concept

1. Design and implement an intervention that manages element interactivity during science instruction, and
2. Measure the effect of the intervention on student achievement and self-concept in science.

Study 5: Effects of a Dual-Approach Instruction on Students' Science Achievement and Motivation

1. Apply the findings from studies 1-4 to design and implement an intervention that manages element interactivity during science instruction in a learning environment that provides for learners' basic psychological needs (i.e., dual-approach instruction which supports students' learning processes and seeks to enhance their motivation), and
2. Measure the effect of the intervention on student achievement and psychological factors.

Chapter 3: Study 1 -

Simultaneous Testing of Four Decades of Academic Self-Concept Models

Note. This chapter has been published as a journal article in a top-tier peer-reviewed journal: *Contemporary Educational Psychology*. Permission to present the final draft of this study in this thesis has been obtained from the journal.

Kadir, M. S., Yeung, A. S., & Diallo, T. M. O. (2017). Simultaneous testing of four decades of academic self-concept models. *Contemporary Educational Psychology, 51*, 429-446. https://doi.org/10.1016/j.cedpsych.2017.09.008

Simultaneous Testing of Four Decades of Academic Self-Concept Models

3.1. Preface

With emphasis on the importance of addressing both cognitive and motivational aspects of learning so as to optimize students' potentials, a series of studies was conducted to examine the interplay between cognitive and motivational variables. There has been extensive research showing that academic self-concept plays a critical role in determining academic outcomes such as achievement, but whether this applies similarly across various curriculum domains and for different components of self-concept needs further exploration. Study 1 starts by reviewing the findings of self-concept research for the last 4 decades and scrutinizing the associations between students' achievement (cognitive) and self-concept (motivational) aspects of learning found in the literature. The study is the first to test the five main findings in self-concept research to date in a single study covering three curriculum domains (English, mathematics, and physics) across three time waves. It also contributes to new knowledge by including the affective component of academic self-concept which has long been neglected. The findings will (1) show the replicability and applicability of self-concept studies, (2) elaborate on the role of academic self-concept in contributing to student achievement, and (3) guide intervention strategies to enhance students' academic self-concept in schools.

3.2. Abstract

In separate studies on academic self-concept, previous research has shown: (1) the distinctiveness of a cognitive and an affective component, (2) the domain specificity of self-concepts, (3) the reciprocal effects of self-concept and achievement, (4) the internal/external frame of reference in self-concept development, (5) the reciprocal effects of the internal/external frame of reference, (6) the big-fish-little-pond-effect, and (7) the interrelatedness of self-concepts in similar domains. The present study demonstrates that all of these seven findings are replicable and may be synthesized in a single study with a sample of students in Singapore. Secondary 1 students (7th graders; N = 275) were surveyed with 24 items about their academic self-concepts in physics, English, and math in two components (cognitive and affective), and their respective achievement scores were recorded over two time-points. Confirmatory factor analysis found that the cognitive and affective components of academic self-concept were separable. The students' self-concepts in different curriculum domains were distinct, supporting the domain specificity of self-concepts. The frame of reference and reciprocal effects were both supported, but only for the cognitive component of self-concept. Positive and statistically significant correlations between physics and math suggest that these curriculum domains were interrelated. Results of self-concept studies in schools can encourage and guide the design of interventions that could enhance students' self-concept for positive sustainable effects on desirable educational outcomes. Attempts to improve learning outcomes should emphasize an enhancement of specific components of academic self-concept in domain-specific and related curriculum domains for optimal effects.

3.3. Introduction

Student self-concept in a school curriculum domain (e.g., science, English or math subjects) is commonly known as academic self-concept (ASC) (Kadir & Yeung, 2016). Students with a positive ASC feel good about their academic ability and are likely to achieve well in school (Guo, Marsh, Parker, Morin, & Yeung, 2015; Kadir & Yeung, 2016, Kadir, Yeung, & Barker, 2013, Marsh, Xu, & Martin, 2012). Apart from academic achievement, a host of other important academic outcomes (e.g., academic and career aspirations, coursework selections, self-regulated learning strategies, positive self-beliefs and motivation) have been found to be substantially related to students' ASC (Guo, Marsh et al., 2015; Guo, Parker, Marsh, & Morin, 2015; Marsh, 1993, 2007; Yeung, Craven, & Kaur, 2012; Yeung, Kuppan, Foong et al., 2010). ASC studies over the past four decades have also yielded important findings leading to the formulation of many ASC models such as the separation of the cognitive and affective components of ASC (Arens, Yeung, Craven, & Hasselhorn, 2011; Marsh, Craven, & Debus, 1999), the domain specificity of ASC (Marsh & Yeung, 1997), the reciprocal effects model (REM; Marsh & Craven, 2006), and social comparisons leading to the internal and external frame of reference (I/E; Marsh, 1986, 2007) model influencing the development of ASC, which also has reciprocal effects (RI/EM; Möller, Retelsdorf, Köller, & Marsh, 2011) and has led to the big-fish-little-pond-effect (BFLPE; Marsh, 1987), as well as the contrast and assimilation effects or interrelatedness of curriculum domains (Xu et al., 2013).

Even though ASC studies have spanned over decades, there are several gaps that still exist in the research. First, ASC models have been developed in isolation. The disparate testing of selective hypotheses is far from the golden standards of scientific research (American Educational Research Association, 1999). Integration and simultaneous testing of the ASC models in a *single* study will make the conclusions more robust (Santer, Wigley, & Taylor, 2011) and serves to further ASC researchers' claims to represent a pan-human phenomenon. The summative results of all the findings would also make it easier for practitioners and researchers to see the implications of the findings holistically and consider the interactions among the different findings when formulating policy and practice. Second, most researchers have focused on the cognitive component of ASC, whereas the affective component of ASC has mostly been ignored. Investigating the affective component is just as critical, in order to understand its role in educational settings. Third, researchers have not distinctly explored the physics ASC of Grade 7 students as most Grade 7 students around the world study general science and not physics as a separate subject or module. Understanding students' physics ASC at an early age and its relations to the other variables is important to help address the challenges students face in that curriculum domain.

These research gaps have been addressed in the present study. Firstly, the findings of past large-scale ASC studies were reviewed and reinforced, then developed into seven hypotheses to investigate whether they are replicable in this particular group of students in Singapore. The importance of replication and reproducibility of studies is well-recognized by scientists and researchers because replicable data can lead to robust conclusions (Santer et al., 2011). Jasny, Chin, Chong, and Vignieri (2011) also shared the value of replicating past work by stating that "replication – the confirmation of results and conclusions from one study obtained independently in another – is considered the scientific gold standard" (p. 1225).

Using ASC and academic achievement measures in physics, English, and math, the seven hypotheses investigated were the: (1) distinctiveness of the cognitive and affective components of ASCs, (2) domain specificity of ASCs, (3) reciprocal effects model (REM), (4) internal/external (I/E) frame of reference model, (5) reciprocal internal/external frame of reference model (RI/EM), (6) big-fish-little-pond-effect (BFLPE), and (7) interrelatedness of ASCs in similar domains. If all seven hypotheses can be supported in a single study with the given sample of students, it would provide a comprehensive overview supporting the replicability of ASC studies and the rigor of the ASC models. By taking all the findings into consideration, it could also better facilitate the design of a holistic ASC enhancement intervention encompassing the various themes discussed in the study. Secondly, we tested all the hypotheses for *both* the cognitive and affective components of ASC, giving additional perspectives and expanding implications to past ASC findings. Thirdly, we investigated Grade 7 students' physics ASC. As most Grade 7 students around the world study general science (as physics is usually introduced into the curriculum at Grade 9 and beyond) and would develop physics ASC only when they are older, the findings of this study would be valuable for researchers planning to conduct longitudinal studies on students' ASC in physics.

3.3.1. Theoretical framework

3.3.1.1. The Cognitive and Affective Components of Academic Self-Concept

Within a specific curriculum domain, researchers have considered the separation of two major components of ASC: the cognitive and affective components (Arens et al., 2011; Marsh, Craven et al., 1999). The cognitive component taps on students' self-perceived competence in the domain (e.g., sense of competence in physics or students' own judgement of their academic ability in physics), whereas the affective component is concerned with students' affective-motivational reactions toward the domain (e.g., how much students like physics and enjoy physics lessons). There are an increasing number of researchers who have operationalized the ASC construct as two distinct factors as they have shown that the cognitive and affective components of ASC can be distinguished from each other (Arens et al., 2011; Arens, Bodkin-Andrews, Craven, & Yeung, 2014; Marsh, Craven et al., 1999; Pinxten, Marsh, De Fraine, Van Den Noortgate, & Van Damme, 2014), even for young students in elementary schools (Arens & Hasselhorn, 2015). Arens et al. (2014) highlighted the importance of distinguishing between the cognitive and affective components of ASC in order to better understand student differences (e.g., are the differences in ASC between groups of students the result of their beliefs about their abilities or their feelings about specific domains?). Other researchers have shown that distinguishing between the cognitive and affective components of student ASC helps in designing more specific interventions to target different academic outcomes as they are found to be predictors of different outcomes. Students' high sense of competence (cognitive), for example, is known to lead to positive achievement outcomes (e.g., Marsh & Scalas, 2010), whereas students with a strong liking (affect) in a domain are found to persist in challenging learning tasks (e.g., Elliot & Church, 1997). Given the differential predictions of the cognitive and affective aspects of academic motivation on educational outcomes as suggested by Yeung et al. (2012), the separate consideration of the cognitive and affective components is likely to benefit more efficient and targeted intervention approaches.

Although Marsh, Craven et al. (1999) and Arens et al. (2011) have demonstrated that the cognitive and affective components of ASC are distinguishable from each other, they have not tested whether each ASC component in a curriculum domain is related to the same component in another curriculum domain or not (e.g., competence in physics could be unrelated to competence in English; affect in physics could be unrelated to affect in

English). This would provide a much stronger scrutiny of the distinctiveness of these constructs. For a thorough scrutiny of the cognitive and affective components of ASC, and for the separation of the two components to be practically useful, a test of the respective relations of each component with domain-specific outcome variables (e.g., achievement scores) would be required. To this end, it would be useful to demonstrate the positive relations between predictors and outcomes within domains and non-positive relations across domains.

One of the purposes in the present study was to provide rigorous scrutiny of the distinctiveness of the two components of ASC and their domain-specific relations with outcome variables. In this investigation, we focused only on the broad conceptualization of the cognitive (sense of competence), and affective (the extent of liking physics) components regarding lower secondary physics, which has not been well-researched, in addition to two other well-researched domains: English and math.

3.3.1.2. Domain Specificity of Academic Self-Concepts

The domain specificity of ASCs has been established by many researchers (e.g., Marsh & Craven, 2006; Yeung, Kuppan, Foong et al., 2010; Yeung & Lee, 1999). That is, students can clearly differentiate their ASCs in various curriculum areas (e.g., English, math, etc). In the school context, a positive ASC can contribute to important educational outcomes, but the relation between achievements and ASCs are known to be significant only within specific domains (Marsh & Yeung, 1997; Möller et al., 2011; Yeung et al., 2012; Yeung & Lee, 1999). Thus, research on ASC has emphasized its domain-specific nature (Arens et al., 2011; Marsh, Kong, & Hau, 2001). The emphasis has also led to the development of instruments that measure self-concepts in distinct areas (e.g., Dillon, 2011; Marsh, 1992, 1993).

Whereas much research has been conducted on the domain specificity of math and verbal ASCs, little is known about the domain specificity of Grade 7 physics, especially for students learning physics as a separate module from science for the first time in school. In the current study, we assessed the domain specificity of ASC in Grade 7 physics, a curriculum domain which has not been thoroughly explored in ASC research. By juxtaposing physics with English and math which have attracted much attention, and comparing their relations with patterns from previous ASC studies, we would be able to test the generalizability of domain specificity across the three domains, for both the cognitive and affective components of ASC.

3.3.1.3. Reciprocal Effects Model (REM)

The heed for the simultaneous enhancement of content proficiency and ASC in respective domains is grounded upon the reciprocal effects found between achievement and the cognitive component of ASC (i.e., sense of competence). The reciprocal effects model (REM) proposed by Marsh, Byrne, and Yeung (1999) maintains that achievement and students' sense of competence are mutually reinforcing such that higher achievement would lead to a higher sense of competence and a high sense of competence would further lead to higher achievement (see Marsh & Craven, 2006; Marsh & O'Mara, 2008). Consistent with the domain specificity findings of previous research, the mutually reinforcing relation is also found to be domain specific. That is, students who achieve well in math would tend to have a high sense of competence in math, which would subsequently lead to higher achievement in math, but not necessarily in other curriculum domains.

So far, the research testing the reciprocal effects between achievement and ASC has focused mostly on the cognitive component and has not thoroughly examined the affective component of ASC. Based on past research findings (Marsh & Craven, 2006; Yeung, Kuppan, Foong et al., 2010), we may envisage that the reciprocal effects would be more apparent for the cognitive component (i.e., how competent I am in physics) than for the affective component (i.e., how much I like physics). In other words, the affective component may not have direct bearing to achievement; at least not as much as would a sense of competence. In the present study, we tested the reciprocal effects between achievement and both components of students' ASC in physics, English, and math curriculum domains.

3.3.1.4. The Internal/External Frame of Reference Model (I/E Model)

The emphasis on domain specificity of ASC came primarily from the consistent findings of distinct ASC factors and their domain-specific relations to other factors. Specifically, studies have found a non-positive (often near-zero) correlation between students' verbal and math ASCs (e.g., Marsh, Byrne et al., 1999; Marsh, Byrne, & Shavelson, 1988) although the correlation between verbal and math achievements is usually high. To explain such a phenomenon, Marsh (1986) proposed an internal-external frame of reference (I/E) model, to show that the development of students' ASC in a particular curriculum domain is primarily based on an *internal* comparison (i.e., comparing their self-perceived ability in the curriculum domain with their self-perceived ability in other curriculum domains) as well as an *external* comparison (i.e., comparing their self-perceived ability in that curriculum domain to their perceived ability of their peers in the same domain). For example, students are likely to have a high English ASC if they perceive that their ability in English is better compared to the rest of their curriculum domains (i.e., internal comparison) and also believe they have a high ability in English relative to their peers (i.e., external comparison).

The internal frame of reference initiates a dimensional comparison process such that achievement in one curriculum domain has a negative effect on ASC in a dissimilar or non-corresponding domain (Möller & Marsh, 2013). For example, a high-ability student with high achievement in all domains (hence the positively significant correlations between achievements) may have a low math competence if he scored worst in math relative to other dissimilar domains such as English, or other languages (Arens et al., 2011). Despite his good math achievement, he perceived his math ability to be worst (thus the low math ASC) due to his higher achievement in other dissimilar domains such as English (thus the high English ASC). This resulted in the low or negative correlations between achievement and ASCs of dissimilar domains. The internal comparison process between math and verbal domains has been widely supported by experimental, longitudinal, and cross-cultural studies (e.g., Marsh, 2007; Möller & Marsh, 2013; Möller, Pohlmann, Köller, & Marsh, 2009).

The external comparison is a process where students' ASC in a domain was developed from the information they garnered from social comparisons: comparing their achievement in the domain with the achievement of their peers in the same domain. For example, if a student's English achievement is higher that his classmates', his English ASC will also be higher. As students' achievement across domains are typically positively correlated, it seemed reasonable to assume that the processes of external comparisons have led to domain-specific ASCs which are also positively correlated (Möller, Streblow, Pohlmann, & Köller, 2006).

In sum, the I/E model hypothesizes that the combined operation of both the internal and external comparisons, depending on the relative weighting given to each, would lead to the low correlation between ASCs (i.e., sense of competence) in dissimilar domains

(Marsh, 1986, 2007; Marsh et al., 2012). The I/E model also predicts positive effects of English and math achievement on English and math ASCs, respectively but negative effects of English achievement on math ASC and math achievement on English ASC, where ASC refers to the cognitive component (i.e., sense of competence). Researchers have replicated the patterns of the I/E model in various cultural and language backgrounds (e.g., Marsh et al., 2001; Möller et al., 2011; Xu et al., 2013, Yeung, Chow, Chow, Luk, & Wong, 2004; Yeung & Lee, 1999). The I/E model has provided an important framework for examining the domain specificity of ASC. However, studies that have further tested the I/E model with the affective component of ASC are lacking. By testing the differential relations between achievement and each of the components of ASC (i.e., competence and affect), we would be able to conduct a rigorous test of the internal and external comparison interpretation. Because the competence component involves more direct social comparisons than the affective component, we would expect the patterns obtained in I/E model to be more apparent for competence than affect. We attempted to contribute to the literature by addressing this issue in the present study.

3.3.1.5. The Reciprocal Internal/External Frame of Reference Model (RI/EM)

The reciprocal internal/external frame of reference model (RI/EM; Möller et al., 2011; Möller, Zimmermann, & Köller, 2014) combines the internal/external frame of reference model and the reciprocal effects model. The RI/EM predicts positive effects of English and math achievement and ASC on subsequent English and math achievements and ASC within domains and negative effects of English and math achievements and ASC on subsequent achievements and ASC across domains. Similar to the reciprocal effects and the I/E models, the affective component of ASCs has not been thoroughly investigated. Therefore, in an attempt to further extend the model, we have included the affective component of ASCs in each domain, and also added the physics domain, which has not been explored in past RI/EM studies. However, since we did not measure subsequent ASC after achievement at time 2, we did not test that part of the model.

3.3.1.6. The Big-Fish-Little-Pond Effect (BFLPE)

Another finding that has emerged from students' frame of reference or social comparison is the big-fish-little-pond-effect (BFLPE, Marsh, 1987). The BFLPE is a theoretical model based on research findings showing that students who are learning in high-ability environments (e.g., selective school or class settings) have lower ASC than their equally able peers educated in average-ability or low environments. The BFLPE model posits that although individual ability is positively related to ASC, average ability within one's school is negatively associated with ASC (Marsh, 1987). According to this model, students' ASC partly depends on their own ability and partly on the ability of the other students in their learning environment. If an average student is placed in a high-ability learning environment, social comparisons can make the student feel less adequate, resulting in a low ASC (Kadir & Yeung, 2016; Seaton, Marsh, & Craven, 2009). In contrast, the student may hold a higher ASC if placed in a lower-ability learning environment. The BFLPE is in line with the I/E frame of reference model (Marsh, 1986) and has shown to be evident across cultures and nations (e.g., Seaton et al., 2009).

3.3.1.7. Interrelatedness of Academic Self-Concepts

Whereas ASC research has emphasized domain specificity and multidimensionality (see Arens et al., 2011), the interrelatedness between ASCs in different but similar domains has not been vastly explored, especially in the Grade 7 curriculum domains of physics and math. In support of the domain specificity and multidimensionality of ASCs, Yeung et al. (2000) argued that the domain specificity of students' ASCs depends on the nature of the domain in question and how the domain is related or similar to other domains (also see Yeung, Chui, & Lau, 1999). Yeung et al. (1999) demonstrated that for curriculum domains that have a common focus (e.g., on commercial studies), students' ASCs tended to be positively correlated with each other. Yeung et al. (2000) also argued that ASCs of a similar nature may not be as distinct from each other as would ASCs in clearly distinctive or dissimilar domains (e.g., math and verbal ASCs). The Marsh/Shavelson model (Marsh & Shavelson, 1985) suggests that ASC can be ordered along a math-verbal continuum. Marsh (1992) suggested that math and verbal ASCs are at the opposite ends of the ASC continuum because they have been found to have the greatest contrast effects (i.e., a negative effect between achievement and ASC across domains) (Möller & Marsh, 2013). Xu et al. (2013) found that curriculum domains that are further apart on the ASC continuum would have stronger contrast effects, but for domains that are closer together on the continuum, the patterns would vary from no significant effects or weaker contrast effects, to assimilation effects (i.e., positive effect of achievement in one domain on ASC of a similar domain).

In the study by Möller et al. (2006), they found positive effects of physics achievement on math ASC and of math achievement on physics ASC. Their results showed that math and physics are interrelated. Therefore, we also expected that patterns of domain specificity would be less prominent between mutually relevant domains, hence supporting the interrelatedness hypothesis (i.e., assimilation effects). In a later study, Möller et al. (2009) posed the question as to whether students would perceive curriculum domains such as physics and math as sufficiently distinct such that better performance in one would lead to poorer ASC in the other (a contrast effect like that posited in the I/E model based on the math and verbal domains), or would the two curriculum domains be perceived as sufficiently similar and related so that better performance in one domain (e.g., math) would lead to the enhancement of the ASC in the other (e.g., physics): an assimilation effect. A recent study by Marsh et al. (2015) tested math- and science-like domains (i.e., biology, physics and math) and listed them as ‘near’ domains which display positive cross-domain effects of achievement on the cognitive component of ASCs across these domains.

In the present study involving the three curriculum domains - physics, English, and math - we hypothesized interrelatedness between physics and math. Math skills are known to be a tool necessary for the computations required in physics, so we would expect math and physics to be closer together on the ASC continuum, compared to between physics and English and between math and English. Specifically, the correlations between math and physics variables are expected to be larger than between English and math or between English and physics. The findings would provide a better understanding of students’ ASCs in similar domains that would enable educators to optimize ASC enhancement effects in different curriculum domains. While all the above studies to date have focused only on the cognitive component of ASC, we have extended the investigation to studying the interrelatedness of physics and math also with the affective component of ASC.

3.3.2. The Present Study

In the present study, secondary 1 students (i.e., 7th graders) in Singapore completed a survey regarding their ASCs in physics, English, and math in two components (competence and affect), and their achievement scores in the physics, English, and math domains at time 1 (before the ASC survey) and time 2 (after the ASC survey) were collected from the school. Assuming ASC studies and models are replicable, we expected support for the hypotheses, which are outlined in greater detail below.

Hypothesis 1. *Distinctiveness of the cognitive and affective components of ASCs.* In line with past studies (e.g., Marsh, Craven et al., 1999), we expected the cognitive and affective components of ASCs to be distinct from each other. Therefore, in the results, we would expect the model fit to be better for the model theorizing the separation of ASC for each domain into its cognitive and affective components, than the model theorizing a global ASC, which combines the cognitive and affective components of ASC of each domain into a single factor. We would also assume that the correlations between the cognitive and affective factors of ASCs would be high (showing interrelatedness, which were in line with previous studies) but less than 1, indicating that they are distinct factors. If the cognitive and affective factors of ASC are distinct from each other, we would also expect them to function differently, resulting in different correlations and paths, with the other variables.

Hypothesis 2. *Domain specificity of ASCs.* Based on past studies (e.g., Arens et al., 2011), we would expect to observe domain specificity in both the cognitive and affective components of ASC. Therefore, we assumed that the correlations among the latent variables of physics, English, and math ASCs, as well as the correlations between ASC and achievement would be positive and statistically significant within domains but weaker across domains, for both the cognitive and affective components of ASC.

Hypothesis 3. *Reciprocal effects model (REM).* Based on previous findings (e.g., Marsh & Craven, 2006), we assumed that there are reciprocal effects between ASC and achievement and that it would be domain specific. Students with high achievement would have high ASC, which would lead to high subsequent achievement within the same domain. We would therefore expect the structural paths from achievement at time 1 to competence and from competence to achievement at time 2 to be positive and statistically significant within domains but not across domains, as found in past studies (e.g., Marsh & Craven, 2006).

Hypothesis 4. *Internal/external frame of reference (I/E) model.* Past studies (Marsh, 1986; 2007) have implied that students develop their ASCs by internal and external comparisons. As a result of such comparisons, students with a high ASC in a domain would impede their ASC in a dissimilar domain, even if they have relatively similar achievement in both domains. Therefore, we would expect positive and statistically significant correlations between the achievements of different curriculum domains but statistically non-significant correlations or negative and statistically significant correlations between the ASCs of dissimilar domains. We would also expect the results to show positive and statistically significant structural paths from achievement to ASC within domains but not across dissimilar domains for the competence component, as found in past studies (e.g., Marsh, 2007).

Hypothesis 5. *Reciprocal internal/external frame of reference model (RI/EM).* Past studies (e.g., Möller et al., 2011) have shown that there are reciprocal effects to the I/E model, resulting in the birth of RI/EM. Since the RI/EM is a combination of the REM and I/E model, we would expect the structural paths from achievement to the competence component of ASC to subsequent achievement within domains to be substantially positive and statistically significant whereas the structural paths across dissimilar domains would either be statistically non-significant (Möller et al., 2014) or negative and statistically significant over time (Möller et al., 2011). As past studies on RI/EM (Möller et al., 2011; 2014) involved the domains of English and math for the competence component of ASC only, we would expect the structural paths from English achievement to English competence and to subsequent English achievement to all be positive and statistically significant, but the paths from English achievement to math competence and to subsequent English achievement to be statistically non-significant or negative and statistically significant.

Hypothesis 6. *Big-fish-little-pond-effect (BFLPE).* Based on previous findings (e.g., Marsh, 1987), we assumed that students' interactions with their learning environment influenced their ASC development. For example, an average student placed in a high-ability learning environment would develop lower ASC than his peer of similar ability placed in a lower ability learning environment. The study was conducted within one school, with no significant variation within and between Grade 7 classes in terms of average academic ability, so we would not expect to observe the BFLPE.

Hypothesis 7. *Interrelatedness of self-concept in similar domains.* Past studies (e.g., Yeung et al., 1999) have shown interrelatedness between domains with similar characteristics, focusing on competence. Therefore, we would expect to observe positive and statistically significant correlations between similar domains (i.e., numerical domains such as physics and math) in ASCs as well as in achievement at time 1 and time 2. In contrast, we expect to observe negative and statistically significant correlations between dissimilar domains (i.e., English and math) in ASCs; and much lower correlations for achievement at time 1 and time 2 between these dissimilar domains. In line with past studies, we would also assume that the structural paths across similar domains (i.e., physics and math) would be positive and statistically significant, in contrast to negative and statistically significant structural paths across dissimilar domains as posited by the I/E model.

3.4. Method

3.4.1. Participants

There were altogether 100 boys and 175 girls from 12 different classrooms in a school in Singapore who participated in the study (*N* = 275; age range = 12.8 to 13.7 years old). Students' participation was voluntary and they were assured that their teachers would not be given any information about their responses. The consenting participants were all in the first year of secondary school (commonly known as 'Grade 7' or 'secondary 1'in Singapore) and formed 63% of the Grade 7 students in the school. There was no systematic difference between the students who volunteered for the study and those who did not, in terms of their demographics and academic abilities. Although all the students were Chinese by race (>75% of Singapore residents are of Chinese origin), all of them were effectively bilingual in English and Mandarin (i.e., Chinese language), as English is the national language (i.e., first language) of Singapore. About 52% of these Singapore students used English as their home language. Whereas 41% of the students spoke Mandarin and the remaining 7% spoke other Chinese dialects at home, English is becoming the major language the younger generation uses at home (see Li, Zhao, & Yeung, 2012). In Singapore, all students formally start learning English in pre-school. English is the medium of instruction in all government schools in Singapore, so all of the curriculum domains (e.g., math, science, geography, history, music, art) are delivered in English. Even though many of the student participants did not speak English at home, they spoke fluently in English with teachers and peers. They also had no problems understanding, reading and writing in English, as evidenced in their high achievement scores in English, feedback from their teachers, as well as with their interactions with the researchers.

At the end of Grade 6, students in Singapore have to take a national examination, known as the Primary School Leaving Examination (PSLE; see the Singapore Examinations and Assessment Board website, in National Examinations). Students in Singapore gain admission to secondary schools based on their PSLE score, which ranged from 0 to 300. The mean PSLE score for this sample of participants was 243. Therefore, when compared to the general secondary 1 cohort in Singapore, these participants were considered to have "higher than average" academic capabilities, judging from their better performance at the PSLE. Also, for this reputable school, only students with a score of about 240 were able to gain admission. These students' academic ability, however, were not as high as those in what is known as the gifted program. There were students with lower PSLE scores who gained admission based on their achievements in sports, music, and the arts, for example, but these were very few. Therefore, the academic ability of the students was, on average, similar to one another, across and within classes, during the time of the study.

3.4.2. Study Measures

The students responded to a 24-item ASC survey on a six-point Likert scale (1 = strongly disagree to 6 = strongly agree). The survey was conducted at the end of the school year. The students responded to the survey items in a randomized order. The items were about two components of ASC (competence and affect) in three curriculum domains, respectively (physics, English, and math). For the competence items, students rated their academic ability in the domain. For the affect items, students rated their liking for the domain. The items (named PC1-4, PA1-4, EC1-4, EA1-4, MC1-4 and MA1-4 in Table 3.1 and Appendix 3A) were adapted from well-validated instruments and randomized in the survey form. To avoid response bias, a few items were negatively-worded in order to discourage students from selecting the same responses for the entire survey without reading each item. Since only the physics component of science was taught before and during data collection, only the students' physics ASC was measured. Apart from these 24 items, background variables such as age, gender, language background, were also used in the survey. These 24 items formed six ASC factors with maximal reliabilities ranging from .90 (for English competence) to .94 (for physics competence and math affect). These high reliabilities provided preliminary support for the factors. In addition to the ASC factors, students' achievement data for physics, English and math curriculum domains were also collected from the school, in order to test the seven hypotheses. The achievement scores, recorded as percentages, were collected at two time-points: achievement at time 1, before the survey data collection, and achievement at time 2, after the survey data collection, within the same school year. The factor variables were physics competence, physics affect, English competence, English affect, math competence, and math affect.

3.4.2.1. Physics competence

This factor is the cognitive component of physics ASC, relating to students' sense of their academic ability in physics. The items were adapted from the Marsh (1992) *Academic Self-Description Questionnaire* (ASDQ) instrument. An example is, "I learn things quickly in PHYSICS classes". A total of four items were used for students to rate their sense of competence in physics, as only physics was taught in the science class during the duration of the data collection, and students were aware that they were learning physics at that time. The maximal reliability for this factor was .94.

3.4.2.2. Physics affect

This factor is the affective component of physics ASC, relating to students' personal interest and enjoyment in learning physics. The items were adapted from the

Marsh, Craven et al. (1999) and Arens et al. (2011) studies which measured students' affect in other curriculum areas. An example is, "I enjoy doing PHYSICS work". The maximal reliability for this factor was .92.

3.4.2.3. English competence

Like competence in physics, this factor is the cognitive component of English ASC. The items were also adapted from the Marsh (1992) ASDQ instrument, for students to rate their sense of competence in English. An example is, "I get good marks in ENGLISH". The maximal reliability for this factor was .90.

3.4.2.4. English affect

This factor is the affective component of English ASC which measured students' interest and enjoyment in English. The items were adapted from the Marsh, Craven et al. (1999) and Arens et al. (2011) studies. An example is, "I like ENGLISH". The maximal reliability for this factor was .93.

3.4.2.5. Math competence

This factor is the cognitive component of math ASC. The items used for students to rate their sense of competence in math were adapted from the Marsh (1992) ASDQ instrument. One item in this factor was negatively-worded: "I do badly in MATHEMATICS tests". Responses to this item were reverse-coded during the analysis, to associate higher scores with more favorable responses. The maximal reliability for this factor was .93.

3.4.2.6. Math affect

This factor is the affective component of math ASC, relating to students' personal interest and enjoyment in learning math. The four items forming this factor were adapted from Marsh, Craven et al. (1999) and Arens et al. (2011). An example is, "I enjoy

MATHEMATICS classes". However, two of the items were negatively-worded: "I hate MATHEMATICS" and "I do not like to learn MATHEMATICS". The responses to these items were reverse-coded during the analysis to associate higher scores with more favorable responses. As with the negatively-worded item in the math competence factor, these items did not pose any problem. Removing these negatively-worded items from the analyses yielded similar results, so they were retained in the instrument. The maximal reliability for this factor was .94.

3.4.2.7. Achievement at Time 1

Students' achievement scores in physics, English and math were collected from the school database at time 1, prior to the survey data collection. The scores were reflective of formative assessment, administered by the school to assess students' understanding of the topics taught in each curriculum domain: physics, English and math. Each assessment totalled 20 marks, assessing about two to three topics in each assessment. On average, students spent about 30 minutes doing questions under settings which were similar to that of formal assessments (e.g., silent conditions with no discussion among students, strict time duration to complete the assessment under the invigilation of their subject teachers), during curriculum time. Students' achievement at time 1 was the average score of three assessments in each curriculum domain, recorded as percentages.

3.4.2.8. Achievement at Time 2

Students' achievement scores at time 2 in physics, English and math were also collected from the school database, about two months after the survey data were collected. These scores were reflective of summative assessment, administered by the school at the end of the school semester, to assess students' general understanding of each curriculum domain: physics, English and math. The total achievement score for each domain was 100 marks, assessing about six to ten topics depending on the domain. On average, students spent about two hours doing the assessment questions in one sitting, under settings which were similar to those of formal assessments (e.g., silent conditions with no discussion among students, strict time duration to complete the assessment under the invigilation of teachers in the school). These assessment scores represented the students' achievement at time 2.

3.4.3. Procedure

Procedures of the research were approved by the university's ethics committee. Informed consent was obtained from the school and the parents of the students before data collection. As suggested by the school, the survey was uploaded onto the school online portal and was open to all secondary 1 students for one week, as the students were used to completing surveys in such a manner. A briefing was given to the students by their teacher, to explain to them what the survey was about and what they were expected to do. Students who were willing to participate in the study keyed in their responses online. A computer laboratory manned by laboratory assistants, who were briefed about the details of the survey, was made available for students' use. As the survey items were simply worded, no student had difficulty understanding the survey, when enquired.

3.4.4. Statistical Analyses

Confirmatory factor analyses (CFAs) and structural equation modeling (SEM) were used to test the adequacy of the hypothesized models to the data in the study (Brown, 2006). All statistical analyses were conducted with Mplus V7 (Muthén & Muthén, 1998-2015). A CFA model was performed separately for each factor. These analyses sought to determine how well each latent factor was defined by the observed ASC variables. In testing the CFA models, we first inspected the factor structure of a measurement model

(Model 1) with 24 variables forming six ASC factors: competence and affect factors for physics, English, and math, respectively (see Figure 3.1). Each variable was allowed to load on to one factor only. Secondly, we inspected Model 2 (see Figure 3.2), in which the competence and affect items of the respective domains pertained to a single ASC factor (i.e., physics, English, and math ASCs). We compared Model 1 with Model 2. SEM was performed to evaluate the relationships among the ASC factors and student achievement; examining the structural paths of student achievement at time 1 to the six ASC factors which then led to subsequent achievement at time 2 (Model 3). Following common practice, goodness of fit for the models was evaluated using a variety of fit indices: Root Mean Square Error of Approximation (RMSEA; Browne & Cudeck, 1993) at its 90% confidence interval (90% CI), the Comparative Fit Index (CFI; Bentler, 1990), and the Tucker-Lewis Index (TLI; Tucker & Lewis, 1973). Using Hu and Bentler's (1999) guidelines for evaluating overall model fit, an RMSEA $< .06$ is typically considered to reflect an adequate model fit to the observed data and TLI and CFI indices of $> .95$ indicated an acceptable and excellent model fit to the observed data, respectively. In addition, we reported chi-square test statistics and carefully inspected the parameter estimates. As the analyses also compared models that were nested, a chi-square difference test was used to evaluate goodness-of-fit between models.

We initially accounted for the non-independence of students nested within classes by adjusting the standard errors using a sandwich estimator (Muthén & Muthén, 1998-2015). However, the standard error resulting from these analyses were unstable and untrustworthy due to the small number of clusters (12 classes). We then conducted the analyses without adjusting the standard errors due to clustering. Since similar conclusions were found with the two modelling strategies, the results reported in the study were based on single-level analysis without adjusting for the clustering.

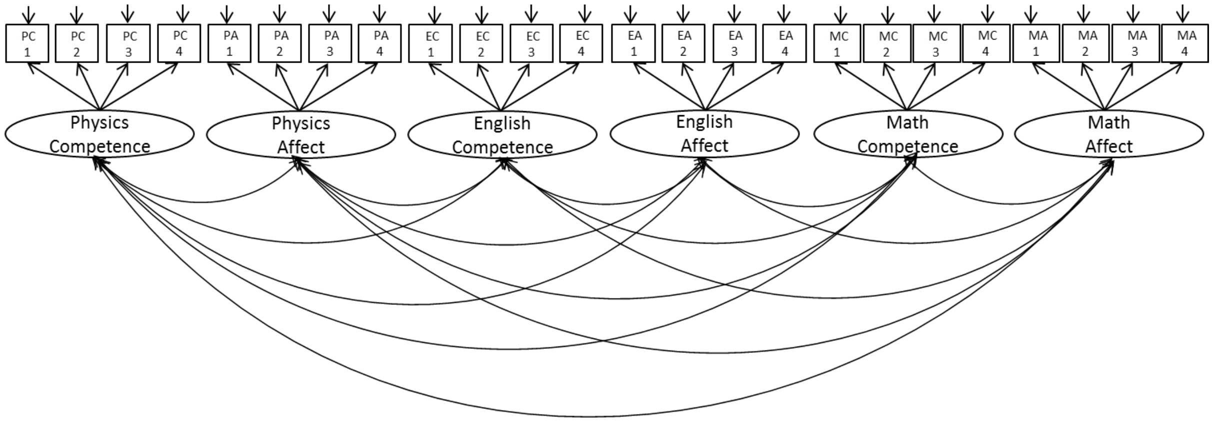

Figure 3.1. CFA Model 1: The proposed confirmatory factor analysis model to test the ability of 24 ASC variables (PC1-4; PA1-4; EC1-4; EA1-4; MC1-4; MA1-4) to form six distinct ASC factors, whereby the self-concept of each domain is separated into its competence and affect components.

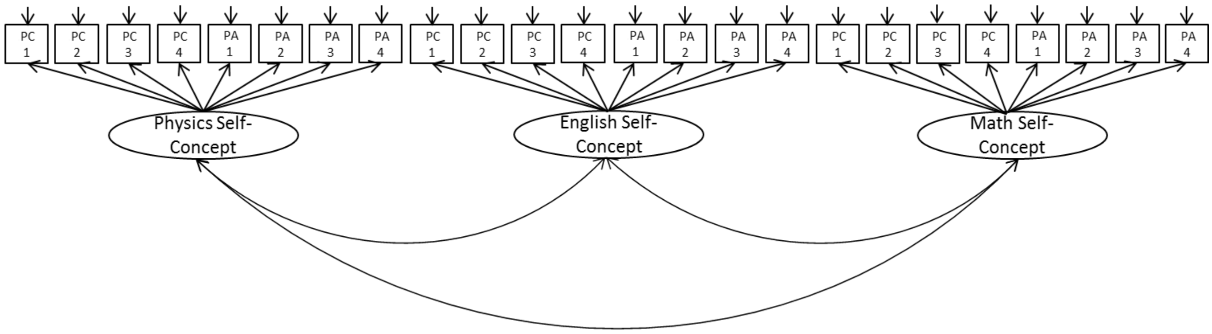

Figure 3.2. CFA Model 2: The proposed confirmatory factor analysis model in which the 24 ASC items (PC1-4; PA1-4; EC1-4; EA1-4; MC1-4; MA1-4) were loaded onto three self-concept factors, whereby the competence and affect components of the self-concept in each domain was combined into one factor.

In order to further test some of the hypotheses, a mediation analysis was conducted. More specifically, to determine the independent contribution of each ASC factor for achievement in each curriculum domain, a multiple mediator model that included all six ASC factors as potential mediators for all three curriculum domains (i.e., physics, English and math) were investigated (Figure 3.3). The effect of achievement at time 1 on all six ASC factors (potential mediators) was tested by regressing the ASC factors onto achievement at time 1 (a_i). Similarly, the relationship between ASC factors and achievement at time 2 was explored by regressing achievement at time 2 onto achievement at time 1 and ASC factors (b_i). Finally, the significance of the product-of-coefficients (a_ib_i) was tested by computing the confidence intervals (CIs) for the mediated effect on the basis of the distribution-of-product method. For a factor to satisfy the criteria for mediation, the 95% CIs for the product-of-coefficients (a_ib_i) must not include zero.

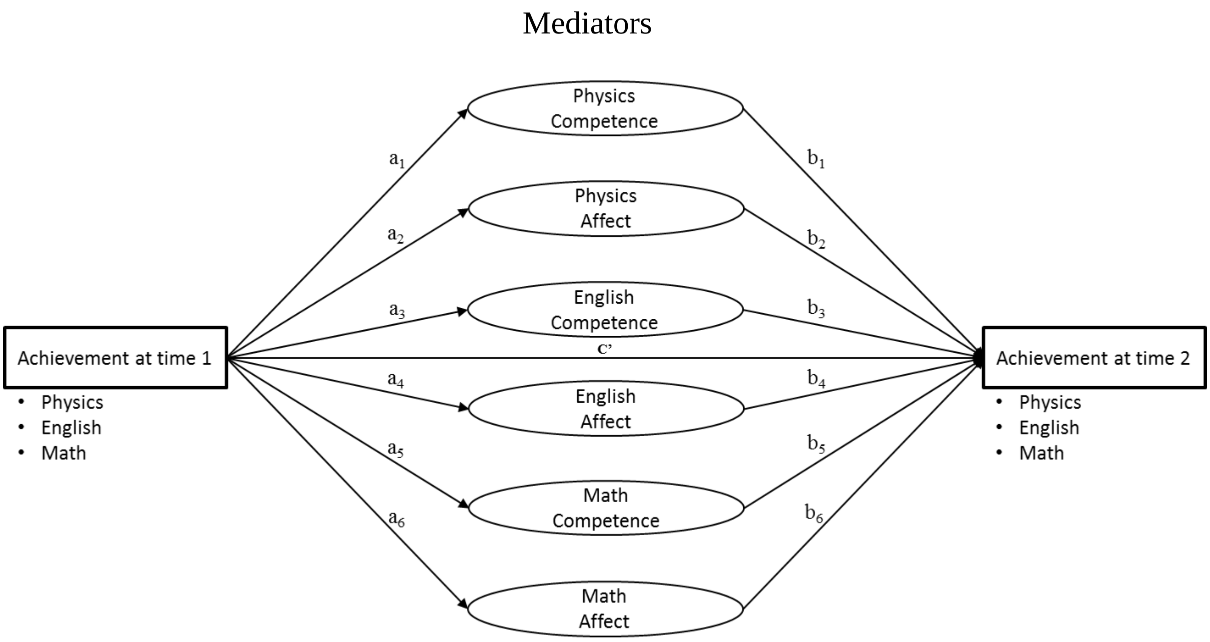

Figure 3.3. Multiple Mediator Model for physics, English and math achievement. C' = Direct effect (including mediator).

The analytical sample consisted of 275 students who were followed through three time waves (i.e., achievement at time 1, ASC survey, and achievement at time 2). The amount of missing data was relatively small (average coverage = 98%). Full information maximum likelihood estimation (FIML), available in Mplus V7 (Muthén & Muthén, 1998-2015) was used to account for the missing data in each model. FIML utilizes all available information during the estimation process and provides consistent and efficient parameter estimates (Enders, 2010). Finally, we tested the hypotheses on ASC by studying the factor correlations and structural paths of the SEM model. According to Kline (2011), a sample size of at least 200 is required for SEM, so the sample size of N = 275 was adequate for the analyses. The following segments provide the details of the results.

3.5. Results

3.5.1. Descriptive Statistics

Descriptive statistics and the bivariate correlations among all the 24 variables measuring ASCs were reported in Table 3.1. The mean of the variables ranged from 3.13 to 5.00. Since the students were nested within classes, we calculated the intraclass correlations (ICCs); that is, the amount of variance explained by class membership. The ICCs ranging from .01 to .08 for the 24 ASC variables indicated that students' responses to the ASC variables were independent of the classes they were in. The ICCs for the six achievement variables were: .08 and .45 for physics achievement at time 1 and time 2, respectively. Similar values were .09 and .41 for math achievement, and .57 and .54 for English achievement.

Table 3.1

Descriptive Statistics and Bivariate Correlations for the Measured Variables of the Study

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1. PC1	-																							
2. PC2	.83***	-																						
3. PC3	.88***	.81***	-																					
4. PC4	.76***	.70***	.73***	-																				
5. PA1	.70***	.62***	.69***	.69***	-																			
6. PA2	.66***	.58***	.69***	.66***	.83***	-																		
7. PA3	.47***	.37***	.44***	.55***	.66***	.62***	-																	
8. PA4	.63***	.58***	.64***	.60***	.76***	.78***	.59***	-																
9. EC1	.02	.00	.03	.12*	.02	.02	.09	-.06	-															
10. EC2	.07	.04	.05	.07	-.07	-.07	-.01	-.07	.71***	-														
11. EC3	-.03	-.08	-.03	.01	-.01	-.02	.00	-.13*	.75***	.62***	-													
12. EC4	-.01	.03	.03	.00	-.12*	-.09	-.05	-.08	.65***	.78***	.57***	-												
13. EA1	-.04	-.12	-.09	-.05	-.02	.00	.07	-.05	.71***	.69***	.68***	.62***	-											
14. EA2	-.13*	-.12*	-.10	-.05	-.04	-.02	.09	-.09	.62***	.51***	.59***	.53***	.69***	-										
15. EA3	-.10	-.15*	-.07	-.04	-.04	-.01	.07	-.10	.71***	.65***	.71***	.61***	.88***	.75***	-									
16. EA4	.01	-.04	.04	.08	.06	.08	.16**	-.02	.62***	.53***	.60***	.45***	.72***	.69***	.76***	-								
17. MC1	.42***	.43***	.34***	.32***	.30***	.30***	.15*	.29***	-.20***	-.21***	-.17**	-.19***	-.21***	-.17**	-.26***	-.11	-							
18. MC2	.50***	.47***	.40***	.38***	.32***	.28***	.15*	.29***	-.13*	-.12*	-.13*	-.16**	-.19**	-.18**	-.23***	-.10	.81***	-						
19. MC3	.37***	.32***	.29***	.28***	.20***	.19***	.09	.19***	-.17**	-.18**	-.17**	-.21***	-.18**	-.20***	-.22***	-.06	.67***	.69***	-					
20. MC4	.50***	.54***	.42***	.41***	.35***	.35***	.17**	.34***	-.14*	-.13*	-.15*	-.21***	-.24***	-.23***	-.27***	-.15*	.78***	.84***	.70***	-				
21. MA1	.34***	.29***	.28***	.28***	.38***	.37***	.20***	.29***	-.18**	-.22***	-.14*	-.25***	-.14*	-.16*	-.17*	-.04	.74***	.68***	.62***	.69***	-			
22. MA2	.29***	.24***	.23***	.29***	.34***	.37***	.24***	.30***	-.07	-.18**	-.04	-.22***	-.07	-.06	-.06	.05	.64***	.64***	.55***	.62***	.82***	-		
23. MA3	.26***	.20***	.19**	.21***	.34***	.31***	.23***	.28***	-.21***	-.27***	-.14*	-.32***	-.14*	-.11	-.17**	-.06	.64***	.59***	.62***	.60***	.84***	.74***	-	
24. MA4	.17**	.15*	.15*	.13*	.26***	.29***	.15*	.20***	-.18**	-.34***	-.16**	-.31***	-.18**	-.10	-.17**	-.05	.54***	.51***	.57***	.54***	.78***	.72***	.81***	-
Mean	3.33	3.46	3.13	3.72	3.97	3.88	4.40	4.36	4.13	3.44	3.95	3.48	4.30	4.46	4.30	4.39	4.77	4.45	4.53	4.32	4.91	4.75	5.00	4.91
SD	1.31	1.30	1.44	1.16	1.25	1.30	0.97	1.23	1.12	1.27	1.18	1.38	1.18	1.09	1.19	1.12	1.31	1.26	1.20	1.33	1.18	1.15	1.29	1.26
ICC	.01	.02	.01	.01	.01	.02	.05	.04	.06	.06	.04	.02	.06	.05	.08	.04	.02	.07	.07	.06	.05	.06	.07	.03

Note. $N = 275$. All variables were measured on a 1-6 Likert scale; PC1-4 = physics competence variables 1 to 4; PA1-4 = physics affect variables 1 to 4; EC1-4 = English competence variables 1 to 4; EA1-4 = English affect variables 1 to 4; MC1-4 = math competence variables 1 to 4; MA1-4 = math affect variables 1 to 4; *SD* = standard deviation; ICC = Intraclass correlations;
*$p < .05$, **$p < .01$, ***$p < .001$

An examination of the bivariate correlations in Table 3.1 showed that the correlations between ASC variables within the same curriculum domains were all positive and statistically significant ($p < .001$). Furthermore, results showed that, among the three domains, the minimum correlations were found between the competence and affect variables of the ASC whereas the highest correlations were found between competence or affect components of the ASC variables within the same curriculum domain. Specifically, in the physics domain, the Pearson correlation coefficients ranged from $r = .37$ (between PC2: physics competence and PA3: physics affect) to $r =.88$ (between physics competence items: PC1 and PC3), for the English domain, the correlations ranged from $r = .45$ (between EC4: English competence and EA4: English affect) to $r = .88$ (between English affect variables: EA1 and EA3), and for the math domain, the correlations ranged from $r = .51$ (between MC2: math competence and MA4: math affect) to $r = .84$ (between math competence variables: MC2 and MC3 and between math affect variables: MA1 and MA3).

3.5.2. Confirmatory Factor Analyses

All the CFA models converged to proper solutions. Table 3.2 presents the model fit statistics. Model 1 which tested the ability of 24 ASC variables to form six distinct ASC factors (competence and affect as separate ASC factors for physics, English, and math domains) resulted in an adequate fit (χ^2 (234) = 464.84, $p < .001$, RMSEA = .06, 90% CI = [.05, .07], CFI = .96, TLI = .95). On the other hand, Model 2 which treated competence and affect together as a single factor for ASC for each of the three curriculum domains (i.e., physics, English and math) did not result in an acceptable fit (χ^2 (246) = 1107.27, $p < .001$, RMSEA = .11, 90% CI = [.11, .12], CFI = .83, TLI = .81). This finding justified the separation of the competence and affect components of ASC.

Table 3.2
Model Fit Statistics for Confirmatory Factor Analyses and Structural Equation Modelling

Model	χ^2	*df*	*p*	RMSEA	90% CI	CFI	TLI
Model 1	464.84	234	<.001	.06	.05 to .07	.96	.95
Model 2	1107.27	246	<.001	.11	.11 to .12	.83	.81
Model 3 (SEM Model)	825.05	357	<.001	.07	.06 to .08	.94	.93

Note. *N* = 275. χ^2 = Chi square test; *df* = degrees of freedom; RMSEA = root mean square error of approximation; CI = confidence intervals for RMSEA; CFI = comparative fit index; TLI = Tucker-Lewis index.

Table 3.3 shows the correlations between the six ASC factors and achievement at time 1 and time 2. As shown in Table 3.3, the factor correlations were reasonable, ranging from r = -.31 (p < .001) (between English competence and math achievement at time 2 and between English affect and math achievement at time 2) to r = .88 (p < .001) (between English competence and English affect).

Table 3.3
Factor Correlations among Academic Self-Concepts and Achievements

	1	2	3	4	5	6	7	8	9	10	11	12
1. Physics Competence	--											
2. Physics Affect	.80***	--										
3. English Competence	.02	-.04	--									
4. English Affect	-.10	-.01	.88***	--								
5. Math Competence	.53***	.37***	-.21***	-.27***	--							
6. Math Affect	.33***	.41***	-.24***	-.16*	.81***	--						
7 Physics Achievement 1	.55***	.39***	-.11*	-.15*	.39***	.26***	--					
8. English Achievement 1	-.03	-.10	.36***	.30***	-.11*	-.14*	.06	--				
9. Math Achievement 1	.39***	.27***	-.25***	-.26***	.67***	.49***	.51***	.05	--			
10. Physics Achievement 2	.59***	.43***	-.11*	-.16*	.44***	.27***	.73***	.21***	.54***	--		
11. English Achievement 2	.05	-.08	.47***	.35***	-.11*	-.18**	.19**	.73***	.06	.37***	--	
12. Math Achievement 2	.44***	.31***	-.31***	-.31***	.77***	.57***	.55***	.09	.81***	.67***	.11	--

Note. *N* = 275. Competence and affect factors of students' academic self-concept were measured in the curriculum domains of physics, English, and math; Achievement 1 = student achievement at time 1 in the curriculum domain; Achievement 2 = student achievement at time 2 in the curriculum domain; * p < .05; ** p < .01; *** p < .001.

3.5.2.1. Correlations among ASC factors

An inspection of the correlations among the six ASC factors (competence and affect factors for physics, English, and math) showed a high positive and statistically significant Pearson correlation coefficient between the competence and affect factors within each domain. The respective correlations between competence and affect factors for physics, English, and math domains were rs = .80, .88, and .81 (p <.001), respectively (see Factor Correlations in Table 3.3).

Across domains, we observed statistically non-significant Pearson correlation coefficients between physics and English ASCs for both the cognitive and affective components with r = .02 (p = .78) between physics and English competence, r = -.01 (p = .87) between physics and English affect, r = -.10 (p = .15) between physics competence and English affect and r = -.04 (p = .57) between physics affect and English competence. On the other hand, negative and statistically significant correlations were found between English and math ASCs, also for both the cognitive and affective components: r = -.16 (p < .05) between English and math affect, r = -.21 (p < .001) between English and math competence, r = -.27 (p < .001) between English affect and math competence, and r = -.24 (p < .001) between English competence and math affect. Negative and statistically significant correlations between English and math ASCs were also found in past studies (e.g., Marsh et al., 2012; Yeung, Kuppan, Foong et al., 2010).

However, across-domain, a different trend was found between physics and math ASCs, indicating interrelatedness between the physics and math domains. Specifically, we found positive and statistically significant correlations between physics and math competence as well as between physics and math affect (r = .53, p < .001 and r = .41, p <.001, respectively). Positive and statistically significant correlations were also observed between physics competence and math affect ($r = .33$, $p < .001$) as well as between physics affect and math competence ($r = .37$, $p < .001$).

3.5.2.2. Correlations among achievement variables

An inspection of the correlations among the six achievement variables showed high positive and statistically significant correlations within the same domains: $r = .73$ ($p < .001$) for both physics achievement at time 1 and time 2 and English achievement at time 1 and time 2, and r = .81 ($p < .001$) between math achievement at time 1 and time 2. However, across domains that were dissimilar, statistically non-significant Pearson correlations were found between English and math achievements at time 1 ($r = .05$, $p = .36$), English achievement at time 1 and math achievement at time 2 ($r = .09$, $p = .12$), English achievement at time 2 and math achievement at time 1 ($r = .06$, $p = .31$), and between English and math achievements at time 2 ($r = .11$, $p = .07$). In contrast, non-constant pattern was seen for the physics and English domains. For example, physics and English achievements at time 1 had a statistically non-significant correlation ($r = .06$, $p = .30$) whereas correlations between physics and English achievements at other times were positive and statistically significant (i.e., $r = .19$, $p < .01$ between physics achievement at time 1 and English achievement at time 2, $r = .21$, $p < .001$ between physics achievement at time 2 and English achievement at time 1, and $r = .37$, $p < .001$ between physics and English achievements at time 2). However, a different trend was found across-domain between physics and math, indicating interrelatedness between the domains, as shown by the high positive and statistically significant correlations with correlation across domain ranging from $r = .51$ ($p < .001$) (between physics and math achievements at time 1) to $r = .67$ ($p < .001$) (between physics and math achievements at time 2).

3.5.2.3. Correlations between achievement variables and ASC factors

Inspecting the correlations between ASC factors and achievement variables showed positive and significant correlations between achievement and ASCs within domains with a Pearson correlation coefficient larger for the competence component than that of the affect component of ASC within each domain. For example, for physics ASC, the correlations with physics achievement at time 1 and time 2 were .55 and .59, respectively ($p < .001$) for physics competence and .39 and .43, respectively ($p < .001$) for physics affect. Similarly, the correlations with English achievement at time 1 and time 2 were .36 and .47, respectively ($p < .001$) for English competence and .30 and .35, respectively ($p < .001$) for English affect and those with math achievement at time 1 and time 2 were .67 and .77, respectively ($p < .001$) for math competence and .49 and .57, respectively ($p < .001$) for math affect.

Across domains, the results showed that the correlations between achievement and ASCs were consistently negative and statistically significant across dissimilar domains (e.g., English and math), and positive and statistically significant across similar domains (e.g. physics and math). For example, the correlations with English achievement at both time 1 and time 2 were -.11 ($p < .05$) for math competence, and -.14 and -.18, respectively ($p < .05$) for math affect. Similarly, the correlations with math achievement at time 1 and time 2 were -.25 and -.31, respectively ($p < .001$) for English competence and -.26 and -.31, respectively ($p < .001$) for English affect. In contrast, for similar or interrelated domains, the correlations with physics achievement at time 1 and time 2 were .39 and .44, respectively (p < .001) for math competence, and .26 and .27, respectively (p < .001) for math affect. Similarly, the correlations with math achievement at time 1 and time 2 were .39 and .44, respectively (p < .001) for physics competence, and .27 and .31, respectively ($p < .001$) for physics affect. The associations between physics and English domains, however, were not consistent, with correlations which were either statistically non-significant or negative and statistically significant. For example, the correlations with physics achievement at time 1 and time 2 were statistically non-significant for English competence (*r*s = -.11, $p = .09$) but negative and statistically significant for English affect (*r*s = -.15 and -.16, $p < .05$, respectively), and the correlations with English achievement at time 1 and time 2 were statistically non-significant for physics competence ($r = -.03$, $p = .59$ and $r = .05$, $p = .42$, respectively) and physics affect ($r = -.10$, $p = .11$ and $r = -.08$, $p = .19$, respectively).

3.5.3. Structural Equation Modeling

Model 3 (see Figure 3.4), the SEM model which tested the structural paths between achievements and the six distinct ASC factors, had a good fit (χ^2 (357) = 825.05, $p < .001$, RMSEA = .07, 90% CI = [.06, .08], CFI = .94, TLI = .93). As seen in Figure 3.4, the factor loadings for Model 3 were all acceptable (all > .50), with the lowest being .69 and the highest being .96.

3.5.3.1. Structural paths within the same domains

The SEM results indicated that students with high achievement in a domain at time 1 also had high achievement in the domain at time 2, as shown from the positive and statistically significant structural paths from achievement at time 1 to achievement at time 2 (see paths on the extreme right of Figure 3.4) within each domain ($\beta = .41$, $p < .001$; $\beta = .55$, $p < .001$, and $\beta = .41$, $p < .001$, respectively for physics, English and math). Due to the known influence of pre-existing knowledge on future achievement within domains, this result of achievement at time 1 positively predicting the achievement at time 2 of the same domain was expected.

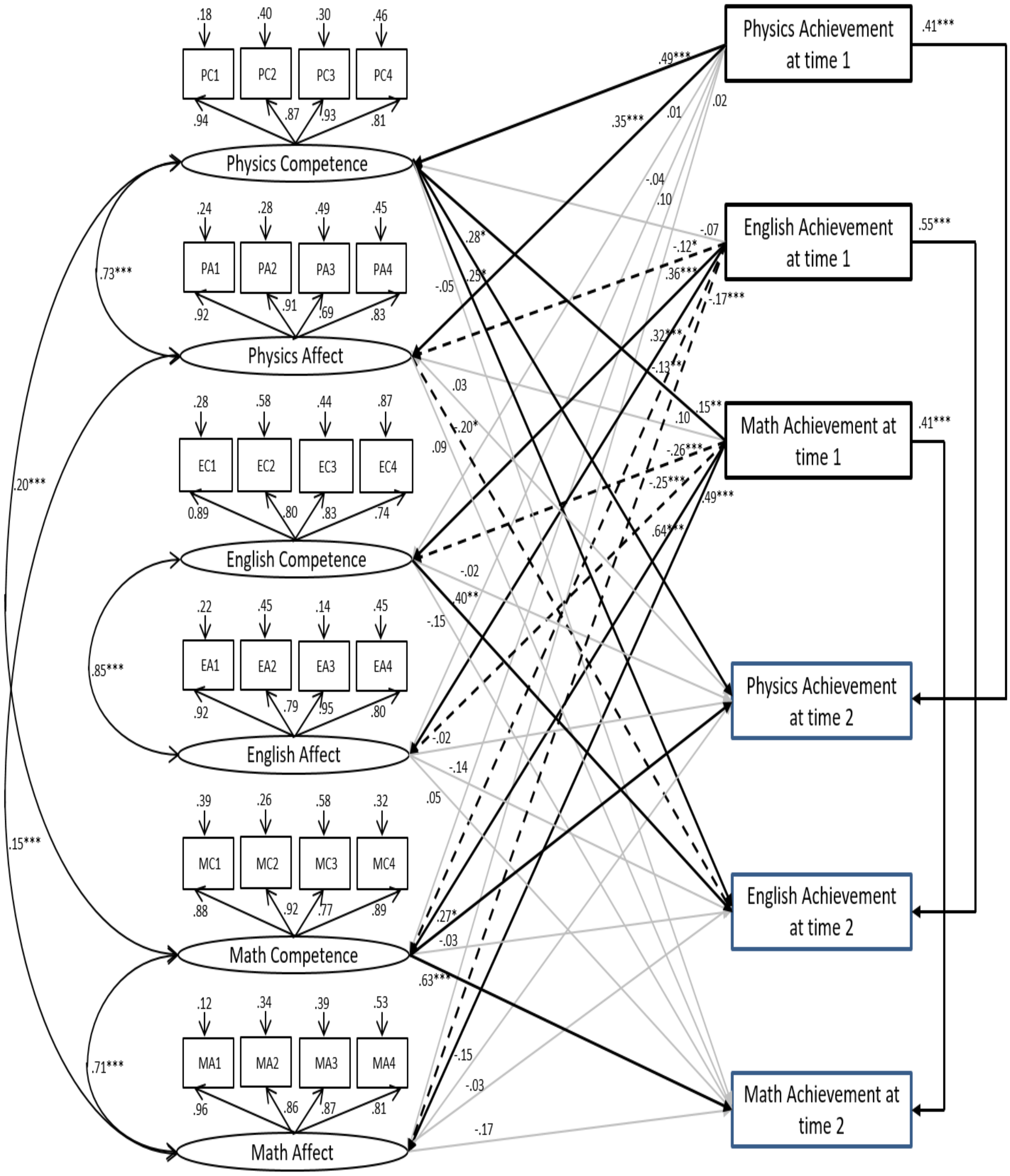

Figure 3.4. SEM Model: Model 3, the results of the structural equation modelling testing the structural paths from achievement at time 1 to academic self-concept to subsequent achievement at time 2 for each domain and across domains, as well as the residual correlations between the academic self-concept factors. For the structural paths, black solid arrows (→) represent positive, statistically significant paths, black dashed arrows (- →) represent negative, statistically significant paths, and grey arrows (→) represent non-significant paths. The figure also displayed the residual variances and the factor loadings of each of the 24 ASC variables (PC1-4; PA1-4; EC1-4; EA1-4; MC1-4; MA1-4). All factor loadings were positive and statistically significant (p < .001). *p < .05, **p < .01, ***p < .001.

Similarly, the results implied that students' achievement at time 1 in a domain positively predicted their ASCs in the same domain, as shown from the positive and statistically significant structural paths from achievement at time 1 to ASC factors within the same domains, for both competence ($\beta = .49$, $p < .001$; $\beta = .36$, $p < .001$, and $\beta = .64$, $p < .001$, respectively for physics, English and math) and affect ($\beta = .35$, $p < .001$; $\beta = .32$, $p < .001$, and $\beta = .49$, $p < .001$, respectively for physics, English and math). From these results, we could also see a consistent pattern of path coefficients for competence being larger than those for affect, within each domain. The results of the chi-square difference test showed that the path coefficient from physics achievement to physics competence was significantly larger than that from physics achievement to physics affect ($\Delta\chi^2$ (1) = 9.92, $p = .002$). Similarly, the path coefficient from math achievement to math competence was significantly larger than that from math achievement to math affect ($\Delta\chi^2$ (1) = 18.26, $p < .001$). In contrast, the path coefficient from English achievement to English competence was comparable to that from English achievement to English affect ($\Delta\chi^2$ (1) = 1.03, $p = .311$). The results indicated that achievement was a stronger predictor of competence than affect for physics and math domains.

Examining the paths from the ASC factors to achievement at time 2 within the same domains showed that competence positively predicted subsequent achievement within domains ($\beta = .28$, $p < .05$; $\beta = .40$, $p < .01$, and $\beta = .63$, $p < .001$, respectively for physics, English and math). The same could not be said for affect as, none of the structural paths from affect to achievement at time 2 within the same domain was statistically significant ($\beta = .03$, $p = .79$; $\beta = -.14$, $p = .25$, and $\beta = -.17$, $p = .08$, respectively for physics, English and math). Moreover, the results of the chi-square difference test showed that the path coefficient from physics competence to physics achievement was comparable to the path coefficient from physics affect to physics achievement ($\Delta\chi^2$ (1) = .95, *p* = .311). In contrast, the path coefficient from English competence to English achievement was significantly larger than that from English affect to English achievement ($\Delta\chi^2$ (1) = 5.12, $p = .024$) and the path coefficient from math competence to math achievement was significantly larger than that from math affect to math achievement ($\Delta\chi^2$ (1) = 14.51, $p < .001$). The results indicated that competence was a stronger predictor of achievement than affect for English and math domains.

3.5.3.2. Structural paths across domains

Examining the structural paths from achievement at time 1 to ASC factors across domains showed different trends. Specifically, physics achievement did not predict the ASCs of other domains, as indicated by the statistically non-significant structural paths from physics achievement at time 1 to both English and math ASCs ($\beta = .01$, $p = .92$ and $\beta = -.04$, $p = .53$ for English competence and affect, respectively and $\beta = .10$, $p = .08$ and $\beta =.02$, $p = .79$ for math competence and affect, respectively). In the same manner, English achievement did not predict physics competence but negatively predicted physics affect, math competence and math affect, as indicated by the statistically non-significant structural path from English achievement at time 1 to physics competence ($\beta = -.07$, $p = .18$) and the negative and statistically significant structural paths to physics affect, math competence and math affect ($\beta = -.12$, $p < .05$, $\beta = -.13$, $p < .01$, $\beta = -.17$, $p < .001$, respectively). On the other hand, math achievement positively predicted physics competence, but did not predict physics affect, for the structural path from math achievement at time 1 to physics competence was positive and statistically significant ($\beta = .15$, $p < .01$) but statistically non-significant to physics affect ($\beta = .10$, $p = .14$). In contrast, math achievement negatively predicted English ASCs, as denoted by the negative and statistically significant structural paths from math achievement at time 1 to both English competence and English affect ($\beta = -.26$, $p < .001$, $\beta = -.26$, $p < .001$, respectively).

Examining the structural paths from ASCs to achievement at time 2 across domains showed that the competence component of ASC in two domains positively predicted subsequent achievement in another domain, indicating that the domains may be similar in one way or another. For example, physics competence positively predicted subsequent English achievement and math competence positively predicted subsequent physics achievement, as indicated by the positive and statistically significant structural paths from physics competence to English achievement at time 2 ($\beta = .25$, $p < .05$), and from math competence to physics achievement at time 2 ($\beta = .27$, $p < .05$), respectively. Apart from these two cases, competence in a domain did not predict subsequent achievement in any other domain as shown by the statistically non-significant across-domain structural paths from English competence to physics and math achievements at time 2 ($\beta = -.02$, $p = .88$, and $\beta = -.15$, $p = .12$, respectively), from physics competence to math achievement at time 2, and from math competence to English achievement at time 2 ($\beta = -.05$, $p = .65$ and $\beta = -.03$, $p = .84$, respectively). Similarly, the affective component of ASCs in all the three curriculum domains did not predict the subsequent achievement in any domain, as implied by the statistically non-significant across-domain structural paths from physics affect to English and math achievements at time 2 ($\beta = -.20$, $p = .07$ and $\beta = .09$, $p = .34$, respectively), from English affect to physics and math achievements at time 2 ($\beta = -.02$, $p = .89$ and $\beta = .05$, $p = .57$, respectively), and from math affect to physics and English achievements at time 2 ($\beta = -.15$, $p = .19$ and $\beta = -.03$, $p = .77$, respectively).

3.5.3.3. Multiple mediator model

In the multiple mediator model that included all the ASC factors, only the competence component of ASC in each domain was significantly associated with subsequent achievement within the same domain. As shown in Table 3.4, physics competence (a_ib_i = .11, 95% CI = [.01, .22], English competence (a_ib_i = .12, 95% CI = [.03, .21], and math competence (a_ib_i = .37, 95% CI = [.22, .52]) satisfied the criteria for mediation for physics achievement, English achievement and math achievement, respectively. Therefore, competence is a mediator of achievement in the same domain.

3.6. Discussion

3.6.1. Findings of Hypotheses

3.6.1.1. Hypothesis 1: Distinctiveness of the cognitive and affective components of ASCs

The findings provided strong support for Hypothesis 1. The CFA results of the study showed that Model 1 which separated the cognitive and affective components of ASC had a better model fit than Model 2 which combined the cognitive and affective components of ASC within domains. Further evidence showing the distinctiveness between the cognitive and affective components of ASCs was also reflected in the correlations that were less than .90 between the competence and affect variables of ASCs within the same domains. Apart from distinctiveness, the results of the correlations also showed that students' sense of competence and affect may function differently, as larger correlations were found between student achievement and competence than affect, within the same domains. Other evidences of the difference in the functionality of competence and affect were found in the results of the chi-square test (which assessed the difference between the path coefficients of competence and affect within the same domains).

Table 3.4

Multiple Mediation Analyses for Physics, English, and Math Achievement

	a_i			b_i			Direct Effect c'			Indirect Effect a_i*b_i			Total Effect $c = \sum_{i=1}^{6} a_i*b_i + c'$		
	Coeff	SE	*p*	Coeff	SE	*p*	Coeff	SE	*p*	Coeff	*p*	95% CI	Coeff	*p*	95% CI
Physics Achievement															
Physics competence	.06	.01	< .001	1.99	.92	.031				.11	.039	.01 to .22			
Physics affect	.04	.01	< .001	.25	.91	.785				.01	.786	-.06 to .08			
English competence	.00	.01	.923	-.15	.99	.882				.00	.935	-.00 to .00			
English affect	-.00	.01	.529	-.13	.98	.891				.00	.894	-.01 to .01			
Math competence	.01	.01	.079	1.68	.82	.040				.02	.189	-.01 to .05			
Math affect	.00	.01	.793	-1.14	.88	.193				-.00	.797	-.02 to .01			
							.35	.04	< .001				.49	< .001	.41 to .56
English Achievement															
Physics competence	-.02	.01	.181	.89	.44	.043				-.01	.257	-.04 to .01			
Physics affect	-.03	.01	.031	-.80	.45	.075				.02	.176	-.01 to .05			
English competence	.08	.01	< .001	1.61	.51	.002				.12	.007	.03 to .21			
English affect	.07	.01	< .001	-.57	.50	.252				-.04	.259	-.10 to .03			
Math competence	-.03	.01	.006	-.08	.40	.840				.00	.841	-.02 to .03			
Math affect	-.04	.01	.001	-.12	.43	.773				.01	.775	-.03 to .04			
							.46	.04	< .001				.56	< .001	.49 to .63
Math Achievement															
Physics competence	.02	.01	.010	-.36	.80	.654				-.01	.659	-.04 to .02			
Physics affect	.01	.01	.137	.78	.81	.335				.01	.417	-.01 to .03			
English competence	-.03	.01	< .001	-1.33	.85	.118				.04	.144	-.01 to .09			
English affect	-.03	.01	< .001	.47	.84	.570				-.01	.575	-.06 to .03			
Math competence	.08	.01	< .001	4.47	.83	< .001				.37	< .001	.22 to .52			
Math affect	.05	.01	< .001	-1.41	.81	.082				-.08	.090	-.16 to .01			
							.38	.04	< .001				.70	< .001	.63 to .77

Note. $N = 275$. Coeff = unstandardized linear regression coefficient; SE = standard error; CI = confidence interval.

Achievement was found to be a stronger predictor of competence than affect for physics and math, and competence was found to be a stronger predictor of subsequent achievement for English and math, as indicated by the results of the chi-square test which showed that although the structural paths from student achievement at time 1 to competence and affect within domains were both positive and statistically significant for each domain, the structural path to competence was significantly stronger than that to affect, within the physics and math domains. Similarly, although the structural paths from competence and affect to achievement at time 2 within domains were both positive and statistically significant for each domain, we found significantly stronger structural paths from competence than from affect to achievement at time 2 within the English and math domains.

3.6.1.2. Hypothesis 2: Domain specificity of ASCs

The findings strongly supported Hypothesis 2, showing that students' ASC is domain specific for both components of ASC, which means that students could clearly differentiate their competence and affect in various curriculum domains. The results of the study showed positive and statistically significant correlations between ASCs, between students' achievement, as well as between ASCs and achievement within domains and either statistically non-significant or negative and statistically significant correlations across dissimilar domains, for both the competence and affect components of ASC. For example, we found that English competence had a negative and statistically significant correlation with math competence, which was in line with other ASC studies (Arens et al., 2011; Marsh & Craven, 2006). On the other hand, English competence and physics competence had a statistically non-significant correlation, which was similar to the findings of Möller et al. (2006) and Yeung, Kuppan, Foong et al. (2010). Domain specificity was also found in the affective component of ASC, which was consistent with the findings of Marsh, Craven et al. (1999) for English and math domains. English affect had a negative and statistically significant correlation with math affect and statistically non-significant correlation with physics competence, showing similar findings with the competence component of English ASC. All in all, the results showed that students who have a strong ASC in a domain may not have a strong ASC in a dissimilar domain, for both competence and affect. It is important to note that the results for domain specificity were correlative in nature and should not be interpreted with a sense of causality.

3.6.1.3. Hypothesis 3: Reciprocal effects model (REM)

The findings provided strong evidence of REM for the competence component of ASC (Hypothesis 3), showing that students with high achievement in a domain are more likely to have high competence in the domain, which would most likely lead to high subsequent achievement in the same domain. This was supported by the consistent results of positive and statistically significant structural paths (in both the SEM and multiple mediator models) from achievement at time 1 to competence and to achievement at time 2 within the three curriculum domains of physics, English, and math. This finding is consistent with past findings (Marsh & Craven, 2006; Marsh & O'Mara, 2008). However, the REM was not supported for the affective component of ASC. While all the structural paths from achievement at time 1 to affect were positive and statistically significant within each domain, the structural paths from affect to achievement at time 2 were all statistically non-significant, as observed in the results of both the SEM and multiple mediator models. This indicated that high achievement in a domain may predict students' affect for the domain, but their affect for the domain would not predict their future achievement in the domain. In summary, the results showed support for Hypothesis 3, but only for the competence component of ASC, not affect.

3.6.1.4. Hypothesis 4: Internal/external frame of reference (I/E) model.

The I/E model posits that students' ASCs are formed as a result of simultaneous internal and external comparisons that they engage in, which are different but connected frames of reference (Marsh, 1986). The results of the correlations and structural path analyses generally showed support for the I/E model (Hypothesis 4) in the English and math domains, with a few exceptional findings. For example, whereas earlier research (e.g., Marsh, 1986, 2007; Marsh, Byrne et al., 1999; Marsh & Shavelson, 1985; Möller et al., 2006) found high positive and statistically significant correlations between verbal and math achievements, the results showed that English and math achievements had statistically non-significant correlations, at both time 1 and time 2, as well as across times. Extending to the physics domain, physics and English achievements had positive and statistically significant correlations across times and at time 2, but had a statistically non-significant correlation at time 1. The disparity in results with existing literature for the correlations between achievements in different domains could be attributed to the high-ability students in the sample. Their achievement in English did not seem to be related to their achievement in a dissimilar domain (i.e., math) for these high achieving students, except for similar domains such as physics and math, which we found high positive and statistically significant correlations between their achievements, and between physics and English achievements. These results were similar to other studies with high-ability students (e.g., Kadir et al., 2013; Plucker & Stocking, 2001; Yeung, Kuppan, Foong et al., 2010).

The positive and statistically significant correlations found between students' competence within the same domains and negative and statistically significant correlations found between students' competence of dissimilar domains (i.e., English and math competence) were similar to past studies supporting the I/E model (Marsh et al., 2012). Similarly, positive and statistically significant correlations were found between achievement and competence within the same domains but not across dissimilar domains, which are in line with the findings of Möller et al. (2006). The same trend was observed for affect. The SEM results (see Figure 3.4) showed further support for the I/E model. Within each domain, achievement had a positive influence on competence, as predicted by the external frame of reference (Möller et al., 2006). Across dissimilar domains, English achievement had a negative and statistically significant path to math competence and math achievement had a negative and statistically significant path to English competence, showing support for the internal frame of reference. These results were consistent with Möller et al. (2009). The same trend was observed for affect. At this juncture, we can conclude that the results of the correlations analyses and SEM showed support for Hypothesis 4, for both competence and affect of dissimilar domains such as English and math.

Extending the research to include the physics domain, the results were somewhat different. Firstly, the correlations between physics and English ASCs, for both competence and affect, were statistically non-significant. The SEM results showing that physics achievement did not predict the ASCs (both competence and affect) of the other domains (i.e., English and math) were similar to the findings of Möller et al. (2006). One possible explanation for this might be that the students participating in the study were newly introduced to the physics domain in secondary 1, as compared to English and math which were introduced at preschool or kindergarten. Their achievement in this new learning domain was not secured enough to exert any sizeable effect on outcomes that were not directly relevant. Another interesting finding was that English achievement had no effect on physics competence (as shown by the statistically non-significant structural path in Figure 3.4, which was in contrast with the negative and statistically significant path found in Möller et al., 2006), but had a negative effect on physics affect (as shown by the negative and statistically significant path from English achievement to physics affect). All in all, the results with the physics domain showed some, but not full support for the I/E model.

3.6.1.5. Hypothesis 5: Reciprocal internal/external frame of reference model (RI/EM)

Similar to past studies (Möller et al., 2011), we observed positive and statistically significant structural paths from achievement at time 1 to competence, and to subsequent achievement at time 2 within the same domains but not across dissimilar domains such as English and math. For example, the structural path from English achievement to math competence was negative and statistically significant (as predicted by RI/EM) but from math competence to English achievement at time 2, the structural path was statistically non-significant. Similarly, the structural path from math achievement to English competence was negative and statistically significant (as predicted by RI/EM) but from English competence to subsequent math achievement at time 2, the structural path was statistically non-significant. These results with the English and math domains were similar to the findings of Möller et al. (2011, 2014).

Different trends were observed for the relations between physics and the English domains. More specifically, the structural paths from physics achievement to English competence and to subsequent physics achievement were all statistically non-significant, and was similar to the structural path from English achievement to physics competence but the structural path from physics competence to subsequent English achievement at time 2 was positive and statistically significant. This is an interesting finding, as structural paths across different domains were expected to be either statistically non-significant or negative and statistically significant. A look at the Secondary 1 physics curriculum showed that there were topics which involved the understanding of text (e.g., topic of heat), and problems requiring students to explain scientific phenomena and provide reasoning for their answers (which required the skills of the English domain). Due to the variety of physics problems presented in the Grade 7 physics curriculum and the fact that physics was newly introduced, the newly-formed physics competence of the students could also predict their subsequent English achievement. More tests need to be done to investigate this possibility.

As the affective component of ASC did not support the REM within domains, it did not support the RI/EM. For example, all the structural paths from physics, English, and math affect to the corresponding achievement at time 2 were statistically non-significant, showing no reciprocal effects from affect to subsequent achievement within domains. Across domains, we found patterns that were similar to the competence component of ASC. For example, the structural path from English achievement at time 1 to math affect was negative and statistically significant (in line with the RI/EM prediction for competence), and the structural path from math affect to English achievement at time 2 was statistically non-significant. Similarly, the structural path from math achievement at time 1 to English affect was negative and statistically significant (as predicted by RI/EM for competence) and the structural path from English affect to math achievement at time 2 was statistically non-significant. Extending the research to include the physics domain, we found similar trends whereby the structural path from English achievement at time 1 to physics was negative and statistically significant and the structural path from physics affect to English achievement at time 2 was statistically non-significant. However, no RI/EM trend as observed as indicated by the statistically non-significant structural paths from physics achievement at time 1 to English affect to physics achievement at time 2. In summary, the results showed some support for the RI/EM in Hypothesis 5 for the English and math domains, but only for competence and not affect.

3.6.1.6. Hypothesis 6: Big-fish-little-pond-effect (BFLPE)

As expected, the BFLPE (Hypothesis 6) was not observed, most probably because of the similar ability-level of the students in each class. The low ICCs of all ASC variables showed that students' ASCs for both competence and affect in all the domains were independent of the class they were in, showing no support for the BFLPE. Another reason for this could be the fact that the students were in Grade 7 and were relatively new to the school and their peers, and that the classes were not streamed into ability-levels as yet (i.e., all the students were considered to be of similar high ability as they met the cut-off achievement criteria for school enrolment). Studies could investigate the BFLPE of high-ability schools at higher grades to see if this effect is prominent, especially at Grades 9 and 10, after ability streaming. Another extension to this study could be to include the achievement and ASC data of a group of students of similar ability but in an average school, to test for the BFLPE.

3.6.1.7. Hypothesis 7: Interrelatedness of self-concept in similar domains

Another interesting finding from the study is that while there were contrast effects across domains (achievement in one domain adversely affecting ASC in another domain) as shown by the I/E model, there were weaker contrast effects between two similar domains (physics and math) such that achievement in math did not adversely affect physics competence. The results were similar to that of Möller et al. (2006), that physics and math were considered similar (but distinct) domains that did not show support for the I/E model (Hypothesis 4). Correlations between variables as shown in Table 3.3 and the structural paths as shown in the SEM model in Figure 3.4 showed that whereas English and math had strong contrast effects, physics and math were more interrelated. This means that students who felt competent in math were more likely to feel competent in physics as well, but unlikely to feel competent in English. Likewise, if they had an interest in math, they were more likely to have an interest in physics than in English. This finding was supported by the results of the correlations analyses which showed that whereas English competence had a negative and statistically significant correlation with math competence, math competence had a positive and statistically significant correlation with physics competence. The results were similar for the affective component of ASC, where there was a positive and statistically significant correlation between physics affect and math affect. In contrast, there was a negative and statistically significant correlation between English affect and math affect and a statistically non-significant correlation between English affect and physics affect. Positive correlations between physics and math ASCs provided some support for Hypothesis 7, that is, the interrelatedness between physics and math domains.

The interrelatedness hypothesis was further supported by the results of the SEM model (see Figure 3.4). Students who achieved well in math also had a high physics competence and students who had a high math competence also achieved well in physics, as shown by the positive and statistically significant structural paths from math achievement at time 1 to physics competence and from math competence to physics achievement at time 2. As math skills are a requirement to do physics, the physics domain shares common features with the math domain, so students' achievement in math has a positive influence on physics competence, and math competence has a positive influence on physics achievement. However, the same claim could not be made for physics. Physics achievement had no influence on math competence and physics competence had no influence on subsequent math achievement at time 2, as denoted by the statistically non-significant structural paths from physics achievement at time 1 to math competence, and from physics competence to math achievement at time 2. An explanation for this could be the focus of the Grade 7 physics curriculum which may or may not require high-level mathematical skills. There was also no influence of achievement on students' affect in the physics and math domains. For example, physics achievement was shown to have no influence on math affect and math achievement did not predict physics affect. The statistically non-significant structural paths from physics affect to math achievement and from math affect to physics achievement also showed no cross-domains influence of affect on achievement for physics and math. Therefore, the interrelatedness (Hypothesis 7) between the physics and math domains were prominent only for the cognitive component of ASC, similar to the findings of Marsh et al. (2015), leading to the conclusions that physics and math were interrelated and considered as “near domains” on the ASC continuum as opposed to the contrast effects of dissimilar domains (e.g., English and math) on the opposite end of the ASC continuum.

3.6.2. Implications of Findings

Treating the cognitive and affective components of ASC as separate and distinct (Hypothesis 1) will make ASC intervention strategies more specific, thus increasing the chances of success. For example, if the targeted educational outcome is to improve student achievement, then intervention strategies should focus on enhancing students’ sense of competence in the domain (cognitive component of ASC). As shown in the study, affect did not predict achievement in any domain, so enhancing students’ liking for a domain may not improve their achievement in the domain. Even though we did not test the association of the affective component of ASC with other educational outcomes in this study, there were studies which have found associations between affect and outcomes such as academic and career aspirations (e.g., Guo, Marsh et al., 2015; Guo, Parker et al., 2015; Marsh, Craven et al., 1999; Yeung et al., 2012; Yeung, Kuppan, Foong et al., 2010). Therefore, if the intended outcome is to enhance students’ academic and career aspirations in that domain, then intervention strategies should focus more on enhancing students’ interest (affective component of ASC) in that domain. If the concern is a holistic development of the students, then neither ASC component should be ignored.

A practical implication for the domain specificity (Hypothesis 2) finding is that intervention strategies to improve student ASC in certain domains should target those specific domains for optimal results. For example, if students’ English achievement needs to improve, then the intervention strategies should focus on improving the students’ sense of competence in English instead of math or other unrelated or dissimilar curriculum domains.

A practical implication for the REM (Hypothesis 3) finding is that intervention strategies for continual student achievement in a domain should focus on improving students' sense of competence (more than affect) in that domain. Motivation strategies such as informative teacher feedback and skill-enhancing learning tasks that are appropriate for students' learning level are some of the intervention that can be put in place in schools to give students opportunities to experience success in the learning tasks, thus increasing their sense of competence in the domain (Craven, Marsh, & Debus, 1991). Strategies that just target on improving students' interest or affect in a domain, may not have sustainable effects for achievement and may not even be successful in improving student achievement in that domain, at least not in the short term (Yeung et al., 2012).

The findings of Hypotheses 4, 5, and 6 imply that students engage in dimensional and social comparisons which contribute to the development of their ASCs in each curriculum domain (Möller & Marsh, 2013). Educators and parents should be aware that achievement in a domain could have negative consequences for ASCs in a dissimilar domain, so teacher and parental support for students are critical. Educators and parents should also be mindful that students' learning environment play an important role in the development of students' ASC which, in turn, affect their achievement and other educational outcomes. Sending students to high-ability schools could lead to the BFLPE which could be detrimental to students' ASC.

The findings of the interrelatedness of curriculum domains (Hypothesis 7) imply that intervention strategies could target improving achievement in similar domains which could, in turn, enhance ASCs in different, but similar domains. This is especially useful for developing positive ASCs in curriculum domains that are newly introduced at later years of school life (i.e., secondary school or high school), such as physics. For example, when schools focus on intervention strategies to improve students' math achievement, not only could it enhance students' math competence and math affect, it could also enhance the students' competence in another interrelated curriculum domain such as physics. Similarly, intervention strategies that focus on enhancing students' competence in math, could not only positively affect their subsequent math achievement, but also their subsequent achievement in another interrelated domain such as physics. Results on interrelated curriculum domains are crucial to determine effective curriculum intervention strategies that could benefit more than one domain.

Although a single study is not sufficient to draw conclusions, the findings in the study did summarize the findings from numerous disparate studies each testing a fraction of the hypotheses. The findings may be generalized to samples with similar backgrounds and could be explored more deeply across a bigger, more diverse sample as part of future studies to establish more generalizable conclusions.

3.6.3. Limitations and Future Directions

It is important to note some limitations in the present study, and how it could be further improved. First, the relatively small sample of 275 students as compared to other ASC studies and the fact that the students came from one school and of a specific ethnicity is a clear limitation. Therefore, definitive conclusions should not be drawn from this sample. However, the objective of replicating and reinforcing the ASC hypotheses was well-achieved and the implications and conclusions were reasonable, although they could be explored further for generalizations.

Second, given the sample comprised students of Chinese ethnicity whose first language was English, it is not representative of most schools in Singapore and around the world. It could be that the hypotheses were replicable only with student samples with characteristics similar to the present sample. Several studies that have shown how students of different cultures report their ASC differently, affecting the mean scores of their ASC (e.g., Arens et al., 2014; Tanzer, Simm, & Marsh, 1997). However, the relations of ASC with achievement scores and other factors were still similar. This is seen from the findings which were comparable to other cross-cultural ASC studies. Therefore, whereas the mean ASC ratings may not be generalized to other schools, the hypotheses could hold true, even in schools with a diverse racial mix.

Third, even though ‘science’ is the domain that is commonly studied by Grade 7 students around the world, the specific branch of science taught to the Grade 7 students in this study was ‘physics’. Past studies have shown that other branches of science such as chemistry, biology and earth science may vary in context from ‘physics’ and thus have different relations with languages and math (e.g., Marsh et al., 2015), possibly giving us slightly different results. However, the main finding that we highlighted in this study is that curriculum domains which share similar features would have higher interrelatedness than curriculum domains that do not share similar features. However, if students were surveyed right after other topics such as biology or chemistry which do not involve mathematical concepts and calculations (i.e., they do not share similar features with math), the results may be very different from the findings for the physics domain demonstrated in this study. Future studies could explore the possible interrelatedness between chemistry and math or between biology and languages such as English for Grade 7 students (the starting point of science module separation), and study their relations over time. Such studies could also investigate whether different topics in the science curriculum would display similar patterns or alter the conclusion.

The fourth limitation is the small gap in time (i.e., five months) between the three time waves of data collection of achievement scores and ASCs. This was because the school had a tight schedule and time constraint was a major factor for the administration of surveys and liaising with researchers. A more effective longitudinal study would be to follow the students over a period of years in their school life. This could also add strength to the tests of reciprocal effects and domain interrelatedness over time.

The fifth limitation is that the only educational outcome measured in this study was achievement. The results showed that the affective component of ASC did not predict achievement. We know from past studies that affect positively predicts other educational outcomes (e.g., Guo, Marsh et al., 2015; Yeung et al., 2012). Future studies could include measurements of a range of educational outcomes to investigate whether affect would predict other educational outcomes such as engagement and career aspirations.

The sixth limitation is about data collection. We could strengthen the results of the hypotheses (i.e., I/E, RI/EM) by collecting another wave of ASC data after students' achievement at time 2. Nevertheless, the set of achievement and ASC data collected for the study were sufficient for us to test the hypotheses.

Finally, the seventh limitation is the strong assumption of a direct link between ASC and outcomes such as achievement. In reality, achievement will not occur without effective instruction. Hence ASC, including a positive belief of potential to achieve (competence) and a positive interest in learning (affect), are just the learners' attitudes which serve as the prerequisites for effective learning and desirable outcomes. The cognitive features involved in the teaching and learning processes that bring about achievement outcomes have not been accounted for in this analysis, and should be considered in future research. For example, future studies can consider students' ASC over time and the way teaching processes and the curriculum may affect their ASC development in each domain.

All in all, the test of all seven hypotheses in ASC research has provided compelling evidence supporting the rigor of the existing ASC theories and models. However, as some of the findings may not be generalized to all student populations, more extensive studies in more schools need to be carried out in future. In spite of the limitations, the reliability of the present data was high, and most results were in line with proven theories and existing models from the literature. The results of this study are especially important because it captured young students' early ASC of physics. Most Grade 7 students around the world do only general science at this age and would develop physics ASC only when they are older, as physics is usually introduced to students at Grade 9 and beyond. The results of this study are valuable to researchers planning to conduct longitudinal studies on students' ASC in physics, and for studies investigating the challenges students face in the physics curriculum and achievement. Future studies can look into students' ASC of physics and other domains over time and the processes in the curriculum that may affect their ASC development.

3.7. Conclusion

The findings of this investigation showed that most hypotheses were accepted with this unique group of students, showing the replicability and applicability of ASC models across students of varying backgrounds, nationalities and cultures. Most of the findings in the study were similar to those of past ASC studies, with some interesting findings that extended previous research. The results of the study have shown that the cognitive and affective components of the student ASCs were separable and distinct from each other and both competence and affect were domain specific. The REM, I/E model, and RI/EM formulated in other ASC studies were supported, but only for the cognitive component of ASC, and mainly for dissimilar domains of English and math. The BFLPE was not observed in this study which comprised participants of similar academic ability. Last but not least, we found interrelatedness between the math and physics curriculum domains, and less contrast effects between the physics and English domains than between the English and math domains. As reflected in the results of the study, students' ASCs positively predicted educational outcomes and have no negative cross-domains effects. Therefore, the main recommendation is that schools should look into intervention strategies to enhance both components of student ASCs, as each component is distinct and predicts specific outcomes of education. Also, certain curriculum domains should be given careful attention as the achievement in those domains could positively affect the ASC as well as the achievement in other similar domains. If enhanced in an appropriate manner, ASC can positively influence educational outcomes in a specific domain beyond the effects of previous achievement and academic performance, so for optimal effects in improving school learning outcomes, ASC intervention strategies should be extensively implemented in schools.

CHAPTER 4: STUDY 2 -

School Achievement and Science Motivation during the Primary-Secondary School Transition

4.1. Preface

Whereas Study 1 focused on self-concept as a motivational variable, Study 2 includes a range of other motivational variables and included students' achievement scores upon entry to secondary education. Specifically, Study 2 extends the correlation analysis in Study 1 by including students' Grade 6 national examination achievement (cognitive) and more motivational variables (non-cognitive) in physics (i.e., self-efficacy, inquiry, engagement, educational aspiration) in the analysis. The findings will help us understand the relations between student achievement and motivational variables during the transition period between primary and secondary school. The purpose is to (1) show the suitability of Grade 7 as a starting point for intervention strategies related to physics, (2) highlight the motivational variables that are most associated to student achievement, and (3) guide intervention strategies to enhance student motivation in learning physics.

4.2. Abstract

This study investigates the relations between students' achievements and their motivation towards physics before and after transition from primary to secondary school. Using a sample of Secondary 1 (Grade 7) students in Singapore (N = 272), confirmatory factor analysis was conducted on survey responses to: self-concept, self-efficacy, interest, inquiry, engagement, and educational aspiration, about learning physics. Achievement scores in science, English, and math used in the analysis included the Primary School Leaving Examination (PSLE) scores in Grade 6, first-term test scores and mid-year examination scores in Grade 7. Achievements in PSLE were found to be weakly correlated with the attitude factors. Grade 7 math and physics test scores had significant relations with physics motivation, and such relations tended to grow stronger over time. Math achievement also had significant relations with physics motivation, which also tended to grow stronger over time. The results imply that students who did not do well in science in primary school (PSLE) could cultivate positive attitudes towards physics in secondary school, given proper instruction in the curriculum domains. The first secondary school year is therefore a critical time to have a curriculum that can enhance positive attitudes towards physics, which may also subsequently lead to better achievements.

4.3. Introduction

The relation between student achievement and motivation has been of interest to many researchers in education and psychology. Much research has been done on students' achievements and motivational attitudes towards school as well as in several curriculum domains like language, mathematics, and science (e.g., Abu-Hilal, 2000; Forbes, Kadir, & Yeung, 2017; Guo, Marsh, Parker, Morin, & Yeung, 2015; Phan, Ngu, Yeung, 2016; Willson, 1983; Yeung, Craven, & Kaur, 2012; Yeung, Kuppan, Foong et al., 2010; Yeung, Kuppan, Kadir, & Foong, 2010). While some researchers have found that achievement and motivational attitudes are significantly correlated (e.g., Marsh & Yeung, 1998; Weinburgh, 1995; Yeung, Kuppan, Kadir et al., 2010), others have suggested that they are weakly correlated or not correlated at all (e.g. Abu-Hilal & Atkinson, 1990). These conflicting findings showed that the relations between achievements and motivational attitudes are inconclusive. In this study, I investigated the relations between different types of achievement and students' motivational attitudes towards Physics in a range of motivational aspects.

There has been much discussion about researchers' measurements of achievements and motivational attitudes. The relation between achievement and motivational attitudes depends on the types of test scores used as achievement indicators (Abu-Hilal & Atkinson, 1990). For example, Marsh and Yeung (1998) found that self-concept and motivational attitude measures related more strongly to achievement in the form of school grades than to standardized tests. According to Abu-Hilal (2000), some researchers have dealt with items that do not measure motivational attitudes effectively, resulting in varying findings.

In the area of science, Willson (1983) did a meta-analysis of 43 studies and found that while most studies reported positive correlations between attitude to, and achievement in, science, 75% of the correlation coefficients analyzed were less than .30 in magnitude. In his study, he found that at elementary levels, correlations were generally quite low until Grade 6. The low correlations suggest that there is little relation between science attitudes and achievement. By Grade 6, motivational attitudes of students tend to be more clearly established, as children who like science do better in it and have more positive attitudes towards it. Willson's study showed a consistent .2-.3 correlation between achievement and attitude scores in grades 6 to 10. At Grade 12, the correlation drops to .04. His study showed that students, after a certain grade, have more or less developed their attitudes, and achievement is less likely to influence their motivational attitudes towards science.

Willson's findings have sparked my inquisitiveness to find out how young students in Singapore of this generation would fare in the achievement-attitude correlation coefficients. Even though there have been studies of achievement-attitude correlations in the science domain, not much has been done to study achievement-attitude relations in physics – an area of science that many students find challenging. In this study, I investigated the relation between students' achievements in a national examination taken at the end of the final year of primary school (Grade 6), and achievements within the first five months of Secondary 1 (Grade 7) to their motivational attitudes towards physics. Apart from examining whether past achievements are related to students' motivation in physics, I also examined whether there was a correlation between students' achievements in different curriculum domains and their motivational attitudes towards physics. The achievement measures used in my study were standardized physics, English, and math test scores and I measured attitudes towards physics in six motivational factors - self-concept, self-efficacy, interest, inquiry, engagement, and educational aspiration. The results would provide a better understanding of the relations between students' achievement in three curriculum domains during the primary and secondary school transition, and their relations with motivational attitudes in physics at Grade 7. The findings would enable educators to optimize self-concept and attitude enhancement effects from a multidimensional perspective. Since I measured students' attitudes using a range of motivational factors, I will refer to students' attitudes as motivation for the rest of the chapter. I hypothesize that students' science achievement in the first year of secondary school is more highly correlated to their science motivation in secondary school than the science achievement at the end of their primary school year.

4.3.1. Relations between achievement and motivation in science

There has been much discussion about researchers' measurements of achievements and motivational attitudes. In the area of science, Willson (1983) did a meta-analysis of 43 studies and found that while most studies reported positive correlations between attitude to, and achievement in, science, 75% of the correlation coefficients analyzed were less than .30 in magnitude. In his study, he found that at elementary levels, correlations were generally quite low until Grade 6. The low correlations suggest that there is little relation between science attitudes and achievement. By Grade 6, motivational attitudes of students tend to be more clearly established, as children who like science do better in it and have more positive attitudes towards it. Willson's study showed a consistent .2 to .3 correlation between achievement and attitude scores in grades 6 to 10. At Grade 12, the correlation drops to .04. His study showed that students, after a certain grade, have more or less developed their attitudes, and achievement is less likely to influence their motivational attitudes towards science.

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4.3.2. Significance of Motivation towards Physics

The significance of investigating students' motivation towards the science curriculum probably stems from the increasing evidence of the rapid decline in students' aspirations in pursuing science-related higher education and careers, even for students who achieve well in science (National Science Board, 2014). With less students pursuing higher studies related to science, there is a decline in scientific literacy in the general populace, as well as a shortage of science teachers (Bawden, 2015; O'Leary, 2001), resulting in a vicious cycle generating greater problems such as threats to the health industry, national security and global competitiveness (National Science Board, 2014, 2015). Physical science, or physics, seems to be the least appealing to students (Smithers & Robinson, 2007). Osborne, Simon, and Collins (2003) suggested that physics is least popular most probably because "the relevance of the physical sciences was difficult for students to identify" (p. 1061). Students' poor attitudes towards physics have also been explained by the task difficulty associated with the subject (Smithers & Robinson, 2007).

Physics is notorious for being a difficult subject to learn where there is a need for a lot of effort to be expended, yet the resulting grades may not always be favorable (Angell, Guttersrud, Henriksen, & Isnes, 2004; Prow, 2003). Since past achievement has been shown to influence motivation when both achievement and motivational variables are measured within a specific domain (e.g., Marsh & Yeung, 1998; Weinburgh, 1995), it is likely that because physics is challenging, and students' academic scores reflect this, that they have a poor attitude towards physics and are consequently less likely to choose to study the subject. In the study, I attempted to explicate whether this is true, using the achievements of a sample of high-ability students in Singapore.

4.3.3. Achievement and Science Motivation

The relation between achievement and motivational attitudes depends on the types of test scores used as achievement indicators (Abu-Hilal & Atkinson, 1990), and the effectiveness of the items used to measure motivational attitudes (Abu-Hilal, 2000), resulting in varying findings. In our study, I measured student achievement during the primary-secondary school transition by using the results of a national examination taken by students at the end of their primary school year (i.e., Grade 6) and the results of their school grades taken at two time-points during the first five months of their secondary school year (i.e., Grade 7), in three curriculum domains: science, English and math. In Singapore, these are the norms when measuring achievement during primary-secondary school transition. I measured attitudes towards science in six motivational factors - self-concept, self-efficacy, interest, inquiry, engagement, and educational aspiration - as these were the factors targeted by the school during the period of our study. *Self-concept* is students' sense of their science competence, *self-efficacy* is students' underlying belief of their ability to manage the work processes in science learning, *interest* reflects students' liking of science, *inquiry* is students' deeper internalization of scientific endeavors, *engagement* reflects students' attentiveness during science lessons, and *educational aspiration* is students' desire to pursue further education in science in the future.

4.3.3.1. Self-concept

In a general sense, academic self-concept can be defined as one's perception of one's general ability in school (Shavelson, Hubner, & Stanton, 1976). In this study, self-concept refers to students' perception of their academic ability in science (sense of competence). When students believe in their academic ability in science, they are more likely to have high achievement in science (Kadir, Yeung, & Diallo, 2017), which would further enhance their sense of competency in science (Marsh & Craven, 2006). The vast studies conducted on academic self-concept over the past four decades have highlighted the benefits of self-concept on academic outcomes such as classroom behaviors, school achievement, educational and career aspirations, and academic choices (Kadir & Yeung, 2016). Educators need to be aware of the importance of enhancing students' self-concept or sense of competence in a curriculum domain and provide learners with the best learning environment to optimize their potential.

4.3.3.2. Self-efficacy

Self-efficacy is an important motivational attitude in student learning. Bandura (1997) defines self-efficacy as "beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (p. 3). It is often taken as a representation of one's sense of competence in a specific domain and relative to a specific standard. According to Bandura, self-efficacy plays a central self-regulatory role of human agency and it can influence the choice of activities, effort and persistence, resilience to adversity, and vulnerability to stress and depression. Empirical studies have supported that students with high self-efficacy are more inclined to put in an effort, engage in tasks, and therefore have higher achievement (e.g., Schunk, Pintrich, & Meece, 2008). Evidence has also shown that this applies also to students in Singapore where the present data were collected (see Lau, Liem, & Nie, 2008; Lau & Roeser, 2002; Liem, Lau, & Nie, 2008).

4.3.3.3. Interest

In the science curriculum, the significance of investigating students' interest in learning science lies with an increasing evidence of a decline in students' interest in pursuing scientific endeavors such as furthering education in science and choosing science related careers (National Science Board, 2014; Office of the Chief Scientist, 2012) Interest should be the focus of motivation because it reflects the positive potential of human learning behaviors (Ryan & Deci, 2000). Students who have interest in learning are likely to persist in learning tasks and activities in the long term (Elliot & Church, 1997).

4.3.3.4. Inquiry

Inquiry is a highly valued construct but least explored in modern science education. In Hofstein and Lunetta (2004), inquiry refers to diverse ways in which scientists study the natural world, propose ideas, and explain and justify assertions based upon evidence derived from scientific work. They elaborated that it also refers to more authentic ways in which learners carry out investigations and, in the process, sense the spirit of science. Learners who are motivated in science learning would most likely desire to carry out investigations to find solutions to science problems themselves than being told the answers.

4.3.3.5. Engagement

Engagement is another key contributor of quality learning and school success (Skinner, Furrer, Marchand, & Kindermann, 2008). Students' engagement in learning tasks keeps them involved in academic work and active in learning tasks that require continuous effort, determination, and perseverance, and is crucial for achievement outcomes (Fredricks, Blumenfeld, & Paris, 2004). There are diverse ways of conceptualizing engagement and different researchers may have different views as to how engagement should be defined. In the current study, I focused on the behavioral aspect of engagement and defined it in terms of students' attention and participation in the learning tasks and classroom activities.

4.3.3.6. Educational aspiration

Among various science domains, physics seems to be the least attractive, and is probably the most problematic area, evidenced by the consistently fewer number of students taking physics courses than other sciences such as chemistry and biology (Durrani, 1998; Gillibrand, Robinson, Brawn, & Osborn, 1999). Measuring students' desire to pursue physics education in the future is a good indication of the effectiveness of the physics lessons. Educators could identify the issues in physics learning and the processes that could be in place to inspire students to pursue physics learning.

4.4. Method

4.4.1. Participants

Secondary 1 students (Grade 7) from a secondary school in Singapore participated in this study (*N* = 272; median age = 13 years old; 40% boys). All the students were of Chinese ethnicity, which is the largest ethnic group of Singapore (>75%). Although the students were Chinese in origin, they were effectively bilingual and over 50% of them spoke mostly English at home. All government schools in Singapore uses English as the medium of instruction and all students start formal English lessons in pre-school. The students were selected for admission into the participating school by merit of their PSLE results, where only students with an aggregate score of about 240 (out of 300) and above would be admitted to this reputable school. There were also students with lower PSLE scores who were admitted to the school for other achievements such as sports excellence, but they were very few. The mean PSLE score for this sample was 242.85 (SD = 7.36).

4.4.2. Material and Procedure

Students' motivation was measured by asking students to complete a survey in which they were asked to rate on a Likert scale of 1 to 6 on six motivational factors: self-concept, self-efficacy, interest in physics, inquiry into physics problems, engagement during physics lessons and aspiration to pursue studies related to physics (Appendix 4A). The items were randomized in the survey form. Background information such as age, gender, and language background were also collected. The variables were:

4.4.2.1. Self-Concept

Four items adapted from the Marsh (1992) *Academic Self-Description Questionnaire* (ASDQ) instrument were used to ask students about the cognitive component of their self-concept (i.e., sense of competence) in physics. Even though most schools teach secondary 1 science as an integration of the three main branches of science, physics, chemistry and biology, this school adopted a modular approach to science, where physics was taught separately from chemistry and biology, so students were able to differentiate their self-concept in physics from their self-concept in other areas of the curriculum. An example is: "I am good at physics".

4.4.2.2. Self-Efficacy

The self-efficacy factor assessed students' belief in their ability to master specific skills taught in physics classes. Five items adapted from the Pintrich, Smith, Garcia, and McKeachie (1993) *Motivated Strategies for Learning Questionnaire* (MSLQ) were used.

An example is: “I can do almost all the work in physics if I do not give up”.

4.4.2.3. Interest

This is the affective component of physics self-concept. The four items used for this factor were from Yeung, Kuppan, Foong et al. (2010) who adapted them from the Marsh, Craven, and Debus (1999) study, Elliot and Church’s (1997) measure of personal interest and enjoyment and the Yeung, Chow, Chow, Luk, & Wong (2004) measure of students’ affect in other curriculum areas. A total of four items were used to ask students about their interest in physics. An example is: “I enjoy doing physics”.

4.4.2.4. Inquiry

As inquiry is central to the science curriculum in Singapore and students are expected to engage in scientific inquiry, this measure was adapted from Yeung, Kuppan, Kadir et al. (2010). Three items asked students the extent to which they engaged themselves in scientific inquiry when solving physics problems and participating in physics learning tasks. An example is: “I do not like to be told answers to PHYSICS problems; I prefer to work through the answers myself”. The other two items were reversed, asking students the extent to which they refused to engage in inquiry (Appendix 4A).

4.4.2.5. Engagement

The measure of individual engagement in physics was based on students’ report of their attention and participation in physics classes. The five items used to measure this factor was adapted from Steinberg, Lamborn, Dornbusch, and Darling (1992). An example is: “I listen carefully when the teacher explains something about physics”.

4.4.2.6. Educational Aspiration

The measure of education aspiration asked students about their aspiration to learn physics at advanced levels in the future. The four items for this measure were adapted from Yeung and McInerney (2005). An example is: “If I could do exactly what I wanted, I would like to study physics in future”.

4.4.2.7. Achievement

The measure of achievement comprised three sets of test scores from: (1) a nation-wide standardized test called the Primary School Leaving Examination (PSLE), (2) a term test, and (3) a mid-year examination. The following provides details of each test.

(1) PSLE scores. This is a standardized test (national examination) taken by all students in Singapore at the end of Grade 6 (final year in primary school). This nation-wide standardized test assesses students in four main areas, namely, science, English, math and mother tongue (Chinese, for the sample in this study). Students were rated by PSLE examiners on a scale of six grades for each area of assessment: A*, A, B, C, D, E, and U (ungraded), A* being the highest grade and U, the lowest. The overall performance of a pupil was reported in terms of an Aggregate Score, which ranged from 0 to 300. This aggregate score was derived from the T-scores (i.e., Transformed Scores) of science, English, and math. The T-score was calculated based on a bell curve. For example, if the Science examination was too difficult with too many students performing badly, there is a potential increase of the raw science score, and vice versa if the examination has many students who scored high marks. The student’s actual score for individual area of assessment is not disclosed. Their examination scripts are neither returned to the students nor the school. The students’ PSLE scores (aggregate scores and grades) were obtained from the school. For the analysis in this study, a numerical value (score) was given to these grades, A* = 7, A = 6, B = 5, C = 4, D = 3, E = 2, and U = 1 (Table 4.2).

(2) Test scores. Test scores were obtained from the school for each of the three

curriculum domains: science, English, and math. These test scores were the sum of the scores of several formative tests taken by the students during the first school term of Grade 7 (i.e., first three months of the school year).

(3) Examination scores. Examination scores were scores obtained from a summative assessment taken at the end of the first school semester of Grade 7 (after five months of school) for each of the three curriculum domains: science, English, and math. As physics was taught in the first semester as part as the school science curriculum, only physics content was tested in the science examination.

Procedures of the research were approved by the ethics committee of the university. Assent was obtained from students, and informed consent from the school, teachers, and the parents of the students were obtained before data were collected. The procedures of the survey were explained by the researchers and the students completed the survey via the school online portal. The students responded to the survey items in a randomized order on a six-point Likert scale from 1 to 6, with 1 indicating strongly disagree and 6 indicating strongly agree.

4.4.3. Statistical Analysis

The students' responses were coded (and some reverse-coded) to associate higher scores with more favorable responses. In preliminary analysis, the alpha reliability of each *a priori* scale formed from respective items. Then confirmatory factor analysis (CFA) was used to test the ability of 25 motivation survey items to form six motivational factors (i.e., self-concept, self-efficacy, interest, inquiry, engagement and educational aspiration).

Mplus V7 (Muthén & Muthén, 1998–2015) was used to conduct the CFA. To evaluate the model fit, absolute fit statistics and incremental fit statistics were both used (Tanaka, 1993). The absolute fit statistics included χ^2 tests of model fit and the root mean square error of approximation (RMSEA; Browne & Cudeck, 1993). The incremental fit statistics included the Comparative Fit Index (CFI; Bentler, 1990) and the Tucker-Lewis Index (TLI; Tucker & Lewis, 1973), also known as the non-normed fit index (NNFI; Bentler & Bonett, 1980). The CFI and TLI vary along a 0 to 1 continuum in which values equal to or greater than .90 and .95 are considered as acceptable and excellent fits to the data, respectively. RMSEA values close to .05 indicate "close fit," values about .08 indicate "fair fit," and values above .10 indicate "poor fit" (Browne & Cudeck, 1993). Based on commonly accepted criteria, support for model fit would require: (a) acceptable reliability for each scale (i.e., alpha = .70 or above), (b) an acceptable model fit (i.e., TLI and CFI = .90 or above and RMSEA < .08), (c) acceptable factor loadings for the items loading on the respective factors (> .30), and (d) acceptable correlations among the latent factors such that they would be distinguishable from each other ($r < .90$).

4.5. Results

4.5.1. Preliminary Analysis

The mean score and the alpha estimate for each motivation factor are given in Table 4.1. All the six *a priori* motivational factors had acceptable alpha reliabilities (α = .93, .85, .91, .75, .87 and .85 for self-concept, self-efficacy, interest, inquiry, engagement and educational aspiration, respectively). These high reliabilities provided preliminary support for the motivational factors.

Table 4.1

Variables Used in the Study to Measure Students' Attitudes

Factors of Attitudes towards physics	**Number of items for each factor**	**Cronbach's Alpha**	**Mean**	***SD***
Self-concept	4	.93	3.42	1.19
Self-efficacy	5	.85	4.30	.78
Interest	4	.91	4.16	1.06
Inquiry	3	.75	4.37	.88
Engagement	5	.87	4.71	.69
Educational Aspiration	4	.85	3.69	1.02

Note: N=272. Items were randomized in the survey. Higher scores reflected more favorable perceptions.

A breakdown of the achievement scores is given in Table 4.2. As can be seen from the table, the minimum score for all curriculum domains was 4.00, implying that no student attained a grade poorer than C, and the maximum score was 7.00, which was the best grade, A*. The mean PSLE score for each curriculum domain was about 6.00, implying that the average student's grade was A.

Table 4.2

Students' Achievement Scores

Students' Achievement	**Mean**	***SD***	**Minimum**	**Maximum**
PSLE			0	300
PSLE Aggregate	242.85	7.36	202.00	263.00
PSLE Science	6.09	.48	4.00	7.00
PSLE English	6.01	.38	4.00	7.00
PSLE math	6.36	.60	4.00	7.00
TEST			0	100.00
Test Science	64.01	10.34	38.40	88.70
Test English	60.09	5.22	40.00	73.30
Test math	74.34	10.69	35.30	95.30
EXAMINATION			0	100.00
Exam Science	65.67	8.90	27.00	88.00
Exam English	60.95	4.49	39.00	70.00
Exam math	75.44	10.12	57.00	86.00

Note: N=272*;* PSLE aggregate scores were used for placement of students to this high-ability school. PSLE science, PSLE English and PSLE math grades were analysed as numerical scores (A*=7, A=6, B=5, C=4, etc). As no student scored a grade poorer than C, the minimum score is 4. Test and examination scores were obtained from the school for respective curriculum domains.

4.5.2. Correlations between Students' Attitudes towards physics

The critical concern of this study was the association between achievement and motivation towards physics. An inspection of the correlations among the six science motivational factors (self-concept, self-efficacy, interest, inquiry, engagement, and educational aspiration) found significantly positive correlations among them (*r*s between .47 and .80). The highest correlation was between interest and educational aspiration in physics (r = .80), and the lowest correlation was between self-concept and inquiry in physics (r = .47) (see Table 4.3).

4.5.3. Correlations between Students' Achievement Scores (PSLE, Test & Exam)

For achievement scores, some interesting patterns were found. Intuitively, I would expect PSLE scores to be substantially correlated. That is, in standardized tests, I would expect high-ability students to achieve well in most areas such that the correlations between domains would be expected to be substantially positive. Nevertheless, the results showed that although the correlation between math scores and science scores in PSLE was positive (r = .11), it was not statistically significant. The correlations between the English and science scores in PSLE (r = .06) and between English and math scores in PSLE (r = -.05) were near zero and statistically non-significant.

The respective correlations for the semester test scores showed a different pattern. Whereas the correlations between the English and science test scores in the semester (r = .06) and the correlation between English and math test scores (r = .05) remained to be near zero and statistically non-significant, the correlation between math and science test scores were positive and statistically significant (r = .51).

Table 4.3
Solution of CFA Model

Item no	SC	SE	IT	IQ	EN	EA	PSc	PEn	PMa	TSc	TEn	TMa	ESc	EEn	EMa
Factor Loadings															
S9Q10	**.94**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S2Q6	**.87**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S9Q3	**.93**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S8Q6	**.81**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S4Q1	.00	**.75**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S8Q1	.00	**.77**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S5Q10	.00	**.77**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S7Q3	.00	**.64**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S4Q9	.00	**.75**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S10Q14	.00	.00	**.92**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S5Q9	.00	.00	**.91**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S8Q5	.00	.00	**.72**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S1Q4	.00	.00	**.83**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S4Q5	.00	.00	.00	**.71**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S9Q1	.00	.00	.00	**.63**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S9Q4	.00	.00	.00	**.79**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S3Q1	.00	.00	.00	.00	**.82**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S6Q7	.00	.00	.00	.00	**.83**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S1Q2	.00	.00	.00	.00	**.75**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S5Q4	.00	.00	.00	.00	**.72**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S7Q8	.00	.00	.00	.00	**.67**	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
S4Q7	.00	.00	.00	.00	.00	**.79**	.00	.00	.00	.00	.00	.00	.00	.00	.00
S10Q13	.00	.00	.00	.00	.00	**.80**	.00	.00	.00	.00	.00	.00	.00	.00	.00
S2Q3	.00	.00	.00	.00	.00	**.60**	.00	.00	.00	.00	.00	.00	.00	.00	.00
S10Q6	.00	.00	.00	.00	.00	**.91**	.00	.00	.00	.00	.00	.00	.00	.00	.00
PSc	.00	.00	.00	.00	.00	.00	**1.00**	.00	.00	.00	.00	.00	.00	.00	.00
Pen	.00	.00	.00	.00	.00	.00	.00	**1.00**	.00	.00	.00	.00	.00	.00	.00
PMa	.00	.00	.00	.00	.00	.00	.00	.00	**1.00**	.00	.00	.00	.00	.00	.00
TSc	.00	.00	.00	.00	.00	.00	.00	.00	.00	**1.00**	.00	.00	.00	.00	.00
TEn	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	**1.00**	.00	.00	.00	.00
TMa	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	**1.00**	.00	.00	.00
Esc	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	**1.00**	.00	.00
EEn	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	**1.00**	.00
EMa	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	**1.00**
Factor Correlations															
	SC	SE	IT	IQ	EN	EA	PSc	PEn	PMa	TSc	TEn	TMa	ESc	EEn	EMa
SC	1.00														
SE	.70**	1.00													
IT	.74**	.78**	1.00												
IQ	.47**	.66**	.65**	1.00											
EN	.49**	.60**	.59**	.57**	1.00										
EA	.67**	.68**	.80**	.57**	.47**	1.00									
PSc	.25**	.20**	.17**	.07	.09	.15*	1.00								
PEn	.04	.03	-.03	.08	.09	-.07	.06	1.00							
PMa	.24**	.14*	.16**	.08	.05	.14*	.11	-.05	1.00						
TSc	.54**	.38**	.39**	.23**	.31**	.31**	.25**	.05	.23**	1.00					
TEn	-.03	.01	-.08	.06	-.01	-.14*	-.02	.40**	-.04	.06	1.00				
TMa	.39**	.22**	.26**	.20**	.26**	.20**	.14*	-.03	.28**	.51**	.05	1.00			
ESc	.59**	.43**	.42**	.31**	.41**	.33**	.32**	.11	.26**	.73**	.21**	.54**	1.00		
EEn	.06	.05	-.06	.06	.10	-.08	.06	.42**	-.05	.19**	.73**	.06	.37**	1.00	
EMa	.43**	.27**	.31**	.27**	.33**	.22**	.13*	-.06	.36**	.55**	.08	.81**	.67**	.11	1.00

Note: N = 272. Parameters estimates are completely standardized. Motivation towards Physics include: SC: Self-concept; SE: Self-efficacy; IT: Interest; IQ: Inquiry; EN: Engagement; EA: Educational Aspiration; Achievement in science include: PSc: PSLE science; PEn: PSLE English; PMa: PSLE math; TSc: Science Test; TEn: English Test; TMa: math Test; ESc: science Exam; EEn: English Exam; EMa: math. *p<.05. **p<.001. PSLE science, PSLE English, and PSLE math correlated with PSLE.

The respective correlations for the semester examination scores showed another pattern. For this end-of-first-semester examination, the correlations between the English and science scores (r = .37) was higher than the correlation between English and math scores (r = .11). The correlation between math and science scores were positive and statistically significant (r = .67).

Between the PSLE scores and the semester test scores, however, there was a clear domain-specific pattern. Positive correlations were found between PSLE and semester test scores for science (r = .25), English (r = .40), and math (r = .28). Whereas English scores in PSLE did not correlate with semester math and science test scores (rs = -.03 and .05, respectively) and semester English test scores did not correlate with math and science scores in PSLE (rs = -.04 and -.02, respectively), positive and statistically significant correlations were found between PSLE math and semester science test (r = .23) and between PSLE science and semester math test scores (r = .14), although these correlations were not as strong as domain-specific correlations for each domain (Table 4.3).

The correlations between PSLE scores and the semester examination showed a clearer domain-specific pattern. Higher positive and statistically significant correlations were found between PSLE and semester examination for science (r = .32), English (r = .42), and math (r = .36). Whereas English scores in PSLE did not correlate with semester math and science examination scores (rs = -.06 and .11, respectively) and semester English examination scores did not correlate with math and science scores in PSLE (rs = -.05 and .06, respectively), positive and statistically significant correlations were found between PSLE math and semester science examination scores (r = .26) and between PSLE science and semester math examination scores (r = .13), although these correlations were not as strong as domain-specific correlations for each domain (see Table 4.3).

4.5.4. Correlations between Students' Achievement and Attitudes towards physics

An inspection of the correlations of each achievement score with the students' motivation towards physics found some interesting patterns (see Table 4.3). Weak correlations were observed between students' motivation towards physics and their PSLE scores; the weakest being with inquiry in physics (*r*s= .07, .08 and .08 with PSLE science, English and math, respectively), followed by engagement (*r*s= .09, .09 and .05 with PSLE science, English and math, respectively). As for the other motivational factors, higher correlations were found with PSLE science and PSLE math than with PSLE English. PSLE English had the lowest correlations with all of the motivational factors towards physics, which were statistically non-significant

Another interesting finding was that even though domain specificity was observed (science achievement scores were more highly correlated to science self-concepts and motivation towards science, compared to other curriculum domains), the correlations of achievement with students' motivational factors were stronger with more recent achievement scores. For example, Grade 7 physics achievement had higher correlations with Grade 7 physics motivation than Grade 6 science achievement. This pattern of stronger correlations of achievement over time with students' motivation towards physics was also observed with math achievement scores (i.e., Grade 7 math achievement had higher correlations with Grade 7 physics motivation than Grade 6 math achievement) but not with English achievement scores.

4.6. Discussion

Whereas students' learning experiences in different domains tend to have distinctly different influences on their development of skills and motivation, competence in certain domains may help students' self-development in other related domains. For example, correlation (r = .52) between semester math and physics test scores and between semester math and physics examination scores (r = .67), although smaller than those within the same subject domain, were positive and statistically significant. This could be because the effective learning of physics often requires the knowledge of math and related logical thinking. Correlations of students' motivation towards science (i.e., physics here) with PSLE math scores were also similar to the correlations with PSLE science. It seems that the science and math achievements in PSLE may have very similar relations with students' motivation towards science (i.e., physics) in Grade 7.

Based on these results, there seem to be some close relations between physics and math. For example, math achievement is not only positively associated with math motivation but is also positively associated with physics achievement. A probable reason for this could be that students who achieve well in math may feel equipped with mathematical skills necessary to do well in physics, thus having positive attitudes towards physics. This new understanding of students' academic motivation would enable us to help students build up their self-concept and enhance their motivation in new learning areas such as physics in secondary school.

As for the motivational attitudes, the correlations of students' motivation towards science (i.e., physics) with PSLE science scores are not high. This means that science achievement in PSLE (or in primary school) may not be very important for positive attitudes towards science in secondary school. This finding is contrary to the assumptions held by most parents and some teachers that PSLE scores will determine students' positive attitudes towards that subject in secondary school. Based on similar findings with math, an inspection of math achievement in PSLE also showed weak relations with students' motivation towards physics. In contrast, the science achievement scores in Grade 7 has significant relations with students' motivation towards science and such relations tend to grow stronger over time, based on the positive correlations (Table 4.3) between students' motivation and examination scores (taken at the end of the semester) than with test scores (taken within the first 3 months in Grade 7). The implications for this is that focus should be given to developing good school science curriculum in Grade 7, as no matter what their PSLE science scores were in the past, students can develop positive attitudes towards science in secondary school.

Math achievement follows a similar pattern as above. Math achievement scores in Grade 7 has significant relations with students' motivation towards physics and such relations tend to grow stronger over time as well (i.e., positive correlations showing a higher correlation between students' motivation and examination scores than with test scores), although not as strong as the relations between science achievement and attitude towards physics. Having a good curriculum for math may improve students' achievement in math, which may positively influence students' motivation in physics, to some extent. However, further research will be necessary to test this implication.

Since students' achievement in Grade 6 does not seem to have much bearing on students' motivation towards physics in the first semester of secondary school, Grade 7 may thus be a critical time for developing positive attitudes towards physics. For physics education, it is important not only to improve physics achievement, but also to enhance motivation towards physics at an early stage in secondary school. It also seems crucial to enhance skills in math as well.

One of the limitations of this study is the sample of high-ability students. Even though I may claim contribution to the understanding of higher-ability students' achievements in their relation to students' motivation towards physics, I am unable to generalize it to the whole Grade 7 student population. However, the findings in this study have important implications that could be beneficial to many other students.

Educators need to be aware of the students' development of motivation towards physics in order to provide them with the best learning environment to optimize their potential. Since there are significant correlations between the science and math domains, curriculum could be designed such that the lessons learned from each of these domains complement each other to strengthen students' skills in both domains. Further implications for parents and educators are that while it is not too late to develop positive attitudes towards science, there should not be complacency that good academic achievement in the past will guarantee good attitudes towards physics in the future. An engaging and interesting physics curriculum is necessary to enhance students' positive attitudes and help them excel in the domain.

CHAPTER 5: STUDY 3 -

Element Interactivity as a Construct for the Analysis of Science Problem- Solving Processes

5.1. Preface

The overarching aim of this thesis is to examine the associations between the cognitive and non-cognitive aspects of students' learning. Whereas Study 1 and Study 2 focused on examining the relations between achievement and motivation (i.e., cognitive and non-cognitive outcomes of learning, respectively), Study 3 focuses on the cognitive aspect of learning by investigating student learning processes which lead to student achievement. Research has shown that by analyzing the interacting elements in problem solving tasks, student learning processes can be better understood, and instruction could be designed accordingly to maximize learning effects. Thus, Study 3 uses element interactivity as a construct to analyze students' problem solving processes in science. The findings will (1) show how learning tasks can be analyzed in terms of element interactivity to assess their suitability for students, (2) shed light on students' level of expertise based on their choice of problem solving strategies, and (3) guide lesson design and instruction to ensure that the learning materials are suitable for students' cognitive levels and not cause cognitive overload.

5.2. Abstract

Element interactivity is a construct that is used by cognitive load theory to explain the complexity in learning tasks. Despite advances in cognitive load research, element interactivity in science problem solving has not been vastly studied. To illustrate how element interactivity gives rise to different types of cognitive load (intrinsic, extraneous, and germane), the ways a group of high-ability Grade 8 students solve a complex science problem were analyzed. Results showed that students who broke down their solutions and managed lower element interactivity scored higher marks. The majority of students used multiple operational lines of low element interactivity and they were found to be in the intermediate stages of developing expertise. The findings provide practitioners with a useful approach to evaluating instruction, learning materials, and student expertise, and to design effective pedagogies to suit the needs of students based on their level of expertise.

5.3. Introduction

The purpose of this study is to revisit the conceptualization of *cognitive load theory* (CLT; Sweller, 1988; Sweller, Ayres, & Kalyuga, 2011) by examining the cognitive processes involved during science problem solving, with a focus on *element interactivity,* or the degree to which learning comprises elements that cannot be learned in isolation. Science problem solving is commonly perceived as a complex learning task due to the need to simultaneously process multiple elements of information. Unless instruction is designed to manage the high cognitive load involved, learning effectiveness may be compromised. Recent literature has shown that element interactivity may be a useful construct for understanding learners' involvement in and mastery of complex tasks (e.g., Ayres, 2013; Beckmann, 2010; Ngu, Yeung, & Tobias, 2014). However, there is limited research on the links between element interactivity, cognitive load, and students' problem solving in science. Also, CLT studies have shown that students' pre-existing knowledge in the domain affects the level of element interactivity that they are able to manage in the domain (Sweller et al., 2011), but have not suggested an effective measure to determine students' pre-existing knowledge. To address these gaps in the literature, I used element interactivity as a construct to (1) determine how the interaction of elements in a science word problem may incur various types of cognitive load, and (2) analyze students' problem solving processes and categorize their expertise level in order to estimate their pre-existing knowledge in the domain. My illustration of the analyses could guide educators to design learning tasks and instruction that match students' existing knowledge levels (i.e., expertise) in the domain to optimize learning.

In the following, element interactivity is defined, and the challenges faced by secondary school students in science problem solving are discussed. I will analyze the cognitive structures and processes involved when students attempt to solve science word problems. They include: limitations of working memory (WM), the effects of different types of cognitive load, and element interactivity in WM. I will illustrate element interactivity by examining how solving a science problem on ‘speed’ imposes three types of cognitive load on the students, which can then be used to modify and optimize the suitability of learning tasks. The tenet is that by analyzing problem solving processes and students’ work in terms of element interactivity, it is possible to analyze almost any learning task for the inherent difficulties presented to learners. Accordingly, educators will be able to modify pedagogies to suit students’ knowledge levels and progress science education to a new level.

5.3.1. Element Interactivity and Cognitive Load Theory

Cognitive load theory (CLT) is an instructional theory developed to address arising cognitive issues during human cognitive processes (Paas, Renkl, & Sweller, 2003; Sweller, 1988; Sweller, van Merriënboer, & Paas, 1998). CLT guides instructional designs to improve learning (Sweller, 2012; Sweller et al., 2011), by making the cognitive load involved in the mental processing of instructional materials more manageable for learners (Yeung, 1999).

CLT suggests that the degree of complexity of information in a learning task can be gauged by *element interactivity* (Leahy, Hanham, & Sweller, 2015). Sweller (2010) defines an element as “anything that needs to be or has been learned, such as a concept or a procedure” (p. 124). He explained that a learning task has low element interactivity if it comprises elements that can be learned in isolation, without much reference to other elements. In contrast, a learning task has high element interactivity if it comprises elements that cannot be learned in isolation, as they heavily interact and need to be simultaneously processed before meaningful learning can occur (Leahy et al., 2015; Sweller et al., 2011). A learning task with high element interactivity is normally considered to be complex for novice secondary school students (i.e., students who lack pre-existing knowledge in the domain of the learning task). In general, most novices will find it difficult to manage the simultaneous interactions of elements, resulting in cognitive issues (Kadir, Ngu, & Yeung, 2015).

Despite this emphasis within CLT on element interactivity as reflective of cognitive load, little research has made element interactivity a focus of analysis to guide instructional design. I argue that if problems are analyzed in terms of element interactivity, areas of high cognitive load can be effectively identified and adjusted to suit all learners' needs.

This study shows how CLT is applied using the concept of element interactivity as a theoretical framework in the analysis of a complex science word problem for junior secondary students. It demonstrates how Grade 8 students' solutions to a science problem dealing with speed can be analyzed in terms of 'operational lines'. An 'operational line' shows the application of an operation to change the problem state of the equation and yet at the same time to preserve the equality of the equation (Kadir et al., 2015). In the study by Ngu et al. (2014), students who used operational lines with lower element interactivity to solve a problem reported less mental effort and performed better than students using operational lines with high element interactivity. In this study, operational lines were measured by counting the number of lines (also known as steps) that a student used as part of their solution to the problem, with each line having one or more mathematical operations such as multiplication, addition, or division. Students' expertise in problem solving can be inferred by the number of operational lines used to solve a problem. This is because students with a high level of expertise tend to omit steps or combine several operational lines (Star & Newton, 2009). In contrast, students with lower levels of expertise tend to use more operational lines, where the element interactivity within each operational line is relatively low. Even though students' test scores may provide an indication of their expertise in the domain, for students scoring the same marks, fewer operational lines could reflect students' ability to manage higher element interactivity. In this regard, element interactivity could provide more information about a student's expertise beyond test scores.

5.3.2. Challenges in Science Problem Solving

Students' expertise in science problem solving, especially in the domain of physics, may be reflected in the way they solve problems in the domain (Ngu, Chung, & Yeung, 2015). Students who are experts in the domain would be able to manage high element interactivity (Sweller et al, 2011), so their solutions to problems would most probably comprise fewer lines of high element interactivity. On the contrary, students who are new learners (i.e., novices) and therefore lack the relevant knowledge in the domain, may use many operational lines with low element interactivity or may not solve the problem at all if they do not have any pre-existing knowledge required to solve the problems. As students in school are usually novices, physics problem solving tasks generally impose a heavy burden on students' WM, as solving the problems require simultaneous processing of conceptual and procedural knowledge from the domains of science and mathematics (Kadir et al., 2015). Such challenges to science problem solving and learning may be why science, especially physics, is widely perceived to be a difficult subject in school (Shen & Pedulla, 2000).

5.3.2.1. Conceptual and procedural knowledge

In this study, the definitions of conceptual and procedural knowledge apply to both science and mathematics, since students need to apply both types of knowledge in both domains concurrently in order to solve physics problems effectively (see DFE, 1995; SOED, 1993). Conceptual knowledge is 'knowing that' and procedural knowledge is 'knowing how' (Ryle, 1976). In science, conceptual knowledge is "the factors and mechanisms which underpin key events" and procedural knowledge is "the controlled manipulation of factors, the prediction and observation of outcomes, and the utilization of observations to draw conclusions" (Howe, Tolmie, Duchak-Tanner, & Rattray, 2000, p. 362). In mathematics, conceptual knowledge is usually defined as "an integrated and functional grasp of mathematical ideas" (Kilpatrick, Swafford, & Findell, 2001, p. 118) and procedural knowledge is the “ability to execute action sequences to solve problems, including the ability to adapt known procedures to novel problems” (Rittle-Johnson, & Star, 2007, p. 562). Procedural knowledge is the ability to construct mathematical operational lines that will arrive at the final answer of average speed. The operational lines constructed will be based on both the procedural and conceptual knowledge of average speed as well as the algorithms used. The simultaneous applications of conceptual and procedural knowledge for both mathematics and science are necessary for students to successfully solve physics problems (Kadir et al., 2015).

5.3.2.2. High element interactivity

Physics problem solving tasks are usually categorized as having high element interactivity as the tasks usually require problem-solvers to simultaneously process multiple elements of conceptual and procedural knowledge from science and mathematics (Kadir et al., 2015). As novices have inadequate existing knowledge in the domain, it makes it difficult for them to integrate new information (Chi, Glaser, & Rees, 1982), without overloading their WM. Teachers need to be able to estimate the level of element interactivity in the learning materials to ensure that novices’ WM is not overwhelmed.

5.3.3. Cognitive Processes Involved in Science Problem Solving

Understanding the human cognitive processes is important for us to make sense of students’ learning capabilities and limitations. Figure 5.1 illustrates a model of the human cognitive processes when students are involved in learning tasks such as science problem solving. The model is based on the components of the human WM advanced by Baddeley and Hitch (2000), which was illustrated by Chinnappan and Chandler (2010) and modified by Kadir et al. (2015).

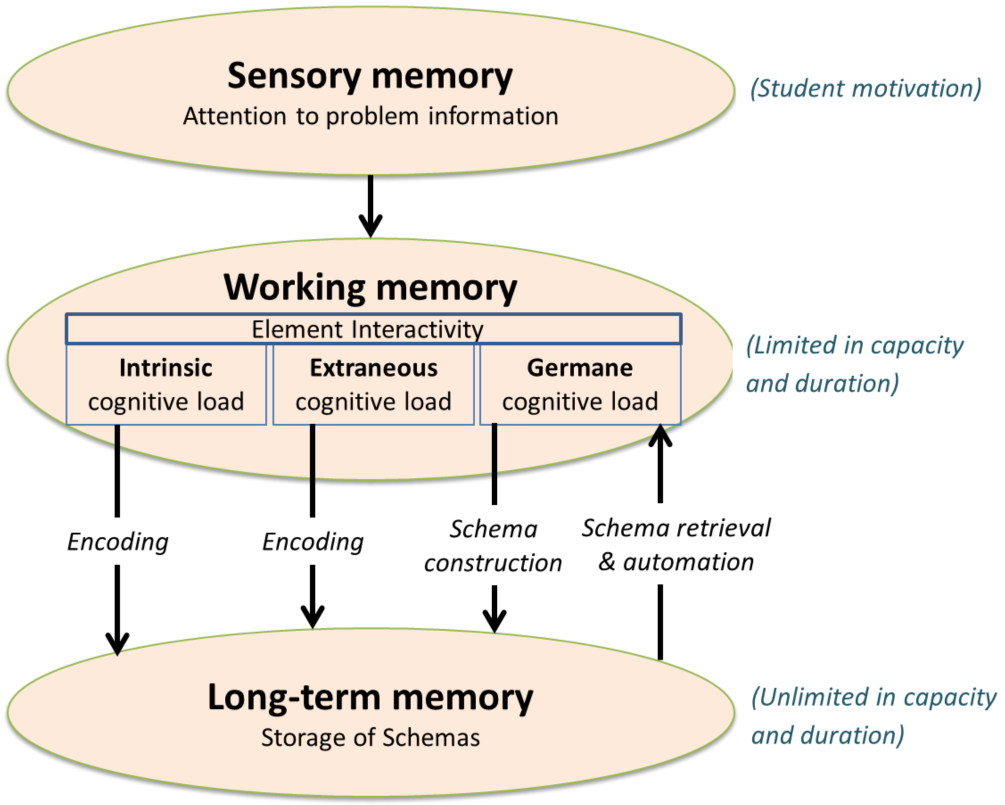

Figure 5.1. Model of human cognitive processes related to element interactivity during learning.

5.3.3.1. Sensory memory

The sensory memory of the brain (top of the model in Figure 5.1) receives incoming signals and information when students are given a cognitive task. When students give the cognitive task enough attention, the input from the sensory memory is passed on and processed in the WM of the brain system (Baddeley, 1986). That is, active processing begins when the learner is motivated or has the intention of attempting the cognitive task.

5.3.3.2. Working memory

Working memory (WM) is defined by Baddeley (1986) as “the temporary storage of information that is being processed in any range of cognitive tasks” (p. 43). It is a cognitive structure where current and active mental processing takes place but can only manage to process a few elements of information at any time because it has a limited capacity (Miller,

1956) and duration (Peterson & Peterson, 1959). If WM limitations are exceeded, learning and understanding is compromised. On the contrary, if the processing of the elements is within the capabilities of WM, the information will be successfully processed and learning will occur. Whenever students are involved in any form of mental activity, their WM experiences cognitive load (middle of the model in Figure 5.1).

The three types of cognitive load identified by CLT are: intrinsic, extraneous, and germane (Paas et al., 2003). Interacting elements in the learning material impose intrinsic cognitive load (Ayres, 2013). Sub-optimal instruction results in inefficient problem solving methods and impose extraneous cognitive load on WM (Sweller et al., 2011). The processing, encoding, and organization of new science knowledge into schemas to be retained in LTM for future use (Figure 5.1), is called germane cognitive load. Learners require enough WM resources to be available for the cycle of constructing, retrieving, and automating schemas (germane cognitive load in Figure 5.1) for successful learning and this should be the primary aim of effective instruction. The involvement of the three types of cognitive load in terms of element interactivity will be described later.

5.3.3.3. Long-term memory

When information is successfully processed through WM, schemas are constructed and transferred to long-term memory (LTM) and stored there (bottom of the model in Figure 5.1). In contrast to WM, LTM has unlimited capacity (Landauer, 1986) as there are no known limits to its immeasurably large storage space (Newell & Simon, 1972). Hence, it can store an infinite amount of information that has been processed by WM (i.e., schemas).

5.3.3.4. Schemas

Schemas are “general knowledge structures that encapsulate numerous elements of information into a single element” (Carlson, Chandler, & Sweller, 2003, p. 629). Successful learning results in the construction of schemas, which are hierarchically organized and stored in LTM (Kalyuga, Ayres, Chandler, & Sweller, 2003) for easy retrieval (Valcke, 2002). Whenever the need arises, these schemas are retrieved from LTM, interact with new elements in WM, and then higher-level schemas are generated (Newell & Simon, 1972), and stored in LTM. These new schemas are especially useful for problem solving as they help the learner to classify a variety of problem states and select the most suitable solution for a specific problem (Chi et al., 1982). Schemas reduce element interactivity and WM load during problem solving because multiple and interacting elements in a schema can be treated as a single element (Sweller et al., 2011).

5.3.3.5. Schema automation

Learning new concepts or solving new science problems requires controlled and conscious effort, which imposes a heavy burden on WM (Carlson et al., 2003). However, with extensive practice over time, cognitive processing becomes automated, resulting in schema automation (Ericsson, 2005). Schema automation is critical for problem solving transfer (Sweller et al., 2011) where learners apply learned knowledge to new situations and contexts. Automated schemas enable information to be processed with less effort through the limited WM (Carlson et al., 2003). This facilitates the construction of new schemas of higher complexity, which increases learners' expertise in the domain (Ericsson, 2006a).

5.3.4. The Present Study

In the present study, element interactivity is used as a construct to analyze (1) a science word problem and (2) students' problem solving processes (see Figure 5.2). The analysis of a science word problem will determine (1a) the complexity of the science problem (intrinsic cognitive load), (1b) cognitive load that does not contribute to learning (extraneous cognitive load), and (1c) cognitive load that contributes to knowledge and skills acquisition (germane cognitive load). The analysis of the students' problem solving processes in terms of operational lines will enable us to categorize their level of expertise in the domain to (2a) novice, (2b) intermediate and (2c) expert, based on the level of element interactivity that they are able to manage. The illustration of the analyses of this study may be useful for teachers when designing or evaluating instruction and assessments for science problems, and to ensure that the learning materials are suitable for students, given their level of expertise. I also examined (3) the relationship between the number of operational lines (i.e., lines showing mathematical operations such as multiplication, addition, division, etc.) that students used to solve a complex science problem and their final score for that problem, as well as (4) the number of operational lines used by perfect-score students (i.e., successful problem solvers). Analyses from (3) and (4) will illustrate how element interactivity can inform us more about students' level of expertise beyond test scores. See Figure 5.2 for an overview of the study.

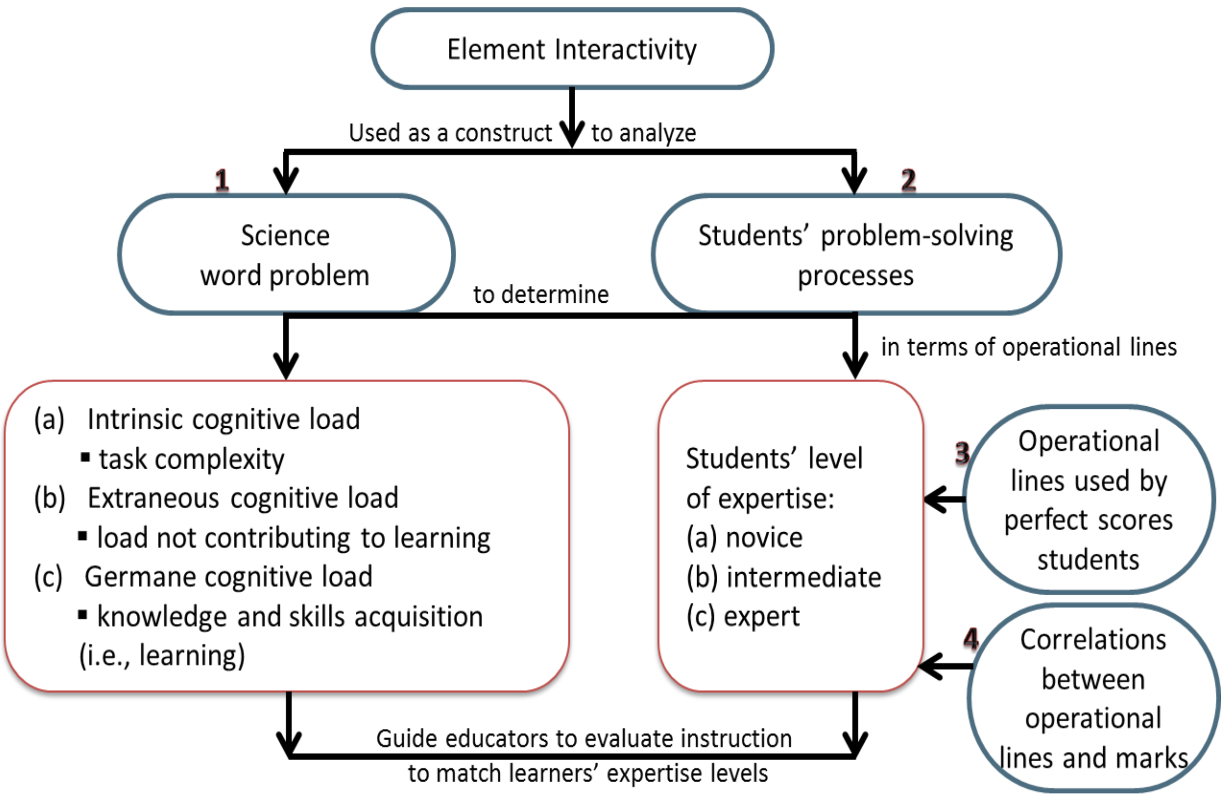

Figure 5.2. An overview of the present study.

5.4. Method

5.4.1. Participants

Grade 8 students (*N*=260, mean age=13.5 years) from a selective secondary school in Singapore were randomly selected by the school teachers to participate in the study. These students gained admission to the school by the merit of their scores at a national examination taken at the end of Grade 6, in which they performed better than 70% of their peers in the cohort, so they were considered to have 'higher than average' ability. These students were selected for this study because I wanted to have a high percentage of students who would attempt the problem for analysis purposes. A pilot trial with lower-ability students found that many students did not attempt the problem (i.e., left it blank), making element interactivity analysis impossible. Nevertheless, the results from this high-ability sample could provide insights into optimizing learning opportunities for the general student population.

All 121 boys and 139 girls who participated in the study were asked to solve a problem task. They were told that the problem task was just a quiz, that their marks would not be used to calculate their total science assessment scores for the year, and that they were free to use any approach to solve the problem. Students were unlikely to undertake any last-minute revision of any learning materials related to the topic, as they were not told what topic the problem would be related to. Students would therefore rely on their existing schemas in their long-term memory to solve the problem. With no performance requirements, the Grade 8 students were at liberty to choose their own approaches to solve the problem. All students were given the same amount of time (10 minutes) to complete the novel problem, and were supervised by their teachers, in silence.

5.4.2. Material

The science word problem concerning speed (Figure 5.3a) was designed by a science teacher in Singapore as an assessment item to evaluate students' conceptual and procedural knowledge of speed related concepts. The total marks (2), were based on a marking rubric designed by and cross-checked by teachers in the school.

a.

The table below shows the average speed of a car at different timing, from the time the car left its start point (12pm) to the time it reached its destination (6 pm). [3]

Based on the information in the table, **calculate the average speed** of the car for the entire journey (Leave your answer in km/h).

Time Interval	12 pm to 2 pm	2 pm to 3 pm	3 pm to 6 pm
Average speed	75 km/h	0 km/h	70 km/h

b.

<table>
<tr><td colspan="4">To effectively solve this problem, students need to apply this formula:
Average speed = total distance travelled by car / total time taken

However, students are required to manipulate the formula using the concept of algebra to find the distance, which is not given in the problem:

distance = average speed X time</td></tr>
<tr><td colspan="2">Method 1 using the step by step method</td><td colspan="2">Method 2 using the combined method</td></tr>
<tr><td>Step 1
line 1
line 2</td><td>Distance travelled from 12pm-2pm
= 75 km/h X 2 h
= 150 km</td><td>Step 1

line 1
line 2
line 3
line 4</td><td>Average speed
= total distance travelled by car / total time
= [(75X2) + (0X1) + (70X3)]/ 2+1+3
= (150 km + 0 km + 210 km) / 6 h
= 360 km / 6 h
= 60 km/h</td></tr>
<tr><td>Step 2
line 1
line 2</td><td>Distance travelled from 2pm-3pm
= 0 km/h X 1 h
= 0 km</td><td></td><td></td></tr>
<tr><td>Step 3
line 1
line 2</td><td>Distance travelled from 3pm-6pm
= 70 km/h X 3 h
= 210 km</td><td></td><td></td></tr>
<tr><td>Step 4
line 1
line 2</td><td>Total distance travelled by car
= 150 km + 0 km + 210 km
= 360 km</td><td></td><td></td></tr>
<tr><td>Step 5
line 1
line 2</td><td>Total time taken by car
= 2 h + 1 h + 3 h
= 6 h</td><td></td><td></td></tr>
<tr><td>Step 6

line 1
line 2</td><td>Average speed
= total distance travelled by car / total time
= 360 km / 6 h
= 60 km/h</td><td></td><td></td></tr>
</table>

Figure 5.3. Science problem on speed.
Note. (a) Problem statement. (b) Methods to solve the science problem on speed.

5.4.3. Procedure and Data Analysis

Students' responses were analyzed in terms of the number of operational lines used to solve the problem and the total marks awarded by teachers. The students' responses were then given to two researchers for marking. Given the time constraints to solve the problem, I would expect the students to use the most efficient method to solve the problem, given their level of expertise in the domain.

5.4.3.1. Operational lines

Analysis of students' responses to the problem in terms of operational lines provided an indication of the level of element interactivity that students were able to manage. Students with a lower level of expertise (i.e., novices) were expected to use more operational lines as the element interactivity in each operational line will be low and more manageable. Students with higher domain expertise were expected to use less operational lines since they would invoke higher element interactivity within each operational line. Two researchers independently coded the students' responses in terms of operational lines, with an inter-rater agreement of 80%, which went up to 100% after a round of discussion. An operational line has to have at least one operation (i.e., multiplication, addition, or division). The final answer was not counted as an operational line. Figure 5.4 shows samples of students' solutions and how the operational lines were coded.

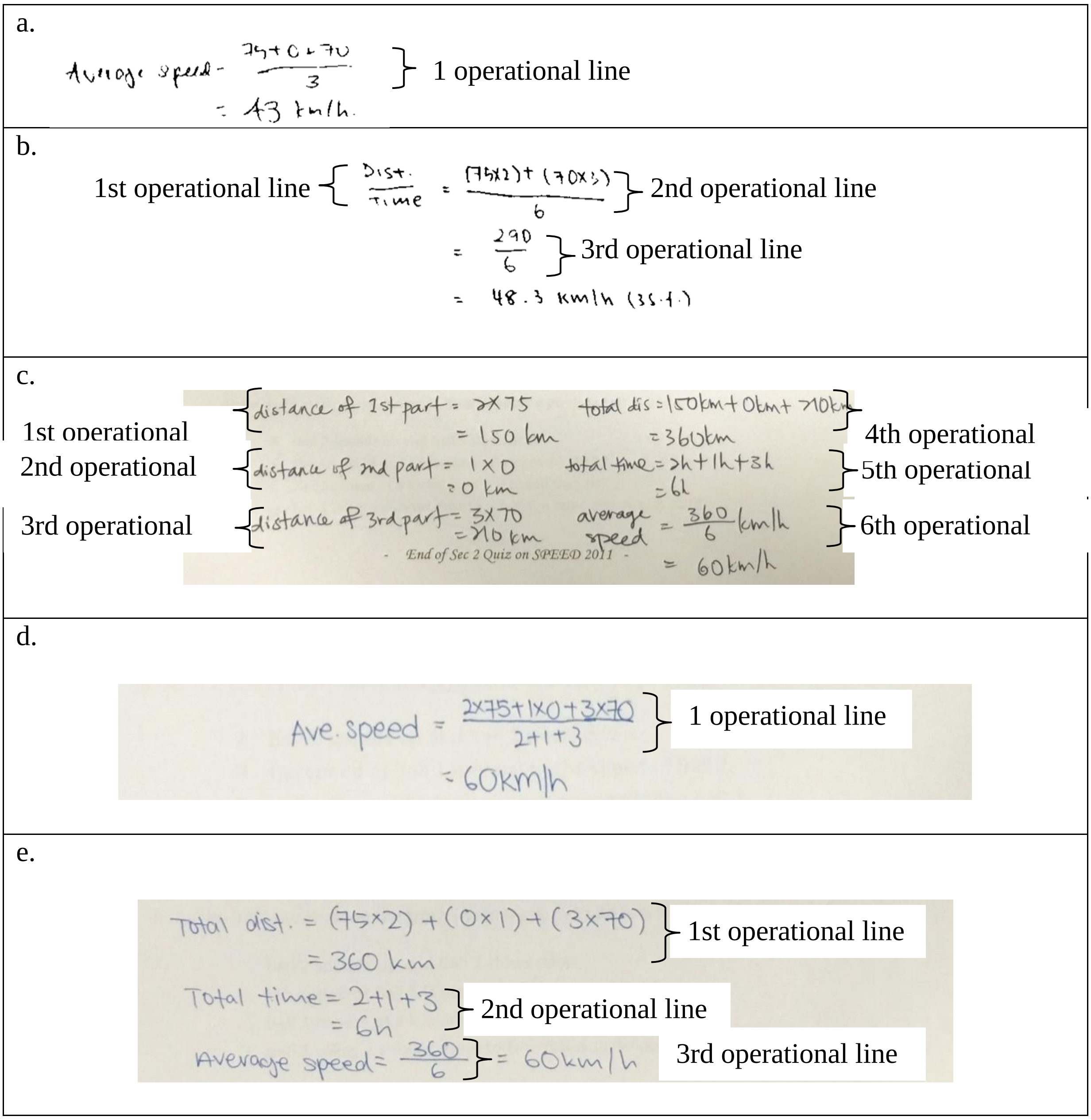

Figure 5.4. Sample of students' responses to the science problem.
Note. (a) Example of a solution that was awarded 0 mark. It is conceptually wrong because speed (instead of distance) was summed and divided by the total number of speed (instead of time). One operational line was used to solve the problem. (b) Example of a solution that was awarded 1 mark. It is conceptually right, based on the 2nd operational line but mathematical calculations were wrong (i.e., it should be 360 instead of 290). Three operational lines were used to solve the problem. (c) Example of a solution resembling Method 1. Six operational lines were used to solve the problem. This solution was awarded the full marks of 2. (d) Example of a solution resembling Method 2. One operational line was used to solve the problem. This solution was awarded the full marks of 2. (e) Example of a solution resembling an intermediate stage between Method 1 and Method 2. Three operational lines were used to solve the problem. This solution was awarded the full marks of 2.

5.4.3.2. Marks

Students' solutions to the problem task were awarded 0 mark, 1 mark, or 2 marks. A perfect score of 2 was awarded to students who applied their conceptual and procedural knowledge successfully and performed the operations correctly. Students who made some minor mistakes such as calculation errors or using incorrect units of measurement, but were able to show conceptual understanding (e.g., dividing the total distance travelled by the total time taken) were awarded 1 mark. Students who demonstrated incorrect conceptual understanding of the problem were awarded zero mark. Figures 5.4a and 5.4b show examples of students' solutions awarded zero and one mark, respectively. A correlation analysis was conducted to investigate the relations between students' operational lines and their marks for the problem solution. The number of operational lines used by students who received perfect scores was also noted.

5.5. Results and Discussion

5.5.1. Analysis of a Science Problem in terms of Element Interactivity

Element interactivity can be measured by estimating the number of interacting elements that need to be simultaneously processed before the learning task can be successfully understood or completed (Sweller & Chandler, 1994). This measurement has been used by several researchers in various learning areas (e.g., Carlson et al., 2003; Leahy et al., 2015; Tindall-Ford, Chandler, & Sweller, 1997). To assess element interactivity, relevant assumptions about the learners are required, since a single element for an expert who has existing domain-specific schemas may equate to many elements for a novice (Sweller et al., 2011).

In the element interactivity analysis that follows, assumptions about learners include: (a) a good understanding of the language used in the problem so as to understand the problem statement (i.e., the general message of the word problem was considered as one element); (b) relevant knowledge of the concept of speed; (c) basic mathematical skills expected of lower secondary students (i.e., an operation such as multiplication, addition, or division was considered as one element); and (d) necessary skills to interpret a table of values (i.e., table interpretation was considered as one element) to solve the problem.

While element interactivity in intrinsic cognitive load is frequently assessed, it is not usually done for extraneous and germane cognitive load. To illustrate the element interactivity in all three forms of cognitive load, I analyzed the science word problem on ‘speed’ (Figure 5.3a) within each type of load. The following section first defines and then analyses each type of cognitive load (i.e., intrinsic, extraneous, and germane) in terms of element interactivity in the word problem.

5.5.1.1. Intrinsic cognitive load

According to Sweller (2010), “the level of intrinsic cognitive load for a particular task and knowledge level is assumed to be determined by the level of element interactivity” (p. 124). Therefore, intrinsic cognitive load can be estimated by examining the number of elements and the interactions among them (Sweller & Chandler, 1994; Tindall-Ford et al., 1997), using the above-mentioned assumptions as a basic guide.

In order to solve the word problem on speed, students needed to understand its objective by reading the words and studying the numbers and units (i.e., magnitudes) in the problem statement. An additional element was that students needed to attend to the data table containing multiple values of time and average speed. Intrinsic cognitive load constitutes the element interactivity involved with simultaneously understanding the words and magnitudes in the problem statement as well as the interpretation of the table of values. Since magnitudes for the total distance and total time were not directly provided in the problem, students needed to deal with four main sub-goals of the problem in order to calculate average speed by: (1) calculating the distance travelled during each of the three time intervals by manipulating the average speed formula; (2) adding individual distances to get the total distance travelled; (3) deriving the time from the time intervals (e.g., 12 pm to 2 pm means a time interval of 2 hours); and (4) summing the times to get the total time travelled for the journey. Novices would be expected to experience a high level of element interactivity in the problem to solve these sub-goals resulting in a high intrinsic cognitive load. They would perceive this problem as complex because of the high number of interacting elements that need to be processed concurrently in their limited WM space.

5.5.1.2. Extraneous cognitive load

The presentation style of instructional materials influences extraneous cognitive load (Leahy et al., 2015). Since extraneous cognitive load does not contribute to learning (Sweller, 2010), it should be kept minimal. Reducing extraneous cognitive load would free up WM resources to manage the complexity of the learning material and may contribute to learning. Element interactivity is not commonly used to explain extraneous cognitive load (Beckmann, 2010). While Sweller (2010) proposed that element interactivity should be a major source of extraneous cognitive load as well as intrinsic cognitive load, it is not until recently that researchers have started to explore how extraneous cognitive load can be attributed to element interactivity (e.g., Kadir et al., 2015).

Students who experience sub-optimal instruction tend to engage in cognitive activities that do not enhance schema acquisition, which impose extraneous cognitive load (Sweller et al., 2011). An example of such an activity is the ‘backward-working phase’ (Larkin, McDermott, Simon, & Simon, 1980) or the ‘means-ends analysis’ (Newell & Simon, 1972), where problem solvers simultaneously consider: (a) the current problem state, (b) goal state, (c) differences between the current problem state and the goal state, (d) problem solving operators that are able to reduce the differences between the two states, and (e) sub-goals that have been established (Sweller, 1988). The simultaneous processing of elements (a) to (e) results in element interactivity that imposes extraneous cognitive load.

Problem solving experts work through solutions with procedural moves that are mostly automated, through retrieval of relevant problem-type schemas that exist in their LTM (Reed, 1993), which are then integrated with the information in the problem to arrive at a solution (van Lehn, 1989). Expert problem solvers draw “on the extensive experience stored in their long-term memory and then quickly select and apply the best procedures for solving problems” (Kirschner, Sweller, & Clark, 2006, p. 76), reducing the element interactivity that constitutes extraneous cognitive load.

Instructional designs may introduce extraneous cognitive load in specific ways (Sweller et al., 2011). Figure 5.3b illustrates two methods, Method 1 and Method 2, of teaching students to solve the word problem. Method 1 comprises six operational lines while Method 2 combines the six operational lines into a one-step solution. Every operational line in the solution for Method 1 has low element interactivity because each involves two elements undergoing just one operation (e.g., multiplication, addition, or division) between them. Thus, each operational line, when considered in isolation, constitutes a low cognitive load. Method 1 is suitable for teaching novices to solve the problem as each operational line clearly shows the knowledge being applied and the procedures that follow. The low element interactivity helps students to manage their thought processes more effectively without overloading their WM. Figure 5.4c shows a sample of a student’s work using an approach similar to Method 1 to solve the problem. Even when a student scored full marks using this approach, the schemas retrieved would not be complex enough for constructing an operational line of high element interactivity. In this study, 11 out of 204 students who got full marks (5.4%) solved the problem using this method resulting in six operational lines, and three students who got full marks (1.5%) used even up to eight operational lines (see Table 5.1). The low percentage of students using six or more operational lines shows that only a few students were novices in this domain.

Table 5.1
Results of Students' Problem-Solving Processes and Performance (N=260)

Marks awarded	**Number of students**	**Number of Operational Lines used to solve problem**							
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
0	31	13	9	8	0	1	0	0	0
1	25	3	4	6	8	2	2	0	0
2	204	44	38	47	42	19	11	2	1

By way of contrast, Method 2 comprises one step with high element interactivity, involving nine values undergoing three different operations (i.e., multiplication, addition, and division) simultaneously, requiring a lot of WM resources. For example, to complete the single step in Method 2, students have to simultaneously:

(1) apply the formula to calculate average speed = total distance / total time taken,

(2) substitute the respective quantities for each variable (i.e., total distance and total time),

(3) calculate the quantities of total distance and total time taken from the table of values because they are not directly provided, which requires an algebraic manipulation of the formula of average speed (i.e., average speed = total distance / total time), making total distance the subject (i.e., total distance = average speed X total time),

(4) calculate the time travelled in hours from each of the three time intervals given in the table of values by multiplying the average speed in that time frame by the time in hours to determine the total distance covered within that time interval,

(5) repeat this step for the other two time frames and sum all three to determine the total distance travelled, and

(6) divide the answer by the total time taken for the journey.

The concurrent processing of the above mathematical procedures, along with the interpretation of the table of values and application of conceptual knowledge, involves a high level of element interactivity and therefore, a high cognitive load. Figure 5.4d shows a sample of the work of a student who used an approach similar to Method 2 to solve the problem. This student could be viewed as an expert because he was able to perfectly solve the problem with one operational line of high element interactivity. In this sample, 21.6% of the students who got full marks solved the problem using this method (i.e., one operational line). This shows that 1 out of 5 students were experts in this domain.

While Method 2 technically has a higher element interactivity compared to Method 1, the solution involves fewer operational lines, and is the preferred option of experts (Star & Newton, 2009). Experts would be recalling most of the required procedural and conceptual knowledge as automated schemas (Kirschner et al., 2006), so the reduction in the number of operational lines is actually a reflection of less element interactivity. Getting experts to use many operational lines will introduce extraneous cognitive load.

For the benefit of novices who are learning to solve such complex problems for the first time, teachers should probably first introduce Method 1 during instruction. This is because novices lack or have unstable links to existing schemas (Ericsson, 2006a) and would not be able to handle much element interactivity. After sufficient problem solving practice, students would gain more knowledge and develop more stable links to schemas. Teachers may then progress to intermediate stages of problem solving. Intermediate stages to bridge the element interactivity gap between Method 1 and Methods 2 could be methods that comprise fewer steps by combining certain mathematical procedures that are more easily managed. Figure 5.4c shows a sample of the work of a student using such an approach. In this sample, 127 out of 204 students who got full marks (62.2%) solved the problem using various versions of this approach, with operational lines ranging from two to four (Table 5.1). This finding shows that the majority of the students in this study were in the intermediate stages of expertise.

5.5.1.3. Germane cognitive load

Germane cognitive load occurs when the learner devotes WM resources to deal with the intrinsic cognitive load of the learning material, contributing directly to the learner's development of cognitive structures such as schema development and automation that increase performance (Sweller et al., 2011). Sweller (2010) and Beckmann (2010) suggest that germane cognitive load should be seen as a result of element interactivity and associated cognitive behaviors that contribute to learning. Kadir et al. (2015) elaborated that germane cognitive load is imposed on WM when existing relevant schemas are retrieved from LTM to interact with the new information in WM (that came from the learning task) to form new higher-level schemas (representing the newly-formed knowledge) which are again stored in LTM. This process, when repeated, will develop the learners' expertise in the domain.

As illustrated in Figure 5.3b, the process of solving the speed problem involves four interacting elements: (1) the concept of average speed = total distance/total time, (2) total distance and total time for each of the three time intervals: 12pm-2pm, 2pm-3pm, and 3pm-6pm, which requires the skill to interpret a table of values, (3) matching of variable and value in a formula (i.e., symbolic representation of relations), and (4) mathematical procedures involving interacting values. After instruction, students should have been exposed to all four elements: (1), (2), (3,) and (4). The retrieval of (1) as a schema from LTM (which is probably not stable at the initial stages of new learning), to interact with (2), (3), and (4) constitutes germane cognitive load because the practice consolidates and automates the mental process (see Figure 5.1). Students who have had practice in solving similar problems would know how to interpret the table of values to make sense of it, apply the average speed formula, and process the multiple interacting elements in the problem to derive the correct solution (i.e., apply scientific concept, recall related formula, and use mathematical skills to solve the problem), as illustrated in Figure 5.4. Ideally, these processes would be recalled as automated schemas from LTM to interact with the new elements in the problem to facilitate the problem solving process, imposing germane cognitive load. Novice or intermediate level students who may not have these schemas in their LTM would experience extraneous cognitive load on their WM to execute these processes, thus reducing available WM to actually solve the essence of the problem.

The speed problem has been designed to differentiate students who understand the concept of average speed and those who do not. Before beginning the mathematical procedural processes required in solving the problem, there are a few decisions that students need to make, based on their science conceptual knowledge on average speed. The correct decisions and methods used to solve the problem will depend on their schema construction and retrieval processes formed during prior instruction. Students with a good understanding of the concept of average speed would be expected to apply the three different values of average speed and time provided in the problem whereas those lacking understanding would not. Conceptual mistakes may include: (1) summing up all the average speeds in the table and dividing them by 3 or 2 depending on the interpretation of whether 0 km/h is to be considered as part of the average speed computation, and (2) dividing the total distance by the total time of 5 hours (instead of 6 hours) because they did not think that the one hour of rest (i.e., 0 km/h) should be considered as part of the average speed computation. For students who made conceptual mistakes but used fewer operational lines to solve the problem, instruction for them should focus more on developing their conceptual knowledge.

Students' conceptual and procedural knowledge depends on the schemas constructed during instruction. If instruction is sub-optimal, domain schemas will be poorly constructed, schema automation will be adversely affected, and students will struggle to solve problems with high element interactivity. However, if instruction is optimal, students will construct conceptually correct domain schemas, which will stabilize with practice over time, making schema automation possible during the problem solving process (Sweller et al., 2011). For example, significant WM resources are required to manage the high element interactivity in simultaneously executing the three operations of multiplication, addition, and division involving nine magnitudes within a single operational line in step 1, Method 2: [(75 X 2) + (0 X 1) + (70 X 3)] / 2+1+3. Expert students would retrieve and automate their science and mathematical knowledge as schemas, thus reducing the element interactivity in the problem. This frees WM resources to deal with the new interacting elements in the problem, introducing germane cognitive load. If the element interactivity is within the capacity of WM, students' success rate in solving complex science problems is increased (Carlson et al., 2003).

5.5.2. Analysis in terms of Marks and Operational Lines

Twelve out of 272 participants did not complete the problem task (i.e., nine students left the problem blank and three students filled up the space with a random number). These students' results were not analyzed. Therefore only 260 students' answers were analyzed in terms of marks and operational lines. Correlation analysis showed that students' mark had a small positive correlation with the number of operational lines they used to solve the problem ($r = .19$, $p < .05$). It implied that students who used more operational lines tended to get the solutions to the problem correct, resulting in higher marks. Since most of the students were at the intermediate stage of expertise, at least so*r*me of them may need to use enough operational lines to facilitate their thought processes and guide them to solving the problem accurately. However, the low correlation between operational lines and score for the problem, although significant, reflects that the number of operational lines may not be commensurate with students' understanding of the concept of speed. An inspection of the data showed that a few students who used fewer lines to solve the problem and some others who used more lines both got it wrong, both due to their wrong understanding of the concept. Therefore, in order to understand students' use of operational lines more accurately, I categorized students' responses into three categories: those that were awarded 0 mark, 1 mark, and 2 marks. Table 5.1 shows the distribution of students whose responses were awarded 0 mark, 1 mark, and 2 marks and the number of operational lines that they used to solve the problem. As shown in Table 5.1, the responses of: 31 students (11.9%) were not awarded any mark, 25 students (9.6%) were awarded one mark and 204 students (78.5%) were awarded a perfect score of two marks. The following section elaborates on the problem solving processes for each category.

5.5.2.1. Zero-mark solutions

Thirty-one solutions were given a score of zero, mostly because incorrect concepts were applied. For example, average speed is the distance travelled per unit time and computed by summing the distance travelled during the whole journey and dividing it by the total time taken to complete the journey. Some of the zero-scoring solutions had the summing of the speeds (instead of distance) and dividing it by three speeds or total time. Figure 5.4a shows an example of such a solution. Most of these students used between one to three operational lines to solve the problem (see Table 5.1). A score of zero is often associated with zero understanding, but these students' solutions, when analyzed in terms of element interactivity, showed that they were able to manage high element interactivity in terms of mathematical procedures. Therefore, for this group of students, instruction should focus on developing their understanding of the scientific concepts of 'average speed' rather than on mathematical procedures for which they already possess relevant schemas. These results showed that an analysis of students' answers using element interactivity would provide useful information about their thought processes and areas of expertise.

5.5.2.2. One-mark solutions

Twenty-five one-mark solutions demonstrated mistakes such as using the wrong units or making mathematical miscalculations. Figure 5.4b shows an example of such a solution. Most of these students have applied the correct concept of ‘average speed’ and used one to six operational lines to solve the problem (see Table 5.1). The majority of this group of students used three to four operational lines, indicating that they were still developing expertise in this domain. Most mistakes were minor and mathematical, and could easily be remedied with teacher advice. Instruction for this group of students could be similar to those whose solution scored two marks, since they were able to manage about the same level of element interactivity.

5.5.2.3. Two-mark solutions

The majority of students (i.e., 204 out of 260) produced solutions that scored the maximum of two marks. Their solutions were perfect both conceptually and in mathematical operations. Figures 5.4c to 5.4e show examples of solutions that were awarded a perfect score. For this group of students, most of them used between one and eight operational lines to solve the problem (see Table 5.1). There is almost an equal distribution of students who used one to four operational lines, with about 20% of students for each case. These results demonstrate that there is variation in the way that students articulate their thought processes. Students who used more than five operational lines form the minority of the students (i.e., 16%). These results showed that the majority of the students were not novices, as they did not need that many operational lines to articulate their thought processes. They were able to combine steps and handle operational lines with higher element interactivity. However, only 21.6% of the perfect-score students used one operational line with the highest element interactivity, so I may conclude that although most of the students were not novices, they were still in the intermediate stage of developing expertise in the domain (i.e., not experts yet). With developing domain expertise over time, these would use fewer operational lines because they would combine steps and be able to handle operational lines with higher element interactivity.

5.6. Conclusion

The solving of science word problems, especially in the area of physics, involves the need to simultaneously process multiple elements such as the application of mathematical and scientific rules, executing problem solving procedures, the manipulation of symbols and values, as well as applying relevant conceptual and procedural knowledge (Carlson et al., 2003; Kadir et al., 2015). This range and variety of elements are often interrelated, making science problem solving activity a cognitive task with high element interactivity (Kadir et al., 2015). Physics problems are challenging for novices because they lack required schemas (including problem-type schemas), which makes it difficult to integrate new information with their inadequate existing knowledge (Chi et al., 1982).

CLT research has tended to use element interactivity as a common explanatory mechanism for intrinsic cognitive load. Recent literature suggests that it should be central to CLT (Beckmann, 2010; Sweller, 2010), but little is known about how the conceptualization can be applied to all types of cognitive load. Researchers have also emphasized the need to reduce extraneous cognitive load to have more WM resources devoted to germane cognitive load, but the 'how' to do this effectively has been hampered due to the absence of a well-articulated explanatory mechanism.

In this study, I used element interactivity to explain all three forms of cognitive load experienced by learners when solving complex problems. This approach may also be used to focus instructors' attention on the level of complexity in problem solving materials prior to administering them to students, enabling instructors to select appropriate teaching strategies to optimize learning opportunities. This is critical because on one hand, materials that are too high in complexity are known to not only hinder learning in the short term, but have adverse long-term effects in terms of student motivation to engage with science (Kadir et al., 2015; Yeung, 1999). On the other hand, materials that are too low in complexity will result in the expertise reversal effect (Kalyuga et al., 2003), which could also lower student motivation. Expertise reversal effect comes about when instructional methods and materials aimed at novice learners become ineffective as learners gain expertise in the domain (Kalyuga, 2007).

Apart from analyzing word problems, I also showed how element interactivity can be a useful construct to evaluate students' work, from which I can estimate their level of expertise. For example, students who used Method 2 (see Figure 5.4d) showed expertise and would be exposed to extraneous cognitive load if they were taught using Method 1, which were tailored for novices. The additional steps in Method 1 would be redundant and would not contribute to the learning of experts in the domain. Teachers therefore need to know their students' level of expertise (novice, intermediate, or expert) and tailor their instructional approaches accordingly, so that element interactivity at every stage of the problem solving process is effectively managed for all students. Optimal learning opportunities occur only when students receive instruction that fits their current knowledge levels and expertise (Sweller et al., 2011).

Additional research is required to generalize the applicability of using element interactivity as a diagnostic tool in other science topics and curriculum domains. However, by examining students' work in a complex learning task through the lens of element interactivity, teachers would be able to:

(1) gain insights about students' thought processes and estimate their level of expertise; and

(2) evaluate the effectiveness of the instructional designs and materials.

5.6.1. Practical Implications for Science Education

In this study, without prompting, high-ability students used more than one operational line to solve the problem, showing that they were at an intermediate stage of expertise. Students of low ability and lacking schemas in the domain may not even attempt to solve the complex problem as the intrinsic cognitive load itself may overload their WM. One way to help students develop expertise in complex problem solving is to provide worked examples followed by more opportunities for them to practice problem solving in the domain, in sequential stages of increasing element interactivity (Ayres, 2013). Effective instruction, learning and practice that match the students' knowledge levels, may help them develop schemas that could become automated (Ericsson, 2005) and increase their expertise in that domain. They would then be able to apply more efficient problem solving strategies reflected in the use of less operational lines (Star & Newton, 2009). Teachers who use element interactivity to provide instruction may therefore optimize learning opportunities for their students. The following provides suggestions on how this may be approached.

5.6.1.1. Isolating interacting elements

Breaking down complex problems into parts or introducing solution steps with less interacting elements lowers the level of element interactivity at each stage of problem solving. The problem in Figure 5.3a is an example of a science problem with high element interactivity and therefore imposes high intrinsic cognitive load on novice problem solvers, who may not be able to process all the interacting elements simultaneously without exceeding their WM capacity. Following the advice of Ayres (2013), the problem may be broken down into separate units to support learning in a sequential manner, focusing on individual units separately.

For lower-ability students or those with less pre-existing knowledge, sub-tasks allow students to focus on one smaller task at a time. One approach is to work out the solution using as many steps as possible, and to then develop each step of the solution to form a sub-task. Figure 5.5 illustrates how the same problem on speed can be broken down into five sub-tasks. Following the steps, students are guided towards carrying out the necessary solution steps to calculate the average speed. This reduces the need for students to search for solution methods, which decreases extraneous cognitive load.

Time Interval	12 pm to 2 pm	2 pm to 3 pm	3 pm to 6 pm
Average speed	75 km/h	0 km/h	70 km/h

Based on the information in the table,

(a) state the total time taken for the car to complete the entire journey;
(b) calculate the distance travelled by the car from 12 pm to 2 pm;
(c) state the period of time when the car is not moving;
(d) calculate the total distance travelled by the car for the entire journey;
(e) calculate the average speed of the car for the entire journey (leave your answer in km/h).

Figure 5.5. An example of how a complex science problem can be broken down into smaller sub-tasks.

Students with intermediate knowledge should be introduced to a method where each solution step constitutes a low element interactivity task, comprising no more than two elements and a mathematical operation. (e.g., Method 1). This will help students to acquire the schemas to solve science problems without overloading their WM. The teacher may encourage the combination of steps to reduce the operational lines (i.e., intermediate stages leading to Method 2) as the students progress in acquiring problem solving schemas. A teacher of intermediate students could begin with Method 1 where each line of the six solution steps constitutes a low element interactivity task. Each solution step comprises no more than two elements and a mathematical operation. Next, the students could progress to a 'two-solution step' stage. The first step would be: total distance travelled in the journey = (75X2) + (0X1) + (70X3) = 360 km and second step: the average speed of the car = 360 km / 6 h = 60 km/h. In terms of element interactivity, the first step of this intermediate stage combines steps 1 to 4 in Method 1 and appears to be a high element interactivity task, but lower than the element interactivity in Step 1 in Method 2, since it does not deal with the division operation with the total time taken for the journey.

The second (and final step) for the intermediate stage involves three main elements: (1) using the value of total distance calculated in Step 1, (2) calculating the total duration of time for the entire travel, and (3) dividing the total distance with the total time taken. Hence, it incurs higher element interactivity than any of the operational lines in Method 2, but lower element interactivity than operation line 1 in Method 2. When students have practiced solving such problems, the teacher can introduce Method 2, which comprises one solution step of high element interactivity, owing to the need to manipulate multiple interacting elements simultaneously in WM (i.e., multiplication of time and speed for distance travelled during the three time intervals, summing up the distances and time taken and carrying out the division operation; all within one solution step).

As students develop problem-based schemas, the combination of multiple solution steps into one step would have lower element interactivity because the schemas (conceptual, procedural and their interactions) could be retrieved from LTM as single elements, greatly reducing the elements that the students have to deal with in WM.

5.6.1.2. Practice

Practice in solving similar problems facilitates the retrieval of existing schemas and the construction of higher-level schemas after interaction with the new elements in WM, eventually leading to the automation of conceptual and procedural schemas (Ericsson, 2005). Schema automation reduces extraneous cognitive load on WM, so more of the limited WM resources will be available to be devoted to managing the element interactivity in germane cognitive load, which is essential for learning (Sweller et al., 2011). With more practice in solving similar problems, WM resources devoted to germane cognitive load will facilitate schema construction and automation of both conceptual and procedural knowledge, enhancing learning. This, in turn, reinforces and increases students' existing knowledge base by having high-level schemas organized in LTM. Students will then be able to solve problems with greater complexity, when these high-level schemas are automated (Ericsson, 2006b).

5.6.1.3. Introducing one type of knowledge at a time

Problem solving involves element interactivity between procedural and conceptual knowledge (Ngu et al., 2015). The challenge with science problem solving tasks is managing both types of knowledge concurrently in order to maximize learning, which often overloads the WM of novices (Kadir et al., 2015). Teachers should be mindful of the need to consider the interactivity of both types of knowledge and attempt to make learning more manageable for the students. For example, for students who are able to manage high element interactivity in mathematical procedures, instruction should focus on developing conceptual understanding in the science domain.

5.6.1.4. Motivation

Based on the model of human cognitive architecture (see Figure 5.1), cognitive processes only occur when students pay attention and are engaged in the learning task. An intelligent student who does not give a learning task any attention will have all his WM resources devoted to other events rather than the targeted task. This means that motivation is an essential factor for learning tasks to be completed (Ryan & Deci, 2016). Therefore, in addition to applying CLT strategies for effective learning, the teaching and learning processes need to be motivating enough to engage the learners.

5.6.2. Recommendations

Educators should capitalize on recent findings from CLT research to improve the effectiveness of teaching and learning in the classroom. The following are recommendations for consideration:

a. estimate the types of cognitive load students may experience during the learning process by identifying and analyzing the element interactivity of the science instructional materials;

b. work out the solution of the problem solving tasks using different methods, and then estimate the element interactivity of each method, to decide which method is most suitable for which students, based on their existing knowledge base;

c. devise effective pedagogical strategies (based on the element interactivity analysis for the different types of cognitive load) to scaffold complex learning tasks to ensure that the level of element interactivity is manageable for the students (given their existing knowledge base) for more effective learning;
d. progress students’ practice in problem solving tasks to generate an appropriate level of germane cognitive load to facilitate schema building and retrieval;
e. introduce relevant work examples (each consisting of a problem and the solution steps to solve the problem) for the students to study prior to solving the problems in order to reduce the problem search and help students to construct problem-based schemas (van Gog & Kester, 2012); and
f. motivate students to learn so that they will pay attention to the learning tasks at hand.

In sum, element interactivity is an important and useful construct to support the generation of more effective instructional procedures. This will further contribute to the research goal of CLT linked to progress in education.

CHAPTER 6: STUDY 4 -

Effects of Managing Element Interactivity on Student Achievement and their Academic Self-Concept

6.1. Preface

Study 4 is an extension of Study 3. While Study 3 used element interactivity as a construct for the analysis of student learning processes, Study 4 used element interactivity for the analysis and design of science instruction. Instruction is critical in generating student thought processes, which presumably leads to effective learning. However, if science instruction causes cognitive overload, students will not learn effectively. As elaborated in Study 1, self-concept is crucial because if students do not believe that they are capable of doing well in science, they may neither give their best nor pay attention to the science learning tasks. When attention is not given to instruction, no learning will take place. Study 4 contributes to the aim of this thesis by investigating the effects of reducing cognitive load at each stage of learning on student achievement and academic self-concept (motivational) in science. The findings will (1) show how learning tasks can be analyzed in terms of element interactivity to assess their suitability for students, (2) highlight the effects of a cognitive strategy of managing element interactivity on student achievement and self-concept, and (3) guide lesson design and instruction to ensure instruction suits students' cognitive levels and not cause cognitive overload.

6.2. Abstract

Element interactivity, an essential feature underpinning cognitive load theory, has been identified as a major construct for explaining complexity in learning materials, but is not commonly used by teachers. The main aim of this study was to illustrate how teachers can manage the element interactivity involved in learning a complex science topic such as density, and to present some preliminary intervention effects following an in-service workshop that enabled teachers to apply an instructional strategy to manage element interactivity. Results showed that Grade 7 students (*N*=156) benefitted from instruction that reduced element interactivity, not only in terms of their achievement, but also in their self-concept. Evidence shows that teachers who understand and are able to use element interactivity to manage instruction will be more effective in designing instruction that benefits their students, thus progressing teacher education to a new level.

6.3. Introduction

Presenting students with learning materials that are compatible with their capabilities is in line with Vygotsky's (1963) zone of proximal development and optimized learning. Learning materials that are too easy may under-challenge students' cognitive capacities, while materials that are too difficult may risk reducing students' self-concept, both of which have negative effects towards students' learning and motivation (Schnotz & Kürschner, 2007, Taconis, 2013). Knowledge of element interactivity enables teachers to design learning and assessment materials as well as instructional approaches that are compatible with their students' level of expertise. When teachers simplify complex problems into their elements and interactions, essential concepts and procedures are clarified resulting in students being more likely to solve word problems successfully. When students experience success in learning, their self-concept increases, as does their achievement and motivation, which optimizes their learning potential (Phan, Ngu, & Yeung, 2016). The main aim of this study was to demonstrate how teachers can manage the element interactivity involved in learning a complex science topic such as density, and to present some preliminary intervention effects of an in-service workshop that enabled teachers to apply an instructional strategy that managed element interactivity on students' achievement and self-concept in physics.

Element interactivity is a construct used by cognitive load theory (CLT) that addresses complexity in learning tasks (Sweller, 1994, 2006, 2010; van Merriënboer & Sweller, 2005). Sweller (2010) defines an element as "anything that needs to be or has been learned, such as a concept or a procedure" (p. 124). He elaborated that if an element can be learned in isolation, with minimal reference to other elements, there is low element interactivity in the learning material. In contrast, if the new material consists of elements that heavily interact and cannot be learned in isolation, then that material is considered to have high element interactivity (Sweller, 2010). There are significant learning benefits for students when teachers' instructional approaches reduce element interactivity for example, by analyzing resources and tasks for: intrinsic cognitive load (e.g., complexity of learning materials), extraneous cognitive load (e.g., sub-optimal instruction), and germane cognitive load (e.g., investing mental effort for consolidation and transfer).

Recent literature on CLT indicates that element interactivity is a useful construct underpinning the understanding of how complex learning tasks are approached by learners (e.g., Ayres, 2013; Sweller, 2010). However, the use of element interactivity to design science instruction and complex word problems to accommodate the needs of students has not been explored. Another area of CLT that is under-researched is the effects of instruction that reduced element interactivity on students' achievement and self-concept. Recently, researchers have emphasized targeting educational interventions to include both cognitive (e.g., achievement) and motivational outcomes (e.g., self-concept) for long-term effects on students' development (e.g., Guo, Parker, Marsh, & Morin, 2015; Shen & Pedulla, 2000). An effective intervention should promote both achievement scores and self-concept in the specific domain. This study was designed to investigate these under-researched areas using CLT as the theoretical framework. In the following, I will show how instruction in high element interactivity topics can be effectively managed by isolating elements. Within the context of *density* I focused on the analysis of word problems using element interactivity to measure their complexity. In the study, I attempted to demonstrate that by defining and analyzing the three types of cognitive load (i.e., intrinsic, extraneous, and germane) in terms of element interactivity, it is possible to analyze most learning materials, resulting in tailored instruction and learning tasks to suit students' knowledge levels. To assess the effectiveness of this strategy, I tested a sample of Grade 7 students in a small-scale experimental study to assess any gains in achievement and self-concept scores.

6.3.1. Cognitive Load Theory and Element Interactivity

Cognitive load theory (Sweller, 1988; Sweller et al., 2011; Sweller, van Merriënboer, & Paas, 1998) was developed by researchers to address cognitive issues in the information processing model of human cognition and was then used to develop instructional models to improve learning (Sweller et al., 2011). Effective learning occurs when there is less cognitive load associated with mental processing of instructional materials (Yeung, 1999), which results in schema construction and automation. Schemas are knowledge structures held in the long-term memory (LTM). Schemas can be retrieved from the LTM (Valcke, 2002) to interact with new elements in the WM and be processed to make sense of incoming information to develop new knowledge, generating higher-level schemas (Newell & Simon, 1972), which are then retained in the LTM.

CLT is particularly effective when applied to the learning of complex materials, when learners are often overwhelmed by the interactions of multiple elements that need to be processed simultaneously before meaningful learning can begin (Sweller et al., 2011). For students engaged in science learning and problem solving, there are many interactive elements including: the application of mathematical and scientific rules, following procedures, the manipulation of symbols and values, and applying relevant conceptual and procedural knowledge – all of which incur a high cognitive load within the limited working memory (WM) of the brain. The high levels of element interactivity in science problem solving tasks are particularly challenging for novice learners who have low pre-existing knowledge in the science domain (van Merriënboer & Sweller, 2005). It is important to note that the level of complexity of problem solving tasks is primarily determined by the degree of interactivity of the elements, not just the number of elements involved in the mental process (Leahy & Sweller, 2005; Pollock, Chandler, & Sweller, 2002). The extent to which the various elements interact in a science problem solving task is related to the cognitive load imposed on students

WM (Kadir, Ngu, & Yeung, 2015), so science problem solving tasks that involve high element interactivity have an increased chance of overloading students' limited WM. When students' WM is overloaded, learning is hindered (Sweller, 1988). Element interactivity is the major source of WM load for all three types of cognitive load which students experience when engaging in a learning task (Sweller, 2010). The three types of cognitive load identified by CLT are intrinsic, extraneous, and germane (Sweller et al., 2011). CLT contends that learning is best facilitated by: adjusting intrinsic load to match the learner's existing knowledge level; reducing extraneous cognitive load to free up WM resources; and optimizing germane cognitive load so that available WM resources can be devoted to cognitive strategies that facilitate schema construction and automation. The following describe each type of cognitive load in terms of element interactivity.

6.3.1.1. Intrinsic cognitive load

Intrinsic cognitive load is imposed by the structure of the learning material (Sweller et al., 2011). The level of interactivity among essential elements of information (Sweller, 2010, p. 124) determines the intellectual complexity of the presented material (Sweller & Chandler, 1994). For example, memorizing the individual symbols in the formula to calculate the velocity of a car ($v = s \div t$) in isolation by rote involves limited understanding, and incurs low element interactivity. The symbols 'v' (velocity), 's' (displacement), and 't' (time) can be independently learned. In contrast, coming to an understanding of the relationship between the elements is a higher element interactivity task. Here in the topic of velocity, the learner is required to process simultaneously the relations between four elements (v, =, s, ÷, t) in order to understand velocity (v) as the displacement made by the car in one unit of time. The degree of element interactivity, and therefore the level of complexity, increases when the unit of each quantity of velocity, displacement, and time are considered in the calculations (e.g., m/s, m and s or km/h, km and h, respectively). Essentially, intrinsic cognitive load can be estimated by examining the number of elements and the interactions among them in presented learning materials (Sweller & Chandler, 1994; Tindall-Ford, Chandler, & Sweller, 1997).

6.3.1.2. Extraneous cognitive load

Sub-optimal instructional procedures related to lesson delivery and instruction (i.e., pedagogy) may also impose cognitive load on WM impeding learning (Sweller, 2010), and are known as extraneous cognitive load. Science can be taught using various methods, some of which may generate extraneous cognitive load, depending on how the information is presented (Leahy, Hanham, & Sweller, 2015). For example, if a teacher uses a diagram that does not clearly explain the concept of velocity, students would experience extraneous cognitive load if they are confused by the diagram or decipher the diagram unsuccessfully, resulting in no or erroneous learning. The use of diagrams that clearly explain the concept of velocity would reduce extraneous cognitive load. Many researchers have found that student learning improved when extraneous cognitive load was reduced (e.g., Liu, Lin, Tsai, & Paas, 2012; Paas, Camp, & Rikers, 2001; Yeung, 1999). A goal of instruction should be to eliminate or reduce extraneous cognitive load (Beckmann, 2010).

When students experience sub-optimal instruction, they engage in cognitive activities that are not involved with schema acquisition (Sweller, 1994). For problem solving tasks, such activities include ‘means-ends analysis’ (Newell & Simon, 1972; Sweller, 1988), ‘problem solving search’ (Simon & Kadane, 1975), and ‘guessing’ or applying knowledge activated by superficial characteristics of the problem triggering the use of ill-developed, faulty schemas (Taconis, 1995). These activities distract learners’ attention (Sweller et al., 2011), contributing negatively to schema acquisition. Reducing element interactivity frees up WM resources to manage the complexity of the learning material for schema development and acquisition which enhance learning.

6.3.1.3. Germane cognitive load

Germane cognitive load is imposed on WM when the learner uses WM resources that contribute directly to schema development and automation (Sweller et al., 2011), resulting in meaningful learning (van Gog, Paas, & van Merriënboer, 2006) and knowledge acquisition (Sweller, 2010). An instructional goal should therefore be to ensure that sufficient WM resources are available to manage germane cognitive load (Sweller et al., 2011). Germane cognitive load is an important facet of CLT, but is the least explored and explained in terms of element interactivity.

According to Sweller (2010), germane cognitive load is "purely a function of the working memory resources devoted to the interacting elements that determine intrinsic cognitive load" and by "assuming constant levels of motivation, the learner has no control over germane cognitive load" (p. 126). Beckmann (2010) states that germane cognitive load should be seen as a result of element interactivity and associated cognitive behaviors because schema formation occur through retrieval of existing schemas from LTM combined with encoding of new information through interacting elements from WM and LTM. For example, if students are asked to find the 'velocity of a truck' (after prior optimal instruction), they would be able to recall the formula of velocity ($v = s \div t$) as a single element (i.e., schema) from LTM. Element interactivity that constitutes germane cognitive load involves retrieving the formula as a single schema to interact with the values of displacement (s) and time (t) given in the word problem. The schema is combined with conceptual and procedural knowledge elements in the problem, and the units of each variable.

Additionally, the level of cognitive load experienced by learners varies, depending on their current knowledge level (Kalyuga, Ayres, Chandler, & Sweller, 2003; Sweller, 2010) which is dependent on the presence of schemas related to the domain. For example, a science teacher with high levels of existing schema, would retrieve the concept deriving from the formula for velocity (velocity is displacement per unit time) as one element (recalled as a schema), while the same velocity formula may constitute several interacting elements for a novice secondary school student whose understanding of velocity as a single schema does not yet exist. In this case, the element interactivity would be higher for the student than for the teacher. Given sufficient WM resources and motivation, students who effectively manage this high germane load will form schemas which could be automated given sufficient practice. While the cognitive load differs for each individual based on their existing knowledge, the level of element interactivity is the same for the word problem. Therefore, estimating the cognitive load of word problems by analyzing the elements and their interactivity is a good starting point for teachers to assess their suitability for the students.

6.3.2. Conceptual and Procedural Knowledge in Science

Both conceptual and procedural knowledge need to be simultaneously processed in WM in order to learn science effectively and for knowledge to be applied when solving science problems. Conceptual knowledge is 'knowing that' and procedural knowledge is 'knowing how' (Ryle, 1976). In this study, conceptual knowledge is defined as 'understanding the meaning' behind the learning task and procedural knowledge is defined as the 'ability to carry out the steps and processes' to solve the problem, also referred to as problem solving skills. Learners' success in using appropriate cognitive strategies in science, mathematics and geography depends on the knowledge and understanding of the domain in which the problems are based on (Taconis, 2013). For example, solving a quantitative problem on Density, such as the one in Figure 6.1, requires an understanding of the concept of density before knowledge and strategies can be applied to solve the problem. Mathematical skills are also required to quantify the solution. Therefore, both conceptual and procedural knowledge have to be simultaneously applied to ensure success when solving this type of problem. The simultaneous processing of conceptual and procedural knowledge has a high level of element interactivity, which imposes a high cognitive load on WM, creating issues in cognitive processing. Figure 6.1 shows the multi-part density question designed by the teachers and Figure 6.2 shows how it was analyzed in terms of element interactivity.

In this study, element interactivity in the topic of Density was reduced by the isolated-elements strategy (Kester, Kirshner, & van Merriënboer, 2006; Pollock et al., 2002). Since the students in the study possessed good mathematical skills, including algebraic manipulations, the teachers focused on introducing the conceptual knowledge of density, before introducing the related procedural knowledge (e.g., applying mathematical procedures to solve density problems quantitatively). Within each type of knowledge, teachers designed their lessons using sequential stages of increasing element interactivity. Simple concepts (e.g., mass) were introduced before difficult concepts (e.g., density) and simple procedures (e.g., using the density formula as it is: density = mass ÷ volume) were introduced before difficult procedures (e.g., algebraic manipulations of the density formula: mass = density x volume).

In a Physics laboratory, a beaker of sugar solution is placed on the teacher's bench. The density of 500 ml of sugar solution is found to be 1.25 g/cm^3.

(a) What is the density of 5.0 ml of the same sugar solution?
(b) A student pours 125 g of sugar solution into a measuring cylinder. What is the volume of the sugar solution in the measuring cylinder?
(c) Another student pours 2.0 cm^3 of sugar solution into a small measuring cylinder. What is the mass of that sugar solution?

(d) A cube of 1.0 cm^3 has a mass of 1.1 g. Will it float or sink in the sugar solution? Explain your answer

Figure 6.1. A science problem on density designed by teachers and given to student.

To effectively solve all parts to this problem, students need to simultaneously manage the following interacting elements:

(1) Understand and apply the concept of density
  - Density is the characteristic of a substance's material / composition (i.e. two items made of the same material have the same density regardless of their size)
  - Density is the mass of the substance in one unit of its volume
  - Relative density between substances and the surrounding liquid causes floating ar sinking

(2) Apply the density formula and perform algebraic manipulation to make volume/mass the subject: Density of solution = mass of solution / volume of solution

	Solution	Element interactivity
(a)	1.25 g/cm3	Evaluating all the information given in the problem, the stud needs to apply the concept that the density of a substance is independent of its size/amount. i.e., volume of 500ml of the sugar solution is the same as 5ml of sugar solution. As the volume decreases the mass decreases proportionately, so density is the same. No calculation is necessary.
(b)	Density = mass/volume Volume = mass / density = 125 g /1.25 g/cm3 = 100 cm3	Since the question asks for volume, students need to perform algebraic manipulation of the formula: density = mass / volu to make volume the subject. The search for values for substitution involves identifying mass from the unit of 'g' sin the problem itself does not state 125 g as the mass of the solution. The value of density can be retrieved from the main problem statement, provided students recognize that the suga solution, whether 500 ml or 125 g, has the same density.
(c)	mass = density x volume = 1.25 g/cm3 x 2.0 cm3 = 2.5 g	Again algebraic manipulation is necessary for those choosing apply the density formula to solve for mass. For those studen who understand the concept of the density formula, less cognitive load will be allocated to solve the problem i.e., the simply multiply the density by volume based on their understanding of density as mass per unit volume.
(d)	It will float. The density of the cube is less than the density of the sugar solution.	To answer this question, students need to compare density values (between cube and solution) and understand that it is relative density that causes floating and sinking, which mean that if the object has a density less than the density of the liqu then it floats in the liquid and vice versa. Those who prefer to do calculations can calculate the density of the cube by applying the density formula. But given that the values are simple, students can do a mental calculation of the density of the cube (1.1 g/cm3) and answer that it should float on water because the its density is less than the density of the solution (1.25 g/cm3).

Figure 6.2. Solution to the science problem on density and its element interactivity.

6.3.3. Isolating-elements Strategy

Learning tasks that have high element interactivity are known to easily overload the working memory. Several researchers have tried to directly remove interacting elements from initial learning tasks in order to reduce the element interactivity, an approach known as the isolated-elements strategy. Pollock et al. (2002) were the first to try this strategy in their study on trade apprentices' learning of electrical safety tests. In phase 1, the researchers isolated the elements by focusing instruction only on basic procedural steps. In contrast, another group of participants received the same instruction but with full element interactivity where they were presented with other explanatory information for further understanding of all parts of the tasks. In phase 2, both groups of participants received the same instructional materials with full interacting elements. In the post-test, the isolated-elements group performed better than the full element interactivity group.

In another experiment, Pollock et al. (2002) isolated the elements by getting the initial instruction to focus on conceptual knowledge instead of procedural steps. Again, the isolated-elements group performed better than the full element interactivity group. Based on these consistent results, they concluded that initial instruction that reduces element interactivity (i.e., isolated-elements group) benefits learners more than when initial instruction contains all (i.e., full) element interactivity of the learning task. Other researchers who studied the effects of isolated-elements strategy included Kester et al. (2006). In their study, learners who experienced the isolated-element strategy in the form of sequenced information (i.e., procedural followed by declarative or declarative followed by procedural) performed better than those who experienced the full element interactivity of the task (i.e., both the declarative and procedural information together). In sum, the results of the experiments on the isolated-elements strategy indicated that it does not matter whether conceptual or procedural knowledge is presented to learners first. Learners benefit equally, as long as element interactivity is reduced by presenting one type of knowledge before the other (i.e., in contrast to presenting both types of knowledge together).

In the experimental study reported below, teachers used the isolated-element strategy by presenting students with conceptual knowledge on density (e.g., the concept of density as the mass in one unit of volume by pictorial representation), followed by procedural knowledge (e.g., relating the pictorial representation to density calculations after their conceptual understanding was established). During instruction on problem solving, the scientific concepts of the word problems were discussed before the procedures of problem solving were explained. Each learning task followed a simple-to-complex sequence (Ayres, 2013; Sweller et al., 2011), where sub-tasks of higher element interactivity were introduced after students had accomplished sub-tasks of lower element interactivity.

6.3.4. Expected outcomes

By managing element interactivity, I expect benefits in terms of achievement scores (a cognitive outcome) and self-concept (a motivational outcome). Science self-concept can be defined as students' academic self-perceptions in the science domain (Kadir, Yeung, & Barker, 2012). Students with a positive science self-concept feel good about their academic ability in science and are likely to achieve well in the science domain (Kadir et al., 2015). Due to the potentially long-term effects that self-concept enhancement may bring to a child's development, researchers have argued for the inclusion of appropriate self-concept enhancement elements in educational interventions (e.g., Guo, Parker et al., 2015). In this study, I hypothesized that if element interactivity was effectively managed, students would be more likely to experience success in their learning, manifested in improved science achievement and enhanced science self-concept.

6.3.5. The Study

I studied the effects of managing element interactivity on students' achievement and self-concept. Students completed a pre-test on Density to measure their existing knowledge of the topic. Following a training program, teachers delivered instruction to students on Density using the isolated-elements strategy to reduce element interactivity in the learning process. After the completion of the lessons, students' learning of the topic was assessed by a post-test. As an added measure, students' pre-test and post-test results of another science topic Properties of Matter taught in the teachers' usual delivery mode (i.e., where element interactivity was not managed) before the workshop, were also collected. I hypothesized that students' gain in scores (i.e., difference between post-test and pre-test scores) as well as their post-test scores in the Density topic would be higher than that in Properties of Matter, since effective management of element interactivity should help students learn more effectively. As for the self-concept measure, since I was not able to collect students' science self-concept scores before the Properties of Matter topic was taught, I could only compare the gain in self-concept scores in Density. Based on past self-concept research showing the decline in adolescents' academic self-concept, especially during the transition periods of years 7 to 9 (Marsh, 1989; Yeung, 2011), it is unlikely to observe a significant gain in students' self-concept attributable to instruction, so I hypothesize that students' science self-concept will be maintained after Density instruction at best.

6.4. Method

6.4.1. Participants

The participants in this study were four Grade 7 science teachers (2 males and 2 females; age M = 35.0 years) and 156 Grade 7 students (83 boys and 73 girls; age M = 13.1 years) from a selective school in Singapore in a high socio-economic area. English is the medium of instruction in all Singapore schools, so the participants were fluent in the English language. All science teachers had engineering degrees and had completed a year of teacher training (specializing in science and mathematics curriculum) at the National Institute of Education in Singapore prior to their teaching career. They had at least seven years of science teaching experience and ranged from 30 to 39 years of age. The Grade 7 students were from four different classes taught by these teachers.

6.4.2. Materials and Procedure

The experiment consisted of four phases: 1) pre-intervention phase, 2) teacher knowledge acquisition phase, 3) students' knowledge and skills acquisition phase and 4) post-intervention phase. Each phase was conducted within the school premises during the first school semester in the first half of the year.

6.4.2.1. Phase 1: Pre-intervention phase

Before the intervention, teachers taught science in their usual way, typical of the traditional lecture-based system. For every lesson, the teachers showed PowerPoint slides and the students who were seated passively in the classroom, copying relevant information in their worksheets and notebooks. One of the science curriculum topics taught in this way was Properties of Matter. The pre-test and post-test results on Properties of Matter were submitted to the researchers as part of the analysis. During this time, students also completed a pre-test on Density before the intervention. The Density pre-test was designed by me, based on the curriculum objectives of the topic determined by the school, after which it was given to the science teachers in the school for review and moderation. The pre-test was less complex than the post-test because the students were not asked to perform any topic-related calculations. The Density pre-test questions mainly assessed students' understanding of floating and sinking, and ideas on relative density, given certain scenarios. The pre-test was marked by the teachers and submitted to the researchers for inter-rater reliability. It was also during this phase that students completed a self-concept pre-test, to measure their science self-concept before the intervention.

6.4.2.2. Phase 2: Teacher knowledge acquisition phase

Participating science teachers attended five one-hour workshops conducted by the researchers after school curriculum hours. During the first two workshops, teachers were introduced to information about students' cognitive processes during learning and how to use element interactivity as an approach to: (1) analyze science word problems, (2) design instruction to meet students' learning needs and (3) design word problems that matched students' ability levels. In workshops three and four, the teachers worked with the researchers to design Density lessons using the isolated-elements strategy (Pollock et al., 2002) to reduce element interactivity and to assist novice learners with learning complex materials (e.g., Ayres, 2013; Kester et al., 2006). In the final workshop, teachers worked with the researchers to design a complex multi-part density problem and analyzed it using element interactivity.

6.4.2.3. Phase 3: Students' knowledge acquisition phase

The acquisition phase for the students was based on the Density lessons designed by their science teachers. All four science teachers delivered their lessons using the same Density lesson plans that were finalized at the end of the fifth workshop. Over seven one-hour lessons in three weeks, students were taught (1) the concept of mass, volume and density, (2) that density is a ratio of mass to volume and thus a property of a material, (3) the density formula (i.e., density = mass / volume) and how to apply it to solve problems in mass, volume and density and, (4) the concept of relative density and how it relates to floating and sinking. Some of the lessons were in the form of hands-on activities and some were theory-based instruction in the classroom.

6.4.2.4. Phase 4: Post-intervention phase

During this phase, students completed a Density post-test designed by the teachers and researchers, as well as a survey measuring their science self-concept after the intervention. The Density post-test questions covered the targeted concepts and procedures in the curriculum which were: (1) density is a ratio of mass to volume and thus a property of a material, (2) applying the density formula (i.e., density = mass ÷ volume) to solve problems in mass, volume and density and (3) applying the concept of relative density to determine whether an object floats or sinks in a liquid.

6.4.2.5. Test scores

The pre-tests and post-tests of the two science topics, Density and Properties of Matter, were assigned 5 marks each, one mark per question. Any error in a question resulted in zero mark assigned to the student for that question. All test questions were marked and awarded scores by the teachers. The researchers were then given the same students' work to score and had an inter-rater agreement of 100%. Students' achievement was determined from these test scores. Comparisons were made between the pre-test and post-test scores for each topic to study students' achievement gain before and after the topics were taught. If students' improved more significantly from pre-test to post-test in the topic of Density (where element interactivity management was present), than in the topic of Properties of Matter (where element interactivity management was absent), then it could be an indication that managing element interactivity during students' learning process had a role in the students' higher achievement.

6.4.2.6. Science self-concept

Each student was given a survey in which they rated on a scale of 1 (strongly disagree) - 6 (strongly agree) how much they agreed with each of four statements describing their sense of competence in science (e.g., "I have always done well in science"). The statements were taken from the self-concept scale in Kadir et al. (2012) who adapted the items from the Marsh (1992) *Academic Self-Description Questionnaire* (ASDQ) instrument. The survey was administered to the students before and after the intervention.

All research procedures were approved by the university ethics committee and the school. Informed consent was obtained from the parents of the students and assent was obtained from the students before data collection. All data were collected by teachers during school curriculum hours.

6.4.3. Statistical Analysis

A paired-samples *t*-test was conducted to compare students' scores on the pre-test and post-test on the science topics of Density and Properties of Matter. This was also done for students' science self-concept, before and after the topic Density was taught. The purpose of the test was to find out if the post-test scores were significantly higher than the pre-test scores for each measure. Cohen's *d* (Cohen, 1977) was used as a measure of effect size for the *t*-test. According to Cohen (1977), d = 0.2, 0.5, and 0.8 could be interpreted as small, medium, and large effects, respectively.

6.5. Results

The results of the study are presented in two parts. Part 1 shows the teachers' analysis of the multi-part density word problem (Figure 6.1) in terms of element interactivity. Part 2 shows the results of the effects of the intervention on students' achievement and self-concept.

6.5.1. Part 1: Teachers' use of element interactivity to analyze a science word problem

Figure 6.1 shows the multi-part density question designed by the teachers and Figure 6.2 shows how it was analyzed in terms of element interactivity. The following shows how the element interactivity of each part of the density question was further categorized into intrinsic, extraneous and germane cognitive load. Analytic assumptions include: (1) students had a good command of the language used in the problem and therefore understand the problem statement (i.e., the general message is considered as one element), (2) students were novices as this was their first encounter with this science problem (i.e., students do not have schemas directly related to the solution the problem) but do possess density-related conceptual and procedural schemas due to prior instruction on density problem solving, (3) students possessed basic mathematical skills and had prior experience in carrying out basic mathematical procedures (i.e., an operation such as multiplication, addition, or division was considered as one element only), and (4) students have similar psychosocial factors related to motivation and anxiety (e.g., students are motivated enough to devote attention to the problem and are not anxious, so their WM is devoted to the problem solving task instead of dealing with anxiety).

6.5.1.1. Intrinsic cognitive load of the density problem

Science word problems typically consist of words, numbers and units that exist in the information of the problem text. These three elements interact as they need to be simultaneously processed in the learner's WM for the problem's context to be understood and for the students to identify ways to solve the problem, based on their existing domain-specific schemas of conceptual and procedural knowledge in science and mathematics. For a given knowledge level, element interactivity of the three element groups stated above is solely determined by the characteristics of the problem, so it constitutes intrinsic cognitive load.
The density problem (see Figure 6.1) is likely to impose a high intrinsic cognitive load on learners because it comprises seven elements: two different volumes with the unit 'ml', two different volumes with the unit 'cm^3', one density quantity with the unit 'g/cm^3' and two different masses with the unit 'g' all of which simultaneously interact with the words in the problem. The simultaneous interaction of these elements, together with the conceptual and procedural processes of mathematics and science interacting with each other will likely impose a substantial intrinsic cognitive load. The conceptual process involves knowledge of the relationship between density, mass, volume, floating and sinking. The procedural process involves the manipulation of the algebraic equation of 'density = mass ÷ volume', where the solution may be density, mass, or volume, depending on the stated problem. These elements interact in the sense that if any one element is omitted, the problem cannot be solved successfully. The high level of interactivity of these elements could overload WM, hindering a successful solution.

To reduce WM overload, following instructional workshops, participating teachers broke the problem down into four parts or sub-tasks (Figure 6.1). This reduced the overall intrinsic cognitive load for students by isolating the cognitive processes required to solve each part of the problem in sequence (Ayres, 2013). The solution for each part still involves some element interactivity between the words and elements within that part, and linking the information to the main problem statement, but if I assume that students' existing schemas of the understanding of the language, numbers, units and the concept of density are robust, the lower level of element interactivity of each part of the problem will be within the capacity of their WM.

6.5.1.2. Extraneous cognitive load of the density problem

Secondary school students who lack conceptual knowledge and problem solving skills may use ineffective strategies when solving problems such as that in Figure 6.1, including guessing and using the means-ends analysis (Newell & Simon, 1972; Sweller, 1988). This latter strategy involves decision making processes where students search their existing schemas to select appropriate mathematical operational moves to complete each step of the problem solving process. According to Beckmann (2010), "mental activities that do not directly contribute to schema acquisition and automation (which is the general goal of learning from a CLT perspective) are considered to result in extraneous cognitive load" (p. 251). Therefore, these searching techniques constitute extraneous cognitive load since the processes are not intrinsic to the problem itself - they are processes adopted by the novice in an attempt to solve the problem, which interact with each other, and exert a substantial extraneous cognitive load on WM, inhibiting learning.

Students who have experienced sub-optimal instruction are likely to have limited conceptual understanding of density. If students memorize the density formula without understanding the underpinning science the problem solving search processes would likely be compromised, exerting additional extraneous cognitive load on the WM. With several values of mass and volume to consider in the problem, those students lacking conceptual knowledge would likely not know which to use or apply correctly. Additionally, memorization of the formula alone, may lead to incorrect information recall, compromising retrieval of the correct formula (e.g., is it volume ÷ mass or mass x volume or mass ÷ volume?) to effectively solve the problem. The element interactivity of the decision-making processes related to formula selection and the search for the correct processes to solve the problem exert a significant amount of extraneous cognitive load on the WM. Nevertheless, this extraneous cognitive load can be reduced if students receive better instruction and more practice sessions which increase their LTM related to problem-type schemas.

Optimal instruction supports the construction and organization of schemas in LTM. Practice sessions in solving similar problems involve the repeated recall of the schemas to interact with the new elements in WM, which eventually lead to the automation of schemas and problem solving processes, reducing the extraneous cognitive load to a manageable level (Yeung, 1999).

6.5.1.3. Germane cognitive load of the density problem

The process of solving the density problem (Figure 6.2) involves several interacting elements: (1a) the formula (density = mass ÷ volume) indicates a relation that density is the amount of mass in g that exists in one unit of volume in cm^3, so the density is expressed in g per cm^3, (1b) based on the formula of density as the mass in one unit of volume, density is a characteristic of the material, (2) density, mass and volume are each associated with a value and respective units, (3) matching of variables and values in a formula (i.e., symbolic representation of relations), (4) mathematical procedures involving interacting elements such as values and variables and, (5) the concept of relative density (i.e., an object will float in a liquid of higher density and sink in a liquid of lower density). After analyzing the problem (intrinsic cognitive load), students who have constructed relevant schemas during prior instruction on density would be able to retrieve these schemas (although they are probably not stable in the initial stages of new learning) from LTM to interact with (1) to (5) above to solve the different parts of the problem. The element interactivity involved in this process constitutes germane cognitive load as it consolidates and automates the mental processes, facilitating the construction and automation of higher-level schemas to solve this and future problems that are of similar nature. The following sections describe in detail, the element interactivity constituting germane cognitive load that occurs in the WM as students solve each part of the multi-part density question (i.e., parts (a) to (d) in Figure 6.1).

6.5.1.3.1. Solving part (a) of the density problem

In order to solve this part of the problem, students need to retrieve the schema, "density is the mass in one unit of volume", to interact with the elements of information in the problem. This element interactivity constitutes germane cognitive load which will eventually lead to the construction of the schema that the density of 5.0 ml of the sugar solution is the same as the density of 500 ml of the same sugar solution (because the amount of mass in 1 unit of volume (1 cm^3 or 1 ml) in both the 5.0 ml and 500 ml of the sugar solution is the same). Following practice in solving similar problems, this schema would stabilize. Using germane resources to manage element interactivity between existing schemas and new elements in the practice problems may result in the construction of a higher-level schema. An example of such a schema (conceptual) is 'density is the characteristic of a material' (i.e., any two objects made of the same material will have the same density regardless of the quantity). Another schema (procedural) that could be formed is 'when the volume of the object decreases, the mass of the object decreases proportionally, so density remains the same', reinforcing the conceptual schema of density as an inherent characteristic of a material. Students with relevant schemas will be able to solve part (a) of the problem without any calculation, and additional problem solving practice will further enhance their conceptual and procedural knowledge. Although the final answer to part (a) is relatively simple, the overall process involves several cognitive processes with element interactivity between existing schemas and information within the problem. Novices with limited schemas related to the relevant density concepts will experience more cognitive load if they also have to use the values given in the problem to come to an answer.

6.5.1.3.2. Solving part (b) of the density problem

In order to calculate the volume of the sugar solution, students need to complete an algebraic manipulation of the density formula to make volume the subject (i.e., volume = mass ÷ density), which requires the retrieval of an appropriate mathematical schema from their LTM. Before substituting the values into the formula, students need to identify '125 g' as the mass of the sugar solution, by recalling the schema (conceptual) that 'g' is the symbol for the unit 'grams', which is one of the units used for mass. Next, students would need to search for the value of density to be substituted into the formula. To be successful, students would need to retrieve the schema (conceptual) that 'density is the characteristic of a material'. This schema, upon interaction with the elements in the problem information, will inform the students that 1.25 g/cm^3 is the density of the 125 g of sugar solution as well, because 125 g and 500 ml of the same sugar solution will have the same density. After substituting the values into the formula, students would then need to apply their mathematical skills to compute the division. The whole process constitutes germane cognitive load which involves the retrieval of the schema (both conceptual and procedural) that identifies 'g' to be a unit of mass and thus '125 g' is the mass of the sugar solution, which interacts with the five elements (125, its unit g, division operation, 1.25 and its unit g/cm^3 to come up with the final answer, 100 cm^3). The interaction between these elements form a new, higher-level schema of density.

6.5.1.3.3. Solving part (c) of the density problem

Solving this part of the problem involves a similar level of element interactivity to that found in part (b). Conceptual and procedural schemas are retrieved from LTM to interact with information in the problem to complete the mathematical procedures, constituting germane cognitive load. Students need to complete an algebraic manipulation of the density formula to determine the mass of 2.0 cm^3 sugar solution (i.e., mass = density x volume), but for this part of the problem the relevant values need to be multiplied instead of divided. As with part (b), there is a need to retrieve the schema 'density is a characteristic of the material' from LTM, (students need to know that '2.0 cm^3 of sugar solution' has the same density as '500 ml of sugar solution') in order to correctly substitute the value of density into the formula. In order to correctly substitute the value for volume, students need to retrieve the schema that identifies 'cm^3' to be a unit of volume, in turn, identifying '2.0 cm^3' as the volume of the sugar solution. As mentioned earlier, these processes constitute germane cognitive load leading to the construction of a higher-level schema of density. Element interactivity between the schemas that are retrieved (both conceptual and procedural) and the interacting elements in the problem (2.0, its unit cm^3, multiplication operation, 1.25 and its unit g/cm^3) results in the final answer, 2.5 g.

6.5.1.3.4. Solving part (d) of the density problem

Solving this part of the problem also involves germane cognitive load element interactivity. To determine whether the cube floats or sinks in the sugar solution, students need to recall the concept of relative density (i.e., an object with lower density than the liquid it is in will float; and an object with higher density than the liquid it is in will sink). Therefore, students need to know the density of the cube, as well as the density of the sugar solution to determine whether the cube will float or sink in the sugar solution. The density of the cube can be derived from information provided in part (d) of the question (i.e., since density is the mass in one unit of volume, so the density of the cube must be 1.1 g/cm^3 since there is 1.1 g of mass in 1.0 cm^3 of its volume) and the density of the sugar solution can be retrieved from the problem statement at the beginning of the problem (i.e., 1.25 g/cm^3). Since the density of the cube (i.e., 1.1 g/cm^3) is less than the density of the sugar solution (i.e., 1.25 g/cm^3), the cube will float in the sugar solution. Recalling schema about the concept of relative density from LTM to interact with new information in the problem to explain the conclusions constitutes germane cognitive load.

6.5.2. Part 2: Effects of Intervention on Students' Achievement and Self-Concept

The results of the experimental study are summarized in Table 6.1. Mean comparisons indicate that students did better in the post-test compared to the pre-test for each measure. A paired-samples *t*-test found that students performed significantly better ($p < 0.01$) in the Density post-test compared to the Density pre-test with a reasonably large effect size of d = 0.78. These results suggest that the element interactivity intervention had positive effects on students' achievement. For the Properties of Matter science topic, which had no intervention, the gain was small (d = 0.15) and statistically non-significant ($p > 0.05$). This could imply that the instructional strategies employed by the teachers, which did not address element interactivity, were not as effective in helping students attain optimal achievement.

Table 6.1
Comparing Scores from Pre-test and Post-test

	Pre-test		Post-test		99% CI				Cohen's
	Mean	*SD*	Mean	*SD*	LL	UL	*t*(155)	*p*	*d*
Density	2.22	1.54	3.56	1.33	0.98	1.70	9.68	< 0.001	0.78
Properties of Matter	2.43	1.58	2.71	1.21	-0.04	0.26	1.93	0.060	0.15
Science Self-Concept (Density)	3.77	1.29	3.98	0.89	-0.04	0.19	1.69	0.090	0.14

Note. N = 156. CI = confidence interval; LL = lower limit; UL = upper limit.

For science self-concept, I found high reliability estimates of alpha > 0.94 and > 0.85 for the pre-test and post-test, respectively. This indicates that the four statements are a good measure of science self-concept before and after the Density topic was introduced. The difference between the pre-test (M = 3.77, SD = 1.29) and post-test (M = 3.98, SD = 0.89) was statistically non-significant ($p > 0.05$). However, this slight gain (d = 0.14), albeit non-significant, is pleasing, considering the typical decline of students' science self-concept in this age group (Marsh, 1989; Yeung, 2011).

6.6. Discussion

The main aim of this study was to illustrate how teachers can manage the element interactivity involved in learning a complex topic such as density, and to present some preliminary intervention effects of a series of in-service workshops that enabled teachers to apply an instructional strategy to manage element interactivity on students' achievement and self-concept in physics. The results of the study indicate positive effects on students' achievement and self-concept when teachers consciously use element interactivity as a construct to manage instruction and understand students' cognitive processes during problem solving.

Given the limited resources of the human working memory, science learning provides inherent challenges when handling complex learning tasks such as science problem solving. The cognitive load involved in learning tasks may be due to the element interactivity in dealing with (1) the nature and complexity of the learning material causing intrinsic cognitive load, and/or (2) sub-optimal instruction that does not contribute to learning, causing extraneous cognitive load; and/or (2) the interaction between pre-existing knowledge from LTM and new information in the WM which leads to learning, causing germane cognitive load. Progress in cognitive load theory has enabled us to understand the nature and consequences of each type of cognitive load. Knowledgeable teachers who devise optimal instruction practices to facilitate students' learning using cognitive load theory and who analyze element interactivity inherent in the learning material (i.e., intrinsic cognitive load), or the methods of learning (i.e., extraneous cognitive load), or the facilitation of schema construction and retrieval (i.e., germane cognitive load) will optimize their students' learning potential.

6.6.1. Practical Implications for Science Education

6.6.1.1. Practice

A significant purpose of instruction in science (and other school curriculum areas) is to facilitate schema construction and consolidation to enable easy retrieval from LTM (i.e., schema automation). One way of facilitating retrieval is through practice. Practice is essential for establishing links between conceptual and procedural elements of science problems in various forms and combinations, and leads to schema automation (Taconis, 2013). As with other learning tasks, practice sessions inevitably introduce cognitive load, which may be intrinsic, extrinsic, germane or a combination thereof. However, the cognitive load involved in practice is somewhat different from the cognitive load during the acquisition stage of new schema when neither the concept nor the procedure is well established. During acquisition, students are given the formula (e.g., density = mass ÷ volume) and other relevant conceptual and procedural knowledge; whereas during practice sessions, the formula is assumed to have become a part of students' schema. As students go through practice sessions with problem solving tasks, they build upon their problem-based schemas, and develop and consolidate their conceptual and procedural knowledge leading to the construction of higher-level schemas in that learning domain, which are retained in the LTM. This enables them to effectively manage element interactivity when solving more complex problems, as they progress in their journey to become experts in that domain. However, to facilitate expertise, practice should be designed with the purpose of optimizing the positive effects of germane cognitive load.

6.6.1.2. Isolating interacting elements

Instruction for novices need to be purposefully designed, beginning with simple problems containing few interacting elements, so that individual attention may be focused on those elements before interactions among them can be understood (Cook, 2006). Complex problems may be modified by breaking them down into simpler learning tasks, so that the simpler task with fewer interacting elements is better managed by students' WM. The problem in Figure 6.1 is an example of such a learning task.

Figure 6.1 is a science word problem that has been broken down into several parts. Each part focuses on one concept, which reduces intrinsic cognitive load. Extraneous cognitive load is also reduced as there is more emphasis on each problem part and results in fewer search processes being required to retrieve strategies to solve the main problem. Students who have successfully acquired the basic knowledge or schema that 'density is a characteristic of a material' or that 'as the mass of an object decreases, the volume decreases proportionally, making the density of the object the same' will be more able to manage the element interactivity in these problem parts. This is because students who have acquired relevant knowledge in the problem domain will have schema automation to manage element interactivity effectively. Students who have not acquired the relevant conceptual and procedural schemas (e.g., those who have not learned the topic or have received poor prior instruction), will likely experience element interactivity for each part of the problem that is too high for their WM. Optimal instruction for these students requires the problem to be broken into smaller units. In summary, it is critical that instruction is designed to suit a range of students' knowledge bases, so that they are able to manage element interactivity effectively. The method of isolating interacting elements has been suggested by Ayres (2013). It allows students to construct simple lower-level schemas before progressing to construct higher-level schemas for the materials that involve more element interactivity (Ayres, 2013; Pollock et al., 2002).

Another approach to reducing element interactivity in complex learning tasks is by introducing relevant knowledge schema, one at a time (Sweller et al., 2011). For example, if students are not able to assimilate both conceptual and procedural knowledge concurrently, teachers could reduce element interactivity by focusing on, for example, procedural knowledge before introducing conceptual knowledge at a later stage (Kester et al., 2006). Once students have acquired the relevant schema for one type of knowledge, the schema becomes automated and recalled as one element, thus reducing the number of elements (and possible element interactivity) that have to be dealt with by the WM, enabling learning of the other type of knowledge (Kadir et al., 2015).

As students do more practice and gain knowledge, their schematic mental webs intensify, making schema automation possible whenever the need arises (Sweller et al., 2011). When conceptual and procedural knowledge are needed to solve science problems, they are best recalled as schemas. This reduces element interactivity, and so more WM resources are made available to process unfamiliar aspects of presented problems, which may constitute a higher cognitive load for those students who have not consolidated relevant schemas. Teachers who are able to analyze science learning tasks in terms of element interactivity will be able to isolate the interacting elements of complex problems to ensure that instruction is optimized towards appropriate levels for their students' knowledge base in the domain.

6.6.2. Recommendations

To improve learning effectiveness and efficiency and to capitalize on recent developments in CLT in science education, I recommend that teachers consider: (1) element interactivity as a starting point for designing and choosing appropriate pedagogy (i.e., instruction and materials) to suit the needs of learners of varying ability levels in order to facilitate learning; (2) additional element interactivity that arises from interactions between problem information and conceptual and procedural elements (in various forms and combinations) that contribute to the different types of cognitive load; (3) delineating and using element interactivity to analyze learning materials with a view to differentiation into simpler sub-tasks followed by increasing the complexity of the learning tasks as students gain more knowledge and procedural skills in the domain; (4) analyzing the element interactivity of methods and procedures used to solve problems and then teaching students the approach with the least element interactivity; (5) promoting germane cognitive load by emphasizing effective schema construction and retrieval automation by selecting cognitive strategies and procedures that effectively build upon students' existing conceptual and procedural knowledge; and (6) paying attention to psychosocial factors that may affect WM resources devoted to learning tasks such as motivating students to devote their attention to science learning tasks, and increasing their self-concept so that they persist with challenging tasks and lower anxiety levels.

6.7. Conclusion

The results found in this study indicate that a teacher-focused element interactivity intervention benefitted students learning, as well as their self-concept. When element interactivity was managed in the topic of Density, students had higher achievement compared to another topic in which element interactivity was not managed. Analysis of science learning tasks in terms of element interactivity related to the three forms of cognitive load points to the practical benefits of using pedagogical strategies that minimize element interactivity and therefore facilitate learning. If element interactivity is effectively managed for students, the construction, development and automation of schemas to solve complex problems in science will be facilitated, making problem solving more manageable and more appealing for the students (Sweller et al., 2011). When students experience success in their science learning, they may develop higher self-concept and thus be more motivated to engage in further science learning, thereby situating science education within a positive learning paradigm.

CHAPTER 7: STUDY 5 -
Effects of a Dual-Approach Instruction on Students' Science Achievement and Motivation

7.1. Preface

The overarching aim of this thesis was to investigate the interplay between the cognitive and motivational aspects of students' learning. Study 5, the final study of this thesis, contributes to the aim by using the findings of Studies 1 to 4 to guide the design of an intervention which addresses both the cognitive and motivational learning processes and examine its effects on cognitive and non-cognitive educational outcomes: student achievement and motivation. Capitalizing on the cognitive and non-cognitive theories of education, the intervention of this study breaks down the complexity of the learning tasks and scaffolding the element interactivity of learning activities in terms of simple-to-complex sequencing of learning tasks, to make learning manageable for novice learners. In addition, interesting and meaningful hands-on activities were incorporated to excite students in a learning environment that also provided students with a sense of *competence* through teacher feedback, sense of *autonomy* through opportunities given for decision-making and a sense of *relatedness* by engaging in teamwork – which are the three basic psychological needs known to be driving forces of motivation. The findings will (1) show how addressing both the cognitive and motivational learning processes will affect student achievement and motivation, and (2) guide lesson design and instruction to ensure that both cognitive and motivational aspects of learning are addressed in order to optimize students' learning potential.

7.2. Abstract

The aim of the present study was to investigate the effects of a *dual-approach instruction* on students' science achievement and motivation. The instruction was designed to facilitate both the cognitive and non-cognitive aspects of students' learning. The effects were assessed through an intervention study with a pretest-intervention-posttest quasi-experimental design. A total of seven teachers and 427 Grade 7 students participated in this study. Four teachers were assigned to the intervention condition and participated in a series of workshops on the *dual-approach instruction*. These teachers then applied the intervention in two science topics, *speed* and *density*, on 231 students. Multiple regression analyses of students' achievement and motivation pre-test and post-test scores indicated that the intervention had a significant effect on students' achievement in complex problem solving, as well as in the following six motivational attributes: self-regulation, engagement, sense of competence, task goal orientation, education aspiration, and career aspiration in science. The results suggest that the dual-approach benefits students in terms of dual outcomes: science achievement and motivation.

7.3. Introduction

Improving students' achievement in the field of science, technology, engineering, and mathematics (STEM) is the goal of many countries (National Research Council, 2015). This is advocated because workers in the globally competitive fields of economic growth, health industries, and national security require knowledge and skills in STEM (Kearney, 2016, National Science Board, 2015; Organisation for Economic Co-operation and Development [OECD], 2011). Students' declining interests in science and scientific pursuits and aspirations are a serious concern to some educators (Kearney, 2016). Decreasing numbers of student enrolments in university science courses lead to shortages of human resources in the field, and of science teachers in schools (Bawden, 2015; O'Leary, 2001). It is often argued that achievement is not the sole key driver of students' choice of pursuing science-related fields (Wang & Degol, 2013). Research indicates that many students who excelled in school science do not choose to pursue science-related careers (National Science Board, 2014). Critically, students' motivation in a subject domain plays an important role in students' decisions to further their education and to choose to work in professions related to the domain (Wang & Eccles, 2012). Therefore, both achievement and motivation in science are necessary for students to have educational and career aspirations related to science.

The purpose of the present study was to investigate whether both achievement and motivation could be effectively promoted through an instruction designed to facilitate students' cognitive and non-cognitive processes on the basis of well-documented theories. This instruction was named the *dual-approach instruction*. Specifically, I focused on whether students' achievement and motivation could be increased through training their teachers to use the *dual-approach instruction* (the intervention). Students' achievement and motivation in the intervention group was compared to those in the control group. The students in the control group did not experience the intervention and were taught by their usual teachers, using their normal teaching approach, which I referred to as *regular instruction*. Based on the work of Forbes, Kadir, and Yeung (2017), I hypothesized that when students learned in an environment which supported both their cognitive and psychological needs, they would be more likely to demonstrate a dual effect of enhanced academic achievement and positive motivational outcomes. The *dual-approach instruction* used: (1) cognitive load theory as a main framework to support students' cognitive processes, and (2) self-determination theory as a main framework to enhance students' motivation by supporting their basic psychological needs. According to Phan, Ngu, & Yeung (2016), *dual-approach instruction* that facilitates both cognitive and motivational aspects of teaching and learning is the best practice for students to optimize their learning in any domain.

7.3.1. Challenges

Improving students' achievement and motivation in science subjects is a challenging task. There have been many reports indicating that passive, teacher-led lessons are still the norm in classrooms all over the world (e.g., Andres, Steffen, & Ben, 2010). This traditional approach to learning has been criticized for its ineffectiveness in learning about science (Wieman, 2007). An effective science teaching approach provides learning opportunities that are not only meaningful, engaging, and motivating, but also within the cognitive capabilities of the students. However, most innovations in science instruction focus on *either* the cognitive (e.g., conceptual development or achievement) *or* non-cognitive (e.g., motivation) aspects of learning. Research findings indicate a strong interplay between students' achievement and motivation, including self-concept (Kadir, 2006; Kadir, Yeung, & Barker, 2012, 2013; Marsh & Craven, 2006), so both cognitive and non-cognitive processes have been used in the intervention reported in this study.

7.3.2. Cognitive Processes

Science, particularly in the field of physics, is widely perceived to be a difficult subject in school due to the complexity of its conceptual and abstract learning tasks (Shen & Pedulla, 2000). According to cognitive load theory (CLT; Sweller, Ayres, & Kalyuga, 2011), complexity in learning occurs when learners are required to concurrently process learning elements that highly interact with one another in the working memory (Leahy, Hanham, & Sweller, 2015). The working memory of the brain is where mental activities take place (Miller, 1956). An element is "anything that needs to be or has been learned, such as a concept or a procedure" (Sweller, 2010, p. 124). When a learning task requires multiple elements to be learned together, the high degree of interactions between them results in high element interactivity (Sweller, 2010). Such learning tasks require a large amount of working memory resources, especially for students who lack relevant prior/background knowledge (Sweller et al., 2011). Due to the limitations of working memory resources in terms of capacity (Miller, 1956) and duration (Peterson & Peterson, 1959), cognitive processing of these type of complex learning tasks easily overloads students' working memory, which impedes new schema construction (Sweller et al., 2011).

A schema summarizes the common elements of related information, categorizes them and provides a generic characterization of the knowledge acquired (Anderson, Spiro, & Anderson, 1978). When information is effectively processed in the working memory, schemas are constructed and then stored in the long-term memory (Carlson, Chandler, & Sweller, 2003), a part of the brain which can store an infinite amount of information

(Landauer, 1986). When required, stored schemas can be retrieved (Valcke, 2002) and automated to interact with new information in the working memory. This process develops new science knowledge as higher-level schemas (Newell & Simon, 1972), which are then retained in the LTM. Therefore, schema acquisition and automation are two of the most important processes in learning and understanding (Carlson et al., 2003) and should be the goal of all instruction. When schema construction is impeded, and learning is repeatedly hindered, students' lack of success in the learning tasks could lead to frustration and negatively affect their motivation and future learning (Kadir, Ngu, & Yeung, 2015).

In this study, the students experienced an intervention designed to reduce element interactivity at every stage of learning and to therefore facilitate the construction, retrieval and automation of schemas. Newly developed schemas provided mechanisms for students to solve more complex problems in the domain because each schema encapsulates interacting elements into a single unit in the working memory, thus reducing cognitive load (Blayney, Kalyuga, & Sweller, 2010). Past research has shown that reducing the element interactivity in complex learning tasks, hence reducing cognitive load, helped students attain higher achievement (Ngu, Cheung, & Yeung, 2015). Therefore, I hypothesized that when element interactivity was effectively managed during the learning process of two conceptually challenging science topics (*speed* and *density*), students would more successfully solve related complex problems than those students who did not receive the intervention.

7.3.2.1. Cognitive strategy used in the intervention

The isolating-elements strategy has been investigated by a number of CLT researchers and has shown to be effective in helping novices manage complex learning tasks (e.g., Ayres, 2013; Kalyuga, 2007; Kester, Kirschner, & van Merriënboer, 2006;

Pollock, Chandler, & Sweller, 2002). It works by reducing element interactivity through initially presenting learners with part-tasks (so students develop partial schemas), before progressing to whole tasks, which are then used to construct full schemas (Ayres, 2013; Pollock et al., 2002). This strategy involves creating sub-goals by removing several interacting elements from the to-be-learned task, and then introducing them at a later stage (Kalyuga, 2007). For example, if the task involves the learning of concepts and procedures, the isolating-elements strategy involves teaching the concepts prior to the procedure or vice versa but not both at the same time. Pollock et al. (2002) found that learners who were taught the concepts before the procedures or procedures before the concepts performed better than those who were taught concepts and procedures concurrently. Kester et al. (2006) isolated two types of information and found that learners benefitted more when presented with one type of information before another (in which the order does not matter) than when both types of information were presented together. Another approach to isolating elements is through scaffolding simple-to-complex sequences of learning activities (van Merriënboer, Kirschner, & Kester, 2003). In the present study, I used two approaches to isolating elements: science learning activities were introduced to the students in a simple-to-complex sequence, and science conceptual knowledge was introduced before procedural knowledge for physics problem solving.

In a study by Blayney et al. (2010), the isolating-elements strategy was found to benefit students with low pre-existing knowledge more than those with high pre-existing knowledge in the domain. This is likely due to students with high pre-existing knowledge possessing schemas that can be retrieved from their long-term memory to interact with new elements in their working memory, using less working memory resources for the cognitive processing (Sweller et al., 2011). Such students will have sufficient working memory resources to process learning tasks with full element interactivity (Kalyuga, 2007). In contrast, students with low pre-existing knowledge lack schemas, so they need to use more of their working memory resources to deal with the incoming information (Blayney et al., 2010). In this study, students were considered to be novices in the topics of *speed* and *density* and so were unlikely to have relevant schemas to help them with the learning processes. Scaffolding of information in a sequence of learning tasks using the isolating-elements strategy was used so as not to overload students' working memory (Ayres, 2013; Gerjets, Scheiter, & Catrambone, 2006).

7.3.3. Non-Cognitive Processes

Non-cognitive processes such as students' psychological needs and motivation are equally, if not more, important than cognitive processes for supporting student learning. According to self-determination theory (SDT; Ryan & Deci, 2016), when students' psychological needs (i.e., sense of competence, autonomy, and relatedness) are satisfied, their motivation is self-determined, and they are likely to function optimally (Deci & Ryan, 2008). Without substantial motivation, students pay less attention to the learning tasks presented to them, their working memory receives less information to process, schemas are less likely to be formed and learning is less likely to occur (Kadir et al., 2015). Even the best cognitive strategies will fail when presented to unmotivated students. Therefore, both cognitive and non-cognitive factors of learning are necessary to help students achieve learning goals and to perform optimally (Phan et al., 2016).

7.3.3.1. Non-cognitive strategy used in the intervention

According to SDT, the highest quality of human motivation results when basic psychological needs for competence, autonomy, and relatedness are supported (Deci & Ryan, 2000). Competence is the feeling of being capable and effective in the way one interacts with the environment (Niemiec & Ryan, 2009), autonomy is the feeling of doing something out of one's own choice, such that one's action is self-determined and volitional (Deci & Ryan, 1985) and relatedness is the feeling of being connected to those around you (Moller, Deci, & Elliot, 2010). These needs, when fulfilled, will produce an energetic driving force for motivated behaviors (Vansteenkiste, Niemiec, & Soenens, 2010). In contrast, when these needs are not fulfilled, motivation, growth, and well-being will be reduced (Deci & Ryan, 2000). Numerous studies using the SDT framework have shown that the fulfilment of students' basic psychological needs for autonomy, competence, and relatedness is critical for their internalization of academic motivation and positive learning outcomes (Niemiec & Ryan, 2009). For example, Jang, Reeve, Ryan, and Kim (2009) found that the fulfilment of students' basic psychological needs was associated with positive learning experiences and higher academic achievement. Similarly, in the study by Ng, Liu, and Wang (2016), students with high motivation reported high satisfaction of their basic psychological needs and also had high achievement. In the intervention, I aimed to fulfill students' basic psychological needs with the goal of enhancing student motivation in science, by designing a science learning environment with essential features that support students' sense of competence, autonomy, and relatedness. The satisfaction of these needs was measured by several learning outcomes such as achievement and motivated behaviors.

7.3.3.2. Types of motivated behaviors

In SDT, motivated behaviors can be placed along a continuum from autonomous to controlled (Ryan & Connell, 1989; Ryan & Deci, 2000). Deci and Ryan (2008) described autonomous and controlled motivation on the continuum:

> Autonomous motivation comprises both intrinsic motivation and the types of extrinsic motivation in which people have identified with an activity's value and ideally will have integrated it into their sense of self. When people are autonomously motivated, they experience volition, or a self-endorsement of their actions. Controlled motivation, in contrast, consists of both external regulation, in which one's behavior is a function of external contingencies of reward or punishment, and introjected regulation, in which the regulation of action has been partially internalized and is energized by factors such as an approval motive, avoidance of shame, contingent self-esteem, and ego-involvements. When people are controlled, they experience pressure to think, feel, or behave in particular ways. Both autonomous and controlled motivation energize and direct behavior, and they stand in contrast to amotivation, which refers to a lack of intention and motivation (p. 182).

The most autonomous type of motivation is intrinsic motivation and is associated with activities in which individuals personally choose to participate (in the absence of external stimuli), because they find the activities interesting and enjoyable (Ryan & Deci, 2000). Extrinsic motivation is subdivided into various forms of regulation ranging from autonomous to controlled. *Integrated* and *identified* regulations are forms of extrinsic motivation considered to be autonomous because individuals identify with an activity's value and ideally will have integrated it into their sense of self, so they do the activity willingly because they see the value in doing it (Deci & Ryan, 2008). *Introjected* and *external* regulations are forms of extrinsic motivation considered to be controlled (Ryan & Deci, 2000). Individuals who experience introjected regulation have partially internalized their behavior but are mostly energized by factors such as approval motive, avoidance of shame and ego-involvements (Deci & Ryan, 2008). Those who experience external regulation do something because of "external contingencies of reward or punishment" (Deci & Ryan, 2008, p. 182).

Research has shown that satisfying students' basic psychological needs would enhance their motivation (Deci & Ryan, 2000). As the intervention involves strategies to support students' basic psychological needs, it was hypothesized that student motivation would be positively affected. In this study, student motivation was measured via several motivation outcomes. Students' behavioral outcomes from motivation (i.e., self-regulation and engagement) and their academic self-concept (sense of competence) were measured because they are among the desired educational outcomes of the school. It was hypothesized that students who were motivated to learn science would be proactive in making sure that they understand the science concepts (self-regulation) and be attentive during science lessons (engagement). Similarly, those who believed that they could do well in science were hypothesized to rate themselves highly on the sense of competence scale. In addition to the behavioral outcomes, several types of motivation along the SDT motivation continuum were also measured (see Figure 7.1, adapted from Gagne & Deci, 2005). Measuring motivation on the SDT continuum would facilitate the identification of the types of motivation most affected by the intervention. The autonomous motivation outcomes were Interest (intrinsic motivation), Task Goal Orientation (identified regulation), and Educational Aspiration (integrated regulation). Career Aspiration was labeled as being part integrated and part introjected. The controlled motivation outcome was Ego Involvement (introjected regulation). Since there were no reward-punishment features in the intervention, external regulation was not measured in this study. Amotivation was out of the scope of this study, so it was also not measured. Since motivation and academic self-concept have been shown to be domain-specific (e.g., Kadir & Yeung, 2016; Yeung, Kuppan, Foong et al., 2010), all motivational factors were measured only within the science domain, as the intervention was on science topics.

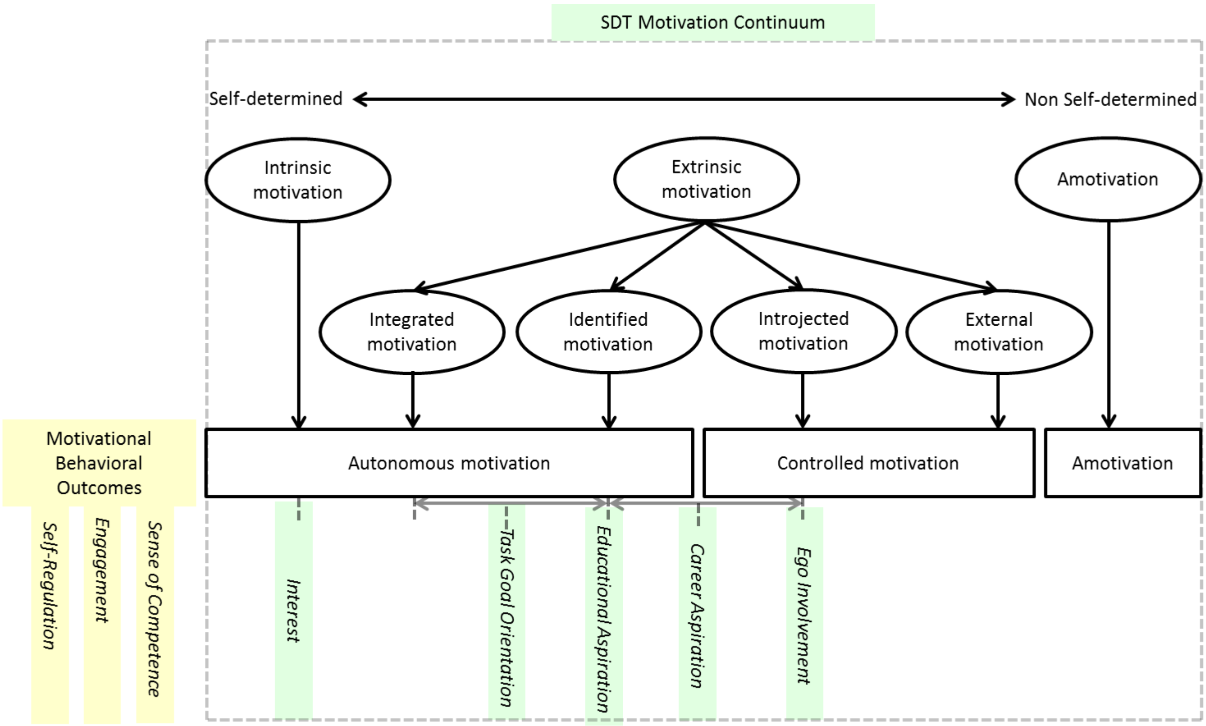

Figure 7.1. Motivational variables on the Self-Determination Theory (SDT) motivation continuum and other motivational behavioral outcomes measured in the study.

7.3.4. Design of the Dual-Approach Instruction

Two science units from the school curriculum (*speed* and *density*) were systematically revised in relation to the learning activities and lesson delivery. Principles of cognitive load theory (isolating-elements strategy) and self-determination theory (supporting students' basic psychological needs) were included, as well as best practices in science learning such as group learning (Hardy, Jonen, Möller, & Stern, 2006) and guided-inquiry (Riga, Winterbottom, Harris, & Newby, 2017). Appendix 7A shows a sample of eight learning activities from the density topic. Appendix 7B provides details on how the activities (1) implemented the isolating-elements strategy to sequence the element interactivity and (2) fulfil students' psychological needs.

The learning sequences for each topic (*speed* and *density*) consisted of seven one-hour lessons based on the original science materials for teachers by McDermott, Shaffer, and Rosenquist (1996) and materials developed in the PbI1@School research (Lau, Foong, Kadir, & Wong, 2011) for students. The PbI1@School research team had modified the teaching materials from McDermott et al. (1996) for use in the first intake of secondary students (Grade 7) in Singapore. *Speed* learning and teaching materials were adapted from Kadir, Foong, Wong, and Kuppan (2011) and *density* materials from Wong, Lim, Kadir, and Foong (2011). At the end of the *speed* unit, students were expected to be able to describe motion in terms of speed, draw a strobe diagram to represent speed, and apply the concept of speed as distance travelled per unit time to solve complex problems quantitatively. At the end of the *density* unit, students were expected to be able to explain why some objects float or sink, draw diagrams to show their understanding of density as a material property, and apply the concept of density as the amount of mass in a unit of volume to solve complex problems quantitatively.

The teaching units were formulated using an adaptation of constructivist (Duit, 1996) approaches, in which learning is deemed as a process in which learners actively construct meaning based on the pre-existing knowledge (Morton, 2012). This is in line with the cognitive processes described by CLT, whereby learning occurs when schemas are retrieved from the long-term memory (i.e., pre-existing knowledge) to interact with the new information (i.e., from the learning materials) in the working memory to construct new higher-level schemas to be stored in the long-term memory, if learning is successful (Sweller et al., 2011). To support these cognitive processes, the principles of structured inquiry-based instruction (Windschitl, Thompson, Braaten, & Stroupe, 2012) were implemented. Yet, following criticisms that the inquiry-based approach to science learning is not effective for novice learners (Kirschner, Sweller, & Clark, 2006), we ensured that learners participated in a *guided-inquiry* approach (Riga et al., 2017) to minimize extraneous cognitive load. The isolated-elements strategy (e.g., Ayres, 2013; Pollock et al., 2002) was included in both topics so that element interactivity was within novice students' working memory capacity.

During the intervention, students were engaged in carrying out hands-on experiments in teams of three or four students, making decisions as a team to decide on the next course of action, interpreting the results with their team members, documenting the results in their own worksheet, and discussing the assumptions and results with the teachers as a class. Such activities are similar with those in Hardy et al. (2006) and are known to help students make sense of scientific principles. The intervention also had processes in place to support students' basic psychological needs of competence, autonomy and relatedness (see Appendix 7C for details). Students' sense of *competence* in the learning environment was facilitated through teachers providing constructive feedback and encouragement to the students, while activities were designed to be within the cognitive capabilities of the students so that they experienced successful episodes during the learning processes. Students' sense of *autonomy* was facilitated through meaningful and interesting hands-on activities with opportunities for students to contribute to team decisions. Teachers ensured that students worked harmoniously as a team and shared their findings with the class to develop a sense of *relatedness* by being a part of a learning community. The collaborative learning environment resembled that of the project work setting described in Wang, Liu, Koh, Tan, and Ee (2011), which included features of teacher facilitation and peer support, and has shown to satisfy students' basic psychological needs. In sum, the role of the teacher is to facilitate and motivate, to structure and guide activities, to ask relevant questions, and to provide support and encouragement when needed.

7.3.5. Design of the Science Knowledge Tests

All summative science knowledge tests were designed by teachers according to the stipulated school science syllabus of each topic: *heat*, *forces*, *speed*, and *density*. Test questions were reviewed by the researchers before being administered to students. The pre-test was conducted before the start of each topic and the post-test at the end of the last lesson of each topic. Each pre-test was designed to assess the pre-existing knowledge of students in the topic area. These questions were reviewed by teachers and researchers as generally having low element interactivity. The post-test of each topic was designed to investigate the learning transfer of each topic: specifically, the ability of students to apply learned concepts to solve novel (new) science problems. Therefore, the pre- and post-test questions were not identical. Each post-test consisted of two sections to differentiate between students' levels of understanding of the learning materials and to uncover any interventions effects due to cognitive strategies (Leahy et al., 2015): one contained simple, low element interactivity questions (as reviewed by teachers and researchers); the other contained more complex, high element interactivity questions.

7.3.6. This Study

The present study adds to the research literature by reporting findings where students in an intervention student group experienced the isolating-elements strategy with sequenced learning activities instead of worked examples and information sheets, combined with strategies from self-determination theory (SDT). The control group experienced *regular instruction* for the same science topics (*speed* and *density*), involving lecture-style delivery of theoretical information from teachers to students (while students copied notes in their worksheets), and one hands-on laboratory session for each topic to affirm what students learned during the theory lessons (see Appendix 7D for a comparison between *dual-approach instruction* and *regular instruction*).

To account for teacher effects (since different teachers taught the control and intervention groups), *prior* to the intervention, we compared all students' achievement scores on two different science topics (*heat* and *forces*), which were taught using traditional instruction strategies. The effectiveness of the intervention was assessed in terms of student achievement and motivation outcomes. Achievement was measured by comparing students' pre- and post-test scores in all four science topics (*heat, forces, speed,* and *density*). Motivation was measured using students' responses to a perception survey administered at the end of the school semester, when all teaching and testing was completed.

7.3.7. Hypotheses

The hypotheses for this study included:

1. Both student groups will attain higher achievement scores in low element interactivity tasks compared with high element interactivity tasks, for all science topic tests.
2. *Heat* and *forces* achievement scores will be similar for both student groups after controlling for students' pre-existing knowledge (i.e., pre-test).
3. *Speed* and *density* (in which the *dual-approach instruction* was applied to the intervention group) achievement scores will be higher in the intervention group for high element interactivity questions only.

4. Motivation scores will be higher in the intervention group.

7.4. Method

7.4.1. Participants

The data were collected from eleven Grade 7 classes (i.e., first year of secondary school, commonly known as secondary one in Singapore) from a school located in the eastern part of Singapore. The school opted to have the entire cohort of Grade 7 students participate in the study. Participation was voluntary and a total of 427 consenting students (232 females and 195 males) were involved in the study. Students were mostly from medium to high socio-economic backgrounds and used English as the main language of communication.

Five classes (196 students: 118 girls and 78 boys, *M* = 13.5 years, *SD* = 0.3) were randomly assigned to be in the control group to experience *regular instruction* in all four science topics: *heat, forces, speed,* and *density.* The remaining six classes (231 students: 114 girls and 117 boys, *M* = 13.4 years, *SD* = 0.40) were assigned to the intervention group to experience *regular instruction* in the science topics of *heat* and *forces* and *dual-approach instruction* in the topics of *speed,* and *density*. All lessons were conducted as part of the school science curriculum, during standard school hours. Each class size was similar, ranging from 36 to 40 students.

All seven teachers teaching the Grade 7 science classes in the school consented to participating in the study voluntarily, without receiving additional pay or incentives. The four teachers who volunteered for the intervention training for the topics of *speed,* and *density* taught the intervention group classes while the remaining three teachers taught the control group classes. Special care was taken to ensure that no teacher taught in both the control and intervention classes. All of teachers had been full-time teachers throughout their career, were of similar age, had similar science teaching experience (i.e., at least 5 years), and had similar motivation and science teaching skills (based on teacher assessment grades acquired from the school) prior to the intervention training.

The study was approved by the Ministry of Education, Singapore. All ethics procedures were strictly followed, participation was voluntary, and data collected were anonymized before analysis. Teachers and students agreed to participate in the study, and to be filmed for the purpose of intervention fidelity. Parents of the student participants provided written consent for their child's participation. Teachers and students were informed that they could withdraw their participation at any time.

7.4.2. Procedure

The participating secondary school separates its science curriculum into physics, chemistry and biology from Grade 7 onwards. Since the school only accepts students who performed well (i.e., top 30%) in the local national examinations at the end of Grade 6, students were expected to be ready to learn the separate branches of science from Grade 7 onwards. At the time of the study during the first half of the year, the school was implementing the physics component of the Grade 7 science curriculum, so only physics topics were used in the study.

In the beginning of the year, all teachers delivered lessons on the science topics of *heat* and *forces* in a similar way, using the same lesson plans and materials finalized by the science department of the school. This instruction, identified as *regular instruction* in the study, was described by science teachers during their interviews. Characteristics matched those in field notes taken by researchers during the *regular instruction* lesson observations.

Four teachers in the intervention group participated in seven 1-hour workshops on *dual-approach instruction*, which were mostly held after curriculum hours. During the workshops, teachers were introduced to knowledge about students' cognitive processes and how to use the isolated-elements strategy to manage element interactivity at each stage of learning. They were also introduced to knowledge about self-determination theory, and how to create learning climates to support students' basic psychological needs: competence, autonomy, and relatedness. Participating teachers viewed video clips of *dual-approach instruction* featuring teachers facilitating hands-on activities, while giving positive feedback and encouraging remarks to motivate students, and these clips were then analyzed, and discussed. Participants received instructional materials on *speed,* and *density* and engaged in activities where they applied their knowledge to: (1) manage element interactivity in the learning materials and instructional delivery, and (2) create learning environments to provide students with a sense of competence, autonomy, and relatedness. Researchers and teachers also role-played some of the of *dual-approach instruction* lesson plans on *speed,* and *density* by taking on the roles of teachers and students. In the final workshop, student learning materials and lesson plans on *speed*, and *density* were finalized by the researchers and teachers. Teachers then delivered lessons on *speed,* and *density* using the *dual-approach instruction* as stipulated in the lesson plans while teachers in the control condition delivered lessons on the same topics using *regular instruction*.

Both the control and intervention groups each taught their topics for seven 1-hour lessons (i.e., 3 weeks). Online questionnaires asking students to rate their motivation were completed in the computer lab in the presence of a teacher, when all four science topics had been taught. All students did the same science achievement tests in the same four science topics before the start (i.e., pre-test) and after the completion (i.e., post-test) of the lessons of each topic. To minimize missing data, teachers arranged for students who were absent to complete online surveys/tests within the next few days.

7.4.2.1. Intervention fidelity

To evaluate the extent to which the intervention was implemented as planned, we focused on five key elements of intervention fidelity: design, workshops on *dual-approach instruction*, intervention delivery, intervention receipt, and intervention enactment (cf., Smith, Daunic, & Taylor, 2007). Lesson observations in the intervention condition indicated that teachers adhered to the co-designed lesson plans, and teacher manual, and were able to administer the lessons within the stipulated timeframe. Lesson observations in the control condition indicated that the teachers were teaching in the same way as described during the interviews prior to the intervention (i.e., using the *regular instruction*).

The workshop series on *dual-approach instruction* was delivered by me, as I had previous experience in delivering professional development programs for science teachers. All teachers in the intervention condition attended all the workshops at the same time to ensure systematic delivery across teachers, and to maximize the fidelity of intervention delivery. In addition to this, the first author was stationed in the school during the period of intervention delivery, so that teachers could readily consult about the intervention. The first author also met with the teachers in the intervention condition every week for a discussion to reflect on the intervention delivery, to ensure understanding of the intervention, and to answer any questions. To evaluate the intervention enactment, all video recordings of the lessons were viewed and checked against the lesson plans and teacher manual. There were no abnormalities or departure from procedures found.

For lessons without a researcher as observer, a 5-minute episode of each video clip was coded for student-teacher interaction and characteristics of the lesson about half-way through each lesson. Analysis of these episodes correlated with field notes taken from the lesson observations i.e., that students in the control condition were passively listening to teacher-talk while taking notes in their worksheets, and mainly following instructions during the two laboratory sessions and students in the intervention condition were engaged in hands-on science activities, discussing their work in teams, recording their findings in guided worksheets, with their teachers working as facilitators of learning, and providing constructive feedback and encouragement to the students. Appendix 7C provides details of observed teacher and student behaviors in the intervention condition, which correlate with guidelines of a learning environment where students are supported in their basic psychological needs of competence, autonomy and relatedness.

7.4.3. Material

Although Grade 7 students in Singapore have not yet received formal physics instruction in primary school, it is possible that some of the students had pre-existing knowledge of the topics, either from their life experiences, enrichment classes or elements of the general science lessons they received from their previous school (i.e., primary school). To measure students' learning gains in the four science topics (*heat*, *forces, speed,* and *density*), pre-tests and post-tests were administered to the students before the first lesson and after the final lesson of each topic, respectively. To measure how students developed in terms of their motivation in science over time, students completed a motivation pre-test survey online at the beginning of the school year (i.e., before the start of their Grade 7 science lessons) and completed the same motivation post-test survey online when all the four science topics had been taught. The duration of time between the pre-test and post-test of each science topic was about 3 weeks, and that of the motivation survey was 20 weeks. Appendix 7E provides an overview of the administration of the tests.

7.4.3.1. Measurement of achievement

Students' pre-test and post-test scores were used to measure their achievement. The pre-test for each science topic assessed students' pre-existing knowledge. Each pre-test comprised five one-mark items and assessed students' understanding of basic concepts of each topic. The items were adapted from Lau et al. (2011). Each item was analyzed in terms of element interactivity by two researchers. Items were modified so that all had low element interactivity, a process that was agreed to by both the researchers and teachers to encourage student engagement in the topic. An inter-rater agreement of 96% was achieved for the coding. Scoring of the pre-test for each of the four science topics was firstly done by the teachers, based on a common marking scheme adapted from Lau et al. (2011). The pre-test scripts were then passed on to the researchers for scoring and an inter-rater agreement of 88% was achieved between teachers and researchers. Teachers and researchers discussed the discrepancies to arrive at the final pre-test score for each student on each of the four topics.

The post-test for each science topic was designed to assess students' understanding and ability to apply their understanding to solve complex problems. Each post-test totaled ten marks and comprised two sections. Section A was designed to include only low element interactivity questions and comprised five one-mark items. Section B was designed to include only high element interactivity questions and comprised structured questions totaling five marks. The items were adapted from Lau et al. (2011), and modified to meet the element interactivity requirements of each section of the post-test. Each item was analyzed in terms of element interactivity and coded as 'low' or 'high' by two researchers. An inter-rater agreement of 82% was achieved for the coding. Discrepancies were discussed to arrive at a common conclusion. As with the pre-test, scoring of the post-test for each of the four science topics was firstly completed by teachers, based on a common marking scheme adapted from Lau et al. (2011). The post-test scripts were then passed on to the researchers for scoring and an inter-rater agreement of 90% was achieved between teachers and researchers. Discrepancies were discussed to arrive at the final scores. Each student had two post-test scores: one for the low element interactivity items from Section A (full score = 5 marks) and another for the high element interactivity items from Section B (full score = 5 marks). Examples of low element interactivity items are given in Appendix 7F and high element interactivity items are given in Appendix 7G.

7.4.3.2. Measurement of motivation

After consulting several scales, student motivation outcomes were measured using different types of motivational items ranging from autonomous to controlled regulation, as stipulated in the SDT continuum (Figure 7.1). The items were given to two expert researchers in the field, who coded them according to the factors, based on the best face validity. Inter-rater codes correlated at 0.82. Confirmatory factors analyses (CFAs) further supported the contention that these items measure the respective motivational factors. The maximal reliabilities (Raykov, 2004) of the eight factors at pre-test and post-test ranged from 0.80 to 0.90. These high reliabilities provided support for the motivational factors. The list of items and the maximal reliability for each motivation factor for both pre-test and post-test are given in Appendix 7H. Student responses to all the motivation items were given on a 6-point Likert scale ranging from 1 (disagree strongly) to 6 (agree strongly). All the items were randomized in the motivation survey form.

7.4.3.2.1. Self-regulation

The self-regulation factor assesses students' reported behavior when they do not understand a science concept. When students are motivated in science, they tend to be proactive in doing something to ensure that they understand confusing science concept. Self-regulation was measured by four items (e.g., "When I'm reading my science materials and do not understand something, I stop and think it over"), adapted from the *Motivated Strategies for Learning Questionnaire* (MSLQ; Pintrich & Degroot, 1990). In the study, this factor has maximal reliabilities of 0.86 and 0.83 for pre-test and post-test, respectively.

7.4.3.2.2. Engagement

The engagement factor measures students' perceptions of their attentiveness during science lessons. Engagement was measured by four items (e.g., "I am attentive to my work in SCIENCE."), adapted from Yeung, Kuppan, Kadir, and Foong (2010) and Steinberg, Lamborn, Dornbusch, and Darling (1992). In the study, this factor has maximal reliabilities of 0.88 and 0.90 for pre-test and post-test, respectively.

7.4.3.2.3. Sense of competence

The sense of competence factor measures students' perceptions of their science ability and is a cognitive component of science self-concept. Sense of competence was measured by four items (e.g., "I am good at science"), adapted from the *Academic Self-Description Questionnaire* (ASDQ; Marsh, 1992) and Kadir et al. (2013). In the study, this factor has maximal reliabilities of 0.90 and 0.86 for pre-test and post-test, respectively.

7.4.3.2.4. Interest

The interest factor measures the extent of students' enjoyment and interest in science. This is an affective component of science self-concept and is also a form of intrinsic motivation and links to self-determined regulation identified by SDT. Interest was measured by four items (e.g., "I find science interesting"), taken directly from Kadir et al. (2013) who adapted the scale from the study by Marsh, Craven, and Debus (1999), Elliot and Church's (1997) measure of personal interest and enjoyment and the Yeung, Chow, Chow, Luk, & Wong (2004) measure of students' affect in other curriculum areas. In the study, this factor has maximal reliabilities of 0.90 and 0.88 for pre-test and post-test, respectively.

7.4.3.2.5. Task goal orientation

The task goal orientation factor measures the degree of students' autonomous motivation in science (i.e., identified regulation) by asking students to rate the reasons that they do their work based on their goals, values and regulations in science. The four items that measured task goal (e.g., "An important reason I do my work in science is that I like to learn new things") were adapted from the *Academic Self-Regulation Questionnaire* (SRQ-A; Ryan & Connell, 1989) and the *School Motivation Questionnaire* (SMQ; Marsh, Craven, Hinkley, & Debus, 2003). In the study, this factor has maximal reliabilities of 0.90 and 0.80 for pre-test and post-test, respectively.

7.4.3.2.6. Education aspiration

The education aspiration factor asked students about their aspiration to pursue science courses at advanced levels in future. This factor measures the degree of students' autonomous motivation (i.e., integrated regulation). Education aspiration was measured by four items (e.g., "I would like to study SCIENCE in college/ university"), adapted from Yeung and McInerney (2005) and Kadir et al. (2012). In the study, this factor has maximal reliabilities of 0.83 and 0.84 for pre-test and post-test, respectively.

7.4.3.2.7. Career aspiration

The career aspiration factor asked students about their aspiration to have a science-related career in future. This factor also measures the degree of students' autonomous motivation (i.e., integrated regulation). Career aspiration was measured by four items (e.g., "I want to have a job that has to do with science"), adapted from Yeung and McInerney (2005) and Yeung, Kuppan, Kadir et al. (2010). In the study, this factor has maximal reliabilities of 0.89 and 0.88 for pre-test and post-test, respectively.

7.4.3.2.8. Ego involvement

The ego involvement factor measures the degree of students' controlled motivation (i.e., introjected regulation) to show others that they are good in science. Ego Involvement was measured by four items (e.g., "I want to show others that I am smart in science"). The items were largely adapted from the introjected items of the *Academic Self-Regulation Questionnaire* (SRQ-A; Ryan & Connell, 1989). In the study, this factor has maximal reliabilities of 0.82 and 0.86 for pre-test and post-test, respectively.

7.4.4. Statistical Analysis

The first stage of the data analysis was testing the validity of the survey instrument. To this end, CFAs were used in different steps (Brown, 2006). In the first step, a CFA model was conducted separately for each factor to determine how well each latent motivational factor was defined by the items. In the second step, a test of longitudinal measurement invariance was conducted for the latent motivational factors measured at the two time-points, pre-test and post-test. The objective of the measurement invariance was to ensure an equal definition of the latent motivational factors over time. Following common practice in CFA, goodness of fit was evaluated using the following indices: the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Root Mean Square of

Approximation (RMSEA) at its 90% confidence interval (CI). Using Hu and Bentler's (1999) guidelines for evaluating overall model fit, a TLI and CFI > 0.95, and RMSEA < 0.05 indicated an adequate model fit to the observed data. To assess the longitudinal measurement invariance, a stepwise procedure (Vandenberg & Lance, 2000), relying on the comparison of progressively more restricted measurement models, was followed. These measurement models were nested and ΔCFI was used to assess measurement invariance (Cheung & Rensvold, 2002). According to Cheung and Rensvold (2002), ΔCFI is robust for testing the between-group invariance of CFA models. An absolute value of ΔCFI smaller than, or equal to 0.01, indicates that the null hypothesis of invariance should not be rejected (Cheung & Rensvold, 2002). If the results of the factor structure analysis and longitudinal invariance test showed that the instrument is valid, the means of each factor was computed and used in all other analyses. The amount of missing data over the two time-points (pre- and post-tests) was small (< 1%) and was handled by the full information maximum likelihood estimation (FIML), available in Mplus V7 (Muthén & Muthén, 1998–2015). FIML utilizes all the available information during the estimation process and provides consistent and efficient parameters and has shown to function well in accounting for missing data in SEM models (Enders, 2010).

Next, MANOVA was conducted to compare the two group's (intervention vs control) means on the achievement and motivational factors at pre-test and post-test. For ease of readership, the descriptive statistics and the *t*-value for each variable were presented. As the data had a hierarchical structure because students in the study were nested in classes, complex statistical procedures such as multiple regression analysis with adjusted standard errors were warranted. Therefore, we estimated two regression models for each of the eight achievement variables and eight motivational factors. All variables were standardized before running the analyses. In Model 1, we predicted students' achievement and motivation at post-test with the groups only. In Model 2, we added students' pre-test scores and gender as predictors to control for pre-existing differences and for the uneven distribution of boys and girls between the groups. We calculated R^2 as a measure of explained variance. Finally, we accounted for the non-independence of the observations by adjusting the standard errors using the sandwich estimator implemented in Mplus V7 (Muthén & Muthén, 1998-2015). According to Hedges (2007), standardized mean differences (i.e., the means of two comparison groups divided by the standard deviation) represent effect sizes. As the standardization of all continuous variables were done before running the analyses, the regression coefficients β of the dummy variables (i.e., groups and gender) represented the standardized mean differences. Therefore, the effects of the intervention condition compared to the control group could be interpreted as effect sizes (Hedges, 2007).

7.5. Results

7.5.1. Descriptive Statistics for the Item Variables

Table 7.1 provides an overview of the descriptive statistics and bivariate correlations of all the 33 item variables in the motivation survey at pre-test, for all participants. The mean of the variables ranged from 3.43 to 5.25. The correlations between motivational variables within the same factors were all positive and statistically significant ($p < .001$). For example, correlations between the variables in the Self-Regulation factor (Sre1-4) ranged from 0.51 to 0.67 and that for the Engagement factor (Eng1-5) ranged from 0.47 to 0.67.

Table 7.1

Descriptive Statistics and Bivariate Correlations for the Measured Motivational Variables of the Study at Pre-Test

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
1 Sre1	-																																
2 Sre2	0.58***	-																															
3 Sre3	0.51***	0.67***	-																														
4 Sre4	0.62***	0.70***	0.62***	-																													
5 Eng1	0.40***	0.47***	0.41***	0.46***	-																												
6 Eng2	0.42***	0.49***	0.38***	0.51***	0.59***	-																											
7 Eng3	0.37***	0.46***	0.39***	0.42***	0.67***	0.58***	-																										
8 Eng4	0.38***	0.52***	0.37***	0.44***	0.47***	0.59***	0.47***	-																									
9 Eng5	0.44***	0.55***	0.43***	0.54***	0.54***	0.61***	0.47***	0.63***	-																								
10 Com1	0.22***	0.31***	0.21***	0.36***	0.22***	0.29***	0.22***	0.24***	0.33***	-																							
11 Com2	0.16***	0.26***	0.21***	0.34***	0.23***	0.23***	0.23***	0.18***	0.34***	0.69***	-																						
12 Com3	0.17***	0.25***	0.18***	0.33***	0.26***	0.23***	0.24***	0.18***	0.31***	0.71***	0.67***	-																					
13 Com4	0.28***	0.35***	0.25***	0.40***	0.28***	0.34***	0.33***	0.24***	0.36***	0.70***	0.60***	0.66***	-																				
14 Int1	0.33***	0.44***	0.31***	0.46***	0.33***	0.39***	0.31***	0.39***	0.46***	0.52***	0.47***	0.55***	0.53***	-																			
15 Int2	0.34***	0.49***	0.35***	0.49***	0.40***	0.45***	0.37***	0.42***	0.51***	0.51***	0.49***	0.57***	0.55***	0.75***	-																		
16 Int3	0.47***	0.53***	0.47***	0.52***	0.41***	0.45***	0.37***	0.50***	0.52***	0.44***	0.40***	0.42***	0.52***	0.65***	0.67***	-																	
17 Int4	0.34***	0.43***	0.38***	0.45***	0.36***	0.32***	0.38***	0.28***	0.36***	0.49***	0.48***	0.51***	0.52***	0.66***	0.66***	0.56***	-																
18 Tgo1	0.50***	0.63***	0.50***	0.61***	0.42***	0.47***	0.38***	0.47***	0.55***	0.45***	0.42***	0.46***	0.52***	0.66***	0.71***	0.63***	0.58***	-															
19 Tgo2	0.51***	0.57***	0.46***	0.57***	0.38***	0.42***	0.37***	0.44***	0.43***	0.38***	0.37***	0.35***	0.41***	0.58***	0.56***	0.57***	0.53***	0.66***	-														
20 Tgo3	0.51***	0.61***	0.48***	0.63***	0.41***	0.47***	0.40***	0.44***	0.53***	0.53***	0.48***	0.53***	0.59***	0.69***	0.70***	0.64***	0.65***	0.73***	0.66***	-													
21 Tgo4	0.48***	0.65***	0.55***	0.64***	0.39***	0.49***	0.42***	0.47***	0.58***	0.46***	0.48***	0.46***	0.52***	0.62***	0.64***	0.64***	0.55***	0.75***	0.62***	0.73***	-												
22 Eda1	0.30***	0.42***	0.34***	0.52***	0.31***	0.38***	0.30***	0.29***	0.43***	0.48***	0.43***	0.50***	0.50***	0.63***	0.65***	0.55***	0.51***	0.62***	0.51***	0.61***	0.63***	-											
23 Eda2	0.25***	0.35***	0.22***	0.34***	0.25***	0.28***	0.30***	0.24***	0.32***	0.37***	0.32***	0.45***	0.41***	0.52***	0.58***	0.43***	0.44***	0.50***	0.36***	0.54***	0.49***	0.55***	-										
24 Eda3	0.30***	0.29***	0.24***	0.31***	0.24***	0.23***	0.24***	0.19***	0.27***	0.32***	0.36***	0.35***	0.35***	0.40***	0.41***	0.33***	0.40***	0.38***	0.32***	0.43***	0.44***	0.46***	0.49***	-									
25 Eda4	0.21***	0.35***	0.21***	0.37***	0.29***	0.33***	0.29***	0.28***	0.42***	0.48***	0.45***	0.50***	0.48***	0.64***	0.62***	0.45***	0.48***	0.54***	0.44***	0.57***	0.52***	0.70***	0.58***	0.45***	-								
26 Caa1	0.32***	0.42***	0.35***	0.43***	0.32***	0.31***	0.33***	0.26***	0.34***	0.38***	0.36***	0.42***	0.40***	0.52***	0.59***	0.47***	0.55***	0.51***	0.44***	0.55***	0.50***	0.51***	0.53***	0.36***	0.50***	-							
27 Caa2	0.27***	0.39***	0.26***	0.38***	0.27***	0.34***	0.28***	0.30***	0.39***	0.42***	0.36***	0.48***	0.44***	0.57***	0.66***	0.49***	0.46***	0.51***	0.38***	0.56***	0.53***	0.57***	0.68***	0.44***	0.58***	0.67***	-						
28 Caa3	0.25***	0.37***	0.26***	0.34***	0.26***	0.31***	0.30***	0.26***	0.37***	0.41***	0.38***	0.46***	0.45***	0.53***	0.61***	0.47***	0.41***	0.48***	0.38***	0.52***	0.51***	0.55***	0.72***	0.47***	0.60***	0.60***	0.77***	-					
29 Caa4	0.17***	0.27***	0.13**	0.22***	0.10*	0.19***	0.16***	0.12*	0.17***	0.35***	0.29***	0.41***	0.31***	0.44***	0.48***	0.33***	0.32***	0.37***	0.25***	0.43***	0.36***	0.42***	0.65***	0.43***	0.54***	0.55***	0.66***	0.69***	-				
30 Ego1	0.15**	0.17***	0.18***	0.18***	0.22***	0.22***	0.24***	0.22***	0.24***	0.34***	0.26***	0.30***	0.31***	0.17***	0.19***	0.26***	0.13**	0.19***	0.17***	0.18***	0.21***	0.21***	0.11*	0.09	0.14**	0.09	0.11*	0.16***	0.08	-			
31 Ego2	0.08	0.14**	0.19***	0.20***	0.15**	0.15**	0.20***	0.07	0.14**	0.28***	0.27***	0.24***	0.27***	0.15**	0.16**	0.16**	0.13**	0.13**	0.13**	0.15**	0.18***	0.22***	0.11*	0.12*	0.19***	0.11*	0.13**	0.20***	0.07	0.62***	-		
32 Ego3	0.12*	0.13**	0.14**	0.13**	0.19***	0.14**	0.18***	0.11*	0.17***	0.22***	0.20***	0.20***	0.22***	0.14**	0.23***	0.19***	0.17***	0.15**	0.16**	0.10*	0.17***	0.16***	0.14**	0.16**	0.16***	0.16**	0.19***	0.19***	0.15**	0.45***	0.47***	-	
33 Ego4	0.05	0.07	0.13**	0.11*	0.08	0.02	0.12*	0.04	0.08	0.18***	0.11*	0.17***	0.21***	-0.02	0.07	0.13**	0.04	0.01	0.05	0.03	0.06	0.04	0.08	-0.00	0.05	0.06	0.08	0.14**	0.07	0.58***	0.59***	0.51***	-
Mean	4.60	4.83	4.82	4.68	4.96	4.83	5.06	5.25	5.06	4.02	4.11	3.94	4.25	4.49	4.58	4.82	4.93	4.74	4.80	4.58	4.62	4.25	3.82	4.01	4.15	4.54	4.26	3.92	3.70	3.90	3.43	4.03	3.82
SD	1.03	0.95	0.98	0.97	0.86	0.86	0.75	0.84	0.87	1.16	1.15	1.29	1.11	1.16	1.14	1.02	1.05	1.01	1.00	1.00	1.04	1.20	1.30	1.14	1.29	1.21	1.26	1.29	1.35	1.20	1.28	1.24	1.29

Note. N = 427. All variables were measured on a 1-6 Likert scale; Sre1-4 = Self-Regulation variables 1 to 4; Eng1-4 = Engagement variables 1 to 4; Com1-4 = Sense of Competence variables 1 to 4; Int1-4 = Interest variables 1 to 4; Tgo1-4 = Task Goal Orientation variables 1 to 4; Eda1-4 = Educational Aspiration variables 1 to 4; Caa1-4 = Career Aspiration variables 1 to 4; Ego1-4 = Ego Aspiration variables 1 to 4; *SD* = standard deviation; *p < .05, **p < .01, ***p < .001.

Similar numbers were observed for Sense of Competence (Com1-4: 0.60 to 0.71), Interest (Int1-4: 0.56 to 0.75), Task Goal Orientation (Tgo1-4: 0.62 to 0.75), Educational Aspiration (Eda1-4: 0.45 to 0.70), Career Aspiration (Caa1-4: 0.55 to 0.77), and Ego Involvement (Ego1-4: 0.45 to 0.62).

Positive and statistically significant correlations were also observed across the motivational behavioral outcome variables (i.e., Self-Regulation, Engagement, and Sense of Competence) and the motivational factors on the autonomous motivation spectrum on the SDT continuum. Variables from Ego Involvement, the only controlled motivation factor, were not statistically correlated with most of the variables from other motivational factors. Overall, the correlations ranged from -0.02 (statistically non-significant correlation between int1: Interest variable 1 and ego 4: Ego Involvement variable 4) and 0.77 (statistically significant correlation between Caa2 and Caa3: Career Aspirations variables 2 and 3).

Table 7.2 provides the bivariate correlations of all the eight latent motivational factors at pre-test, for all participants. The results showed positive and statistically significant correlations across all the motivational factors, with Ego Involvement having the lowest correlational coefficients with all the other motivational factors. The highest correlation was between Interest and Task Goal Orientation (*r* = 0.84) and the lowest was between Engagement and Ego Involvement (*r* = 0.20).

Table 7.2
Latent Factor Correlations of Motivational Variables at Pre-Test

	1	2	3	4	5	6	7	8
1. Self-Regulation	--							
2. Engagement	.73***	--						
3. Sense of Competence	.40***	.48***	--					
4. Interest	.54***	.62***	.72***	--				
5. Task Goal Orientation	.68***	.71***	.67***	.84***	--			
6. Education Aspiration	.42***	.49***	.66***	.75***	.70***	--		
7. Career Aspiration	.40***	.41***	.58***	.70***	.62***	.77***	--	
8. Ego Involvement	.22***	.20***	.37***	.21***	.22***	.21***	.21***	--

Note. *N* = 427. All motivational factors were measured on a 1-6 Likert scale; ****p* < .001.

7.5.2. Validity of Motivation Survey Instrument

All CFA models converged without problems during the estimation. The model, which tested the ability of 33 motivational variables to form eight distinct motivational factors, resulted in an adequate fit at both pre- and post-tests. The goodness-of-fit indices for the model are: χ^2 (467) = 934.78, $p < 0.001$, CFI = 0.94, TLI =0.93, RMSEA = 0.05, 90% CI = [0.04, 0.05] at pre-test and χ^2 (467) = 812.16, $p < 0.001$, CFI = 0.95, TLI = 0.94, RMSEA = 0.04, 90% CI = [0.04, 0.05] at post-test. Furthermore, an examination of factor loading estimates showed that the survey items measuring student motivation (indicators) were highly related to their purported motivational factors with standardized factor loadings ranging from 0.70 to 0.89 at pre-test and 0.72 to 0.86 at post-test (see Appendix 7I). The results of the longitudinal measurement invariance showed that the instruments were measuring the same constructs over time (i.e., pre-test and post-test). Indeed, comparing the model with equal factor loadings and the baseline model (i.e., Appendix 7J: Model 2 vs. Model 1) provided strong evidence of measurement invariance for factor loadings for all eight motivational factors (the absolute value of the difference of the CFI between nested models $|\Delta CFI| \leq .01$) and partial intercepts in all but the Self-Regulation, Engagement, Interest, and Ego Involvement factors over time.

7.5.3. Descriptive Statistics for the Motivational factors and Achievement Variables

Table 7.3 shows the descriptive statistics of the eight motivational factors and eight achievement variables at pre-test and post-test for the control group and the intervention group. The low intraclass correlations (ICCs) indicated only small differences between classrooms in the mean levels of the variables. The ICCs indicated that less than 10% of the variance in all of the motivational variables (ranging from 0.02 to 0.08) and most of the achievement variables was attributable to the classroom level, with the exception of six variables (i.e., pre-tests of *heat*, *forces*, and *speed*, Low element interactivity (EI) post-test of *heat* and high EI post-tests of *speed* and *density*. For these six variables, between 11% and 19% of the variance could be attributed to variability on the classroom level. Table 7.3 showed that the control group had pre-test mean scores ranging from 1.99 to 2.08 and the intervention group had pre-test mean scores ranging from 1.97 to 2.02 out of the full marks of 5. The low scores also showed that both groups did not have high pre-existing knowledge in any of the four science topics, prior to instruction.

Table 7.3

Descriptive Statistics for Achievement and Motivation Measures at Pre- and Post-test for Control and Intervention Groups

Cognitive & Motivation Measures			**Control Group** ***n*** **= 196**	**Intervention Group** ***n*** **= 231**	
			Mean (*SD*)	**Mean (*SD*)**	**ICC**
Pre-test	Achievement	Heat	2.04 (0.66)	2.02 (0.56)	0.11
		Forces	1.99 (0.71)	1.98 (0.69)	0.13
		Speed	2.08 (0.78)	1.97 (0.63)	0.12
		Density	1.99 (1.12)	1.87 (1.00)	0.04
	Motivation	Self-Regulation	4.83 (0.76)	4.65 (0.86)	0.05
		Engagement	5.01 (0.63)	5.05 (0.71)	0.04
		Sense of Competence	4.03 (1.00)	4.13 (1.04)	0.04
		Interest	4.66 (0.94)	4.74 (0.94)	0.03
		Task Goal Orientation	4.67 (0.88)	4.71 (0.89)	0.03
		Education Aspiration	4.01 (0.98)	4.10 (1.02)	0.03
		Career Aspiration	4.12 (1.03)	4.09 (1.16)	0.03
		Ego Involvement	3.72 (1.04)	3.85 (0.98)	0.03
Post-test	Achievement	**Low Element Interactivity Problems Post-Test**			
		Heat	4.21 (0.77)	4.04 (0.99)	0.12
		Forces	4.18 (0.82)	4.10 (0.83)	0.02
		#Speed	3.92 (0.77)	4.10 (0.74)	0.04
		#Density	3.91 (1.10)	4.06 (1.00)	0.04
		High Element Interactivity Problems Post-Test			
		Heat	2.23 (1.29)	2.22 (1.35)	0.05
		Forces	2.26 (1.57)	2.19 (1.48)	0.06
		#Speed	2.22 (1.41)	3.50 (1.34)	0.19
		#Density	2.27 (1.40)	3.38 (1.31)	0.16
	Motivation		***n*** **= 196**	***n*** **= 230**	
		Self-Regulation	4.21 (0.80)	4.63 (0.70)	0.03
		Engagement	4.57 (0.84)	4.83 (0.72)	0.05
		Sense of Competence	3.62 (0.93)	3.95 (0.93)	0.02
		Interest	4.13 (0.98)	4.40 (0.88)	0.09
		Task Goal Orientation	4.20 (0.89)	4.61 (0.74)	0.08
		Education Aspiration	3.56 (0.93)	3.94 (0.97)	0.05
		Career Aspiration	3.46 (0.97)	3.83 (1.05)	0.05
		Ego Involvement	3.53 (1.03)	3.65 (1.05)	0.02

Note. ICC = intraclass correlation coefficient; # denotes intervention topics

The descriptive statistics also showed that students in both groups were similar in terms of their achievement and motivation at pre-test. Results from the *t*-test showed no statistically significant differences between the control and intervention groups in terms of the pre-test means of all the four science topics: *heat* ($t(425) = 0.33$, $p = 0.744$), *forces* ($t(425) = 0.24$, $p = 0.809$), *speed* ($t(425) = 1.50$, $p = 0.136$), and *density* ($t(425) = 1.26$, $p = 0.209$). This showed that both groups of students had similar levels of pre-existing knowledge in the topics. Additionally, the *t*-test results showed that both the intervention and the control groups were similar in their levels of motivation in seven factors at pre-test: Engagement ($t(425) = -0.51$, $p = 0.613$), Sense of Competence ($t(425) = -0.98$, $p = 0.328$), Interest ($t(425) = -0.95$, $p = 0.344$), Task Goal Orientation ($t(425) = -0.40$, $p = 0.692$), Education Aspiration ($t(425) = -0.85$, $p = 0.396$), Career Aspiration ($t(425) = 0.30$, $p = 0.764$), and Ego Involvement ($t(425) = -1.36$, $p = 0.176$). In contrast, the control group had significantly higher means in Self-Regulation at pre-test ($t(425) = 2.31$, $p = 0.021$).

As seen in Table 7.3, all students had higher mean scores in the low element interactivity than the high element interactivity post-tests. This trend was observed for all four science topics: *heat*, *forces*, *speed*, and *density*. The results from the *t*-test showed that students in the control and intervention groups were similar in both the low and high element interactivity post-test achievement in the topics of *heat* ($t(425) = 1.91$, $p = 0.057$; $t(425) = 0.11$, $p = 0.914$, respectively) and *forces* ($t(425) = 1.10$, $p = 0.272$; $t(425) = 0.47$, $p = 0.637$, respectively), which were the two science topics that both groups of students experienced similar *regular instruction*. In contrast, the *t*-test results showed that students in the intervention group had significantly higher achievement in the high element interactivity post-test in the topics of *speed* ($t(425) = -9.58$, $p < 0.001$), and *density* ($t(425) = -8.45$, $p < 0.001$), during which they had experienced the *dual-approach instruction*. For achievement in the low element interactivity post-test, students in the intervention group had significantly higher achievement than the control group in the topic of *speed* ($t(425) = -2.48$, $p = 0.014$), but both groups of students were similar in their achievement in *density* ($t(425) = -1.49$, $p = 0.137$). As for students' post-test motivation, the students in the intervention group had significantly higher means which were statistically significant in all seven autonomous motivational factors: Self-Regulation ($t(425) = -5.71$, $p < 0.001$), Engagement ($t(425) = -3.50$, $p = 0.001$), Sense of Competence ($t(425) = -3.59$, $p < 0.001$), Interest ($t(425) = -2.95$, $p = 0.003$), Task Goal Orientation ($t(425) = -5.14$, $p < 0.001$), Education Aspiration ($t(425) = -4.06$, $p < 0.001$), and Career Aspiration ($t(425) = -3.73$, $p < 0.001$). There was no significant difference between both groups in the controlled motivation factor, Ego Involvement ($t(425) = -1.25$, $p = 0.213$). 0.021). Further statistical analyses were carried out with multiple regression models.

7.5.3. Multiple Regression Models

Results from the two multiple regression models (i.e., Model 1 and Model 2) for each of the 16 outcome variables are presented in Table 7.4. The results showed intervention effects on student achievement in *speed* and *density* high element interactivity tests, as well as student motivation in six factors.

7.5.3.1. Intervention effects on student achievement

As expected, for the topics *heat* and *forces* in which there was no intervention, no significant difference in student achievement was found between the two groups of students, in both Models 1 and 2, for both the low and high element interactivity post-tests (see Table 7.4). In contrast, the results showed statistically significant positive effects of *dual-approach instruction* on students' post-test achievement in high element interactivity for *speed* ($\beta = 0.85$, $p < 0.001$) and *density* ($\beta = 0.76$, $p < 0.001$) in Model 1. The statistically significant positive effects remain strong in Model 2 for both the intervention topics *speed* ($\beta = 0.81$, $p < 0.001$) and *density* ($\beta = 0.72$, $p < 0.001$) in the high element interactivity post-tests. The effect sizes were large for both.

Table 7.4
Results from Multiple Regression Analyses

	Heat: Low EI				Heat: High EI				Forces: Low EI				Forces: High EI			
	1		2		1		2		1		2		1		2	
	β	SE	B	SE	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE
Groups	- 0.19	0.19	- 0.20	0.19	- 0.02	0.17	- 0.02	0.17	- 0.10	0.09	- 0.16	0.08	- 0.05	0.18	- 0.07	0.18
Gender			0.08	0.12			0.06	0.11			0.51***	0.11			0.21**	0.08
Pre-test			0.12*	0.05							0.08	0.08				
R^2	0.01		0.02		0.00		0.00		0.00		0.07		0.00		0.01	

	#Speed: Low EI				#Speed: High EI				#Density: Low EI				#Density: High EI			
Model	1		2		1		2		1		2		1		2	
	β	SE	B	SE	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE
Groups	0.23*	0.12	0.22	0.12	0.85***	0.10	0.81***	0.10	0.15	0.13	0.15	0.10	0.76***	0.12	0.72***	0.11
Gender			0.06	0.09			0.29***	0.07			0.21*	0.09			0.35***	0.08
Pre-test			- 0.01	0.05							0.23***	0.06				
R^2	0.01		0.02		0.18		0.20		0.01		0.08		0.14		0.17	

	Self-Regulation				Engagement				Sense of Competence				Interest			
	1		2		1		2		1		2		1		2	
	β	SE	B	SE	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE
Groups	0.26***	.08	0.31***	0.04	0.16	0.11	0.16*	0.08	0.17***	0.04	0.14**	0.04	0.14	0.09	0.11	0.08
Gender			0.05	0.04			0.03	0.05			0.18**	0.06			0.17***	0.05
Pre-test			0.48***	0.04			0.47***	0.05			0.34**	0.09			0.34***	0.07
R^2	0.07		0.30		0.03		0.25		0.03		0.21		0.02		0.18	

	Task Goal Orientation				Educational Aspiration				Career Aspiration				Ego Involvement			
	1		2		1		2		1		2		1		2	
	β	SE	B	SE	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE
Groups	0.23**	0.08	0.21***	0.07	0.20***	0.06	0.17***	0.05	0.18***	0.05	0.17***	0.04	0.07	0.06	0.03	0.06
Gender			0.14**	0.05			0.18**	0.06			0.18**	0.06			0.08	0.05
Pre-test			0.47***	0.07			0.31***	0.07			0.24***	0.06			0.52***	0.04
R^2	0.05		0.30		0.04		0.19		0.03		0.14		0.01		0.29	

Note. EI = Element interactivity; # denotes intervention topics; groups were coded: 1 = students who experienced intervention for topics Speed and Density, 0 = students in the control group who did not experience any intervention; gender was coded: 1 = male, 0 = female; High EI variables for speed, density, heat and forces were not measured prior to the intervention (pre-test). *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$

There were no intervention effects in either model for the low element interactivity post-tests. The results indicated that students in the intervention group had higher achievement in speed and density than the control group, but only for the high element interactivity post-tests of those topics.

As shown in Model 1, a comparably high amount of variance was explained by speed and density in high element interactivity post-tests (R2 = 0.18 and R2 = 0.14, respectively). The results were similar for Model 2: the largest amounts of variance in the achievement variables were also explained by high element interactivity post-tests of speed and density (R2 = 0.20 and R2 = 0.17, respectively).

As seen from Model 2 in Table 7.4, gender was a significant predictor of achievement in five variables, including three from the intervention topics: high element interactivity post-tests of speed and density ($\beta = 0.29$ and $\beta = 0.35$, respectively, $p < 0.001$), low element interactivity post-test of density ($\beta = 0.21$, $p = 0.015$) and both low and high element interactivity post-tests of forces ($\beta = 0.51$, $p < .001$ and $\beta = 0.21$, $p = 0.006$). This indicates that boys had significantly higher achievement than girls in these five variables. The results also showed that pre-test results were positively significant predictors of achievement in low element interactivity post-tests of heat ($\beta = 0.12$, $p = 0.031$) and density ($\beta = 0.23$, $p < 0.001$). This shows that students who did better in the low element interactivity pre-tests also had higher achievement in the low element interactivity post-tests of density and heat.

7.5.3.2. Intervention effects on student motivation

The results indicated that students in the intervention group had higher science motivation than the control group on most of the motivational variables. As displayed in Table 7.4 in Model 2, statistically significant positive effects of *dual-approach instruction* were found in students' motivation behavioral outcomes in terms of their Self-Regulation ($\beta = 0.31$, $p < 0.001$), Engagement ($\beta = 0.16$, $p < 0.05$), Sense of Competence ($\beta = 0.14$, $p < 0.01$), as well as motivation on the SDT continuum: Task Goal Orientation ($\beta = 0.21$, $p < 0.001$), Education Aspiration ($\beta = 0.17$, $p < 0.001$), and Career Aspiration ($\beta = 0.17$, $p < 0.001$). Model 1 had similar results, with slightly different magnitudes of β. Small effect sizes were observed in all of the motivational variables. No significant differences were found between the groups in Interest and Ego Involvement.

As shown in Model 1, the highest amount of variance was explained by Self-Regulation ($R^2 = 0.07$) and the smallest amount of explained variance occurred in Ego Involvement ($R^2 = 0.01$). In Model 2, the largest amounts of variance were explained by Self-Regulation and Task Goal Orientation ($R^2 = 0.30$); the smallest ($R^2 = 0.14$) was observed in Career Aspiration.

As seen in Model 2, gender was a significant predictor of motivation in five variables: Sense of Competence ($\beta = 0.18$, $p < 0.01$), Interest ($\beta = 0.17$, $p < 0.001$), Task Goal Orientation, ($\beta = 0.14$, $p < 0.01$), Education Aspiration ($\beta = 0.18$, $p < 0.01$), and Career Aspiration ($\beta = 0.18$, $p < 0.01$). The results indicated that boys had significantly higher motivation in science than girls in these variables. Pre-test was a positively significant predictor of motivation in all motivational variables.

7.6. Discussion

This study is the first to design a *dual-approach instruction* that incorporates both the cognitive and non-cognitive aspects of learning in a science learning environment and examines its effectiveness on students' achievement and motivation. Given that much research has shown the importance of both the cognitive and non-cognitive aspects of learning (e.g., Forbes et al., Phan et al., 2016), it is surprising that intervention studies incorporating both aspects of learning in the one learning environment to study the effects on student learning and motivation are scarce. In this study, the cognitive aspect of learning was incorporated using cognitive load theory as a theoretical framework, where element interactivity was managed at every stage of learning to ensure that students would not experience cognitive overload. This study adds to the literature in that the isolating-elements strategy from CLT is applicable to, and can be implemented in learning tasks, such as hands-on science activities, to ensure that learning is within students' cognitive capacities. The non-cognitive aspect of learning was incorporated using self-determination theory as a theoretical framework, where students' basic psychological needs were supported in the learning environment with the hope of nurturing student motivation. The results in the study showed that incorporating both aspects of learning in a learning environment benefited the students both in terms of their achievement and motivation in a range of factors. Although we cannot definitely rule out the possibility that gender differences or pre-existing differences within some factors potentially account for the results, this possibility is reduced by the analysis which controlled for gender and students' pre-test scores on each outcome measure. The analysis increases the internal validity of the intervention effects detected in this study. Thus, the results provide strong support for the conclusion that experiencing the *dual-approach instruction* has a positive impact on students' achievement and motivation.

7.6.1. Achievement

All hypotheses were supported. The students had higher mean scores in the low element interactivity than the high element interactivity post-tests, as hypothesized (i.e., Hypothesis 1). This was probably because low element interactivity tasks were less likely to overload the working memory than high element interactivity tasks. There was no significant difference between the control and intervention groups in their achievement in the science topics (i.e., *heat* and *forces)* taught using the *regular instruction*. The results supported Hypothesis 2 and showed that when the intervention was not present, the two groups were similar in their science achievement. This finding provided evidence as to the effectiveness of the intervention. The effectiveness of the intervention was further supported by the results which showed that the students in the intervention group had significantly higher achievement than those in the control condition, in solving complex (i.e., high element interactivity) problems in the topics of *speed* and *density*: the topics in which they experienced the intervention. The results supported Hypothesis 3. The finding that students performed better when element interactivity of complex tasks is broken down into successive modules of simpler, lower element interactivity learning tasks is consistent with prior research (e.g., Gerjets et al., 2006; Ngu et al., 2015). It is also consistent with the proposition that when learning tasks are sequenced in gradual increments of element interactivity for students lacking in pre-existing knowledge, learning will be more effectively facilitated, resulting in higher achievement compared to learning in environments where element interactivity is not effectively managed (i.e., Blayney et al., 2010).

However, there was no difference between the control and intervention groups in their achievement in low element interactivity post-tests in the topics of *speed* and *density*, as hypothesized (i.e., Hypothesis 3). This was probably because the low element interactivity problems were simple enough for the students to solve using the knowledge and skills gained from their *regular instruction* experiences. This finding is in line with the findings of past research studies showing that CLT strategies (incorporated in the intervention) were most effective on high element interactivity learning tasks (e.g., Leahy et al., 2015), and not simple tasks which do not overload the working memory (Sweller et al., 2011).

7.6.2. Motivation

Apart from achievement, students in the intervention group also had higher motivation in science, in terms of behavioral outcomes such as self-regulating their learning (i.e., Self-Regulation), beliefs that they are capable of doing well in science (Sense of Competence), and motivational outcomes such as autonomous motivation (i.e., Task Goal Orientation and Aspirations in pursuing science-related education and career paths). These findings support Hypothesis 4. Students' higher motivation could be attributed to the specific design of their learning environment to nurture their sense of competence, autonomy and relatedness. The finding that students have higher motivation when their basic psychological needs are met is consistent with prior research (e.g., Jang et al., 2009). There was no significant difference in students' Ego Involvement between the control and intervention groups, which implies that students in both groups did not differ in terms of extrinsic motivation such as peer pressure. This finding is consistent with the study design since Ego Involvement was not a focus for the intervention. There were also no significant differences between the two groups in terms of their attentiveness during science lessons (Engagement) or their intrinsic motivation in learning science (Interest). Even though prior research has shown positive associations between the fulfillment of basic psychological needs with student engagement and intrinsic motivation (Niemiec & Ryan, 2009), the high values reflected in the descriptive statistics indicated a ceiling effect (Vogt, 2005), that is, students in both groups reported such high engagement and interest in science that no significant difference could be observed in the post-tests between groups.

7.6.3. Implications for Policy and Practice

The presented findings provide clear evidence that the *dual-approach instruction* resulted in superior learning outcomes in terms of achievement and motivation. To maximize student achievement and motivation, teachers should design science lessons that are not only authentic, meaningful, and enjoyable to nurture intrinsic motivation (Kadir, 2006; Ng et al., 2016) but are also sequenced based on students' pre-existing knowledge, so that element interactivity (i.e., cognitive load) at every stage of learning is manageable for effective learning (Kalyuga, 2007). The schemas formed when students successfully meet learning sub-goals of simpler tasks helps them achieve (and experience) success prior to the main goal of tackling complex tasks without overloading their working memory (Kalyuga, 2007; Sweller et al, 2011). The success experienced by students increases their sense of competence, which is crucial for their continued motivation and success (Kadir et al., 2013; Marsh & Craven, 2006). Therefore, when teachers design instructional materials that are within students' cognitive capacities, students are more likely to be motivated to maintain their focus and attention on learning tasks, resulting in positive learning outcomes (Paas & Ayres, 2014; Paas, Tuovinen, van Merriënboer, & Darabi, 2005). In addition to attending to cognitive load, another recommendation for teachers is to create a learning environment that also supports students' basic psychological needs (Niemiec & Ryan, 2009; Wang et al., 2011). Instead of passively transmitting knowledge, teachers should present students with learning tasks that challenge them, allow them to excel, and provide constructive feedback and encouragement (fulfilling a sense of competence). Teachers should also explain rationales for learning tasks, provide ample opportunities for students to share their ideas and make decisions, ask students questions and listen attentively, avoid coercion, and minimize evaluative pressure (fulfilling a sense of autonomy). Last but not least, teachers should maximize friendly interactions with each student, ensuring that no student is isolated, treat all students with respect and kindness, and show them that their contribution to the learning community is valued (fulfilling a sense of relatedness).

7.6.4. Limitations and Future Research

As with most research, this study has its share of limitations. First, we did not have subjective measures of cognitive load and students' perceptions of their competence, autonomy, and relatedness at regular intervals during their science intervention. Instead, we only had objective measures. Future research could obtain subjective measures from students about various aspects of the intervention in order to be able to measure the interaction effects of the CLT and SDT interventions, and determine the causal effects of students' achievement and motivation. Second, we did not have a 2 X 2 experimental design which would separate the students into four groups: (1) no intervention, (2) motivation intervention only, (3) cognitive load intervention only, and (4) both cognitive load and motivation intervention. With such a design, we could see more clearly which intervention was the most effective. Future research could administer such a design. From this study, we can conclude that intervention features increased academic achievement in complex academic tasks and reduced the downward trend of academic motivation common in adolescents. Third, we had a short intervention period of 10 weeks and due to ethics, students were aware that classes would revert to regular science lessons after the intervention period, which could have affected student motivation. Past educational research indicates that student motivation decreases in adolescents (from about Grade 5 onwards) and so breaking this downward trend would take time. Future research could look into extending the intervention period. However, the fact that the short intervention period of 10 weeks improved student achievement and reduced the downward motivation trend is a positive sign that it could have greater positive effects if implemented over a longer period of time, involving more science topics. Fourth, the study involved students with high academic ability in a school with generally high socioeconomic status. The results may not be generalized to students of low ability or even those of average ability. Future research could involve student participants of lower academic ability to investigate the intervention effects in such a population.

7.7. Conclusion

The benefits of the *dual-approach instruction* are clear in the study: students who experienced instruction where their cognitive and psychological needs were met had higher achievement and motivation than those who did not. While several studies have shown that the fulfillment of these basic psychological needs led to positive learning outcomes and motivation, this study supplements the literature by demonstrating that when these needs were met and combined with tailored instruction aligned with students' cognitive capacities, it led to superior learning outcomes in two areas: achievement and motivation. It is recommended that science lessons should incorporate both cognitive and motivational aspects of learning to optimize student learning and to nurture positive attitudes towards science, including aspirations to pursue science-related studies and careers in the future.

CHAPTER 8: GENERAL DISCUSSION

8.1. Overview

Science learning, especially in the area of physics, is known to be complex and cognitively demanding (Angell, Guttersrud, Henriksen, & Isnes, 2004). If the complexity of learning and cognitive load is not efficiently managed by educators then ineffective instruction practices are likely to result in learning deficiencies. These may then lead to undesirable consequences such as poor achievement, lowered sense of competence (Marsh & Craven, 2006), and lack of motivation to learn science (Paas, Tuovinen, van Merriënboer, & Darabi, 2005). Over the years, researchers have emphasized the important roles of both the cognitive and motivational aspects of student learning (Kadir, 2006; Ng, Liu, & Wang, 2016; Kuppan, Munirah, Foong, & Yeung, 2010; Osborne, Simon, & Collins, 2003; Wang & Degol, 2013). In spite of this understanding, studies that looked into the interplay of both of these processes are still lacking, especially in science instruction. The aim of this thesis is to provide a better understanding of the cognitive and motivational aspects of science learning, through a series of five studies. In this chapter, a summary and discussion of the main findings of the studies are presented. Next, some strengths of the thesis are discussed along with the theoretical and methodological contributions, elaborating on the implications for educational policy and practice. The chapter concludes also with a segment addressing the limitations of the thesis and suggesting several future directions for research.

8.2. Summary of Main Findings

In this thesis, I found that there are significant relations between the cognitive (i.e., cognitive processes and achievement) and the non-cognitive (i.e., motivation) aspects of learning. These relations can be seen in all the five studies in this thesis. As the findings of each study have been discussed in great detail at the end of each chapter of the thesis, in this section, I provide a summary of the main findings.

8.2.1. Study 1

Extensive self-concept studies over the past decades have shown that academic self-concept plays an important role in contributing to educational outcomes such as student achievement. As such, a review of four decades of self-concept research was conducted in Study 1 to summarize the five main findings from past research and to test their replicability on a sample of Grade 7 students from Singapore. Study 1 showed that most of the past findings (e.g., Marsh & Craven, 2006) were consistent with our sample: that both the cognitive and affective components of academic self-concept were positively correlated with student achievement, and the cognitive component of self-concept (i.e., sense of competence) in a curriculum domain was the stronger predictor of academic achievement (as a cognitive outcome) in the domain. This means that when students believe that they can do well (sense of competence) in a subject domain such as physics, they are more likely to excel in the physics domain. The findings from Study 1 highlighted that academic self-concept plays an important role in determining student academic outcomes such as school achievement, and therefore the importance of enhancing students' academic self-concept in schools. The recommendation is that instruction should be designed to develop students' sense of competence, to increase the likelihood of higher achievement.

8.2.2. Study 2

Whereas Study 1 highlighted the significantly positive relations between students' academic self-concept in a subject domain with student achievement in that domain, research has shown that there are several other motivational factors that influence students' achievement and attitudes in learning (Forbes, Kadir, & Yeung, 2017; Ford & Nichols, 1991; Yeung, Kuppan, Kadir, & Foong, 2010). Therefore, in Study 2, the relations between students' cognitive and non-cognitive outcomes were investigated, including several other motivational factors (e.g., self-efficacy, engagement, and educational aspiration). The findings of Study 2 showed that all of the assessed motivational variables were positively correlated with student achievement, which is similar to the results found in past studies (e.g., Guo, Parker, Marsh, & Morin, 2015; Yeung, Kuppan, Kadir et al., 2010). This demonstrates that student motivation plays a role in contributing to education outcomes such as achievement and should be strongly considered when designing instruction for everyday lessons. In addition, the correlation analysis showed that Grade 7 students' science motivation is more highly correlated with their science achievement in Grade 7 than Grade 6 science achievement in primary school. This implies that Grade 7 is a good starting point for intervention studies. Even if students have not performed well in Grade 6, effective instruction in Grade 7 that enhances both cognitive and motivational processes may help them learn more effectively and nurture their motivation, contributing to positive educational outcomes.

8.2.3. Study 3

Studies 1 and 2 demonstrated the positive associations between achievement and motivation, indicating that effective instructional design needs to nurture students' motivation. Before this could be done effectively, we needed to understand the *processes* underpinning student achievement and motivation. Since science learning involves the interaction of multiple elements such as science conceptual and procedural knowledge, and scientific and problem-solving skills (Carlson, Chandler, & Sweller, 2003; Kadir, Ngu, & Yeung, 2015), it is often perceived by students as complex (Angell et al., 2004; Shen & Pedulla, 2000). Cognitive science researchers use *element interactivity* as a construct to explain and understand the complexity of learning materials (Leahy & Sweller, 2005; Ngu, Chung, & Yeung, 2015; Sweller, 2010). Element interactivity is the level at which learning elements such as conceptual information and procedural knowledge interact (Sweller, 2010). Learning tasks with high element interactivity means that the learning elements cannot be learnt in isolation and the high level of interactions of the learning elements contributes to high cognitive load which easily overloads the working memory, impairing learning (Sweller, Ayres, & Kalyuga, 2011). Therefore, it is necessary to ensure that the element interactivity in any learning tasks is not too high, for learning to be effective. Study 3 focused on investigating the cognitive processes of student learning leading to achievement, and illustrated how element interactivity can be used for: (1) the analysis of student cognitive processes during problem-solving to provide an indication of student expertise in the domain, and (2) analysis of science problems, to guide instructional design to suit students' cognitive levels. The results of Study 3 illustrated how element interactivity provided an indication of students' expertise in problem solving beyond what their test scores indicated. Element interactivity was found to be negatively associated with achievement. Novices (i.e., students who lack the expertise to solve science problems due to lack of knowledge and skills) who attempted high element interactivity problems had lower achievement than novices who attempted lower element interactivity problems. This result reinforces past studies (Ayres, 2013; Blayney, Kalyuga, & Sweller, 2010; Gerjets, Scheiter, & Catrambone, 2006; Paas & Ayres, 2014). This study thus demonstrates how to use element interactivity as a tool to design instruction that caters to students' cognitive needs.

8.2.4. Study 4

Since element interactivity was found to be a useful construct for problem analysis and instructional design in Study 3, it was used as a tool to design the instruction in Study 4 and Study 5. Study 4 involved an intervention using the isolating-elements strategy (Pollock, Chandler, & Sweller, 2002). This strategy reduces element interactivity (and thus cognitive load) by breaking down complex learning tasks with many interacting elements into sub-tasks with less interacting elements (Kalyuga, 2007). However, the implementation of this strategy in my experiment goes beyond what previous studies have attempted, by focusing on students' actual learning activities, instead of information sheets and worked problems (Sweller et al., 2011). The isolating and sequencing of the learning elements in students' instructional worksheets were done by me, in collaboration with the teachers. Student achievement improved as a result of the intervention, particularly novices who achieved more success when they experienced the isolating-elements strategy during the learning of complex tasks than when they did not (Blayney et al., 2010). Apart from higher achievement in science, students also benefitted from the intervention in terms of their science self-concept. This result is in accordance with past self-concept research and showed that when students achieved success in a subject domain, it enhanced their self-concept in that domain (Marsh & Craven, 2006). Study 4 added to the research literature by showing that the strategy worked positively when implemented on students' learning tasks, and concurrently enhanced student achievement and academic self-concept. Such findings point to the promise of instruction designed in accordance with students' cognitive capabilities for effective learning, contributing to higher achievement.

8.2.5. Study 5

Based on the results of previous research studies, instruction that focuses only on the cognitive aspects of learning has limited outcomes. Therefore, Study 5 extended the intervention of Study 4 by not only implementing the isolating-elements strategy in students' learning tasks, but also putting in place important motivational processes (i.e., supporting students' basic psychological needs of competence, autonomy and relatedness implicit in Self-Determination Theory, cf. Deci & Ryan, 1985; Ryan & Deci, 2017) in an intervention named *dual-approach instruction*. Study 5 also included more motivational variables related to science, in addition to science self-concept. Past research studies were extended by incorporating both the cognitive and motivational processes of student learning into a single intervention. Similar to past studies (e.g., Ayres, 2013; Blayney et al., 2010) and consistent with Study 4, it was found that the intervention helped students achieve success in solving complex science problems. In addition to higher achievement, students in the intervention group also had higher science self-concept and autonomous motivation in science than those in the control group. This is consistent with previous research, which found that students who had their basic psychological needs fulfilled reported positive learning experiences, higher motivation, and higher academic achievement than students who did not (e.g., Jang, Reeve, Ryan, & Kim, 2009; Ng et al., 2016). In sum, in Study 5, I found that when instruction addresses both the cognitive and motivational processes of student learning, students had dual benefits in terms of their positive achievement and motivational outcomes, including having aspirations to pursue science-related higher education and careers. The results of this study provide a promising theoretical framework and model for instruction indicating that all lessons should involve both the cognitive and motivational aspects of learning to ensure that the learning environment is conducive for students to achieve their optimal best.

8.3. Discussion of General Findings

The results from the five studies included in this thesis have shown that learning encompasses two aspects: cognitive and non-cognitive, with each playing a critical role in student learning and educational outcomes. In this thesis, I have addressed each aspect of learning as a process and an outcome. The cognitive aspect was addressed in terms of the cognitive processes (i.e., managing element interactivity) during the learning process and achievement as an educational outcome. The non-cognitive aspect was addressed in terms of supporting students' basic psychological needs (i.e., creating a learning environment which fulfilled students' need for a sense of competence, autonomy and relatedness), during the learning process and student motivation as an educational outcome. Figure 8.1 summarizes the main themes of the thesis and the following segment elaborates on how both the cognitive and non-cognitive aspects of learning have been addressed by this thesis.

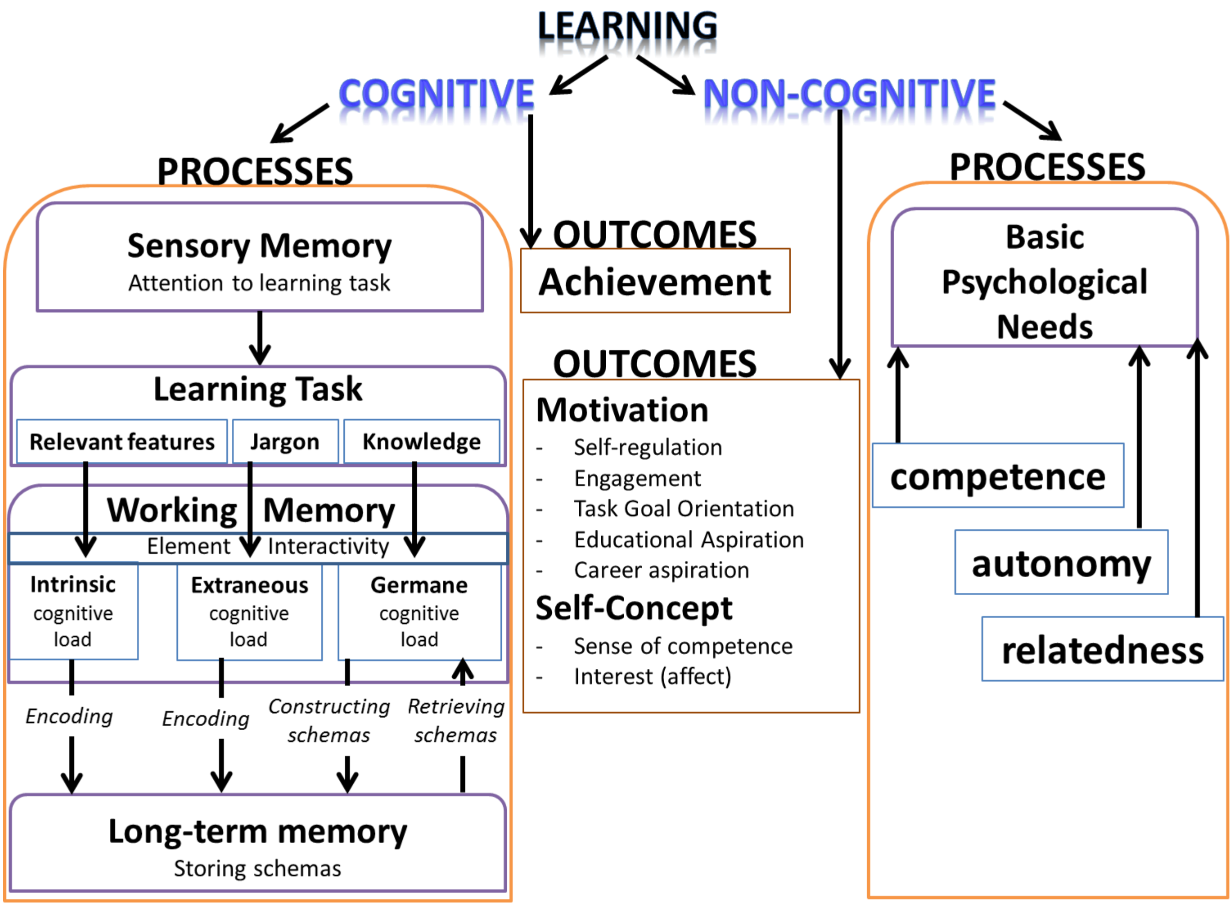

Figure 8.1. The cognitive and non-cognitive aspects of learning addressed by the thesis

8.3.1. Instructional Processes

In this thesis, instructional processes refer to the instructional design and procedures in place in everyday science lessons for students. This includes the teaching and learning methods, learning environment, as well as the learning tasks and materials used to deliver the science lessons. In this thesis, I have argued for the inclusion of both the cognitive and motivational aspects of learning into everyday instructional processes for optimal educational outcomes, a view supported by evidence from the five reported studies.

8.3.1.1. Cognitive Process: Managing Element Interactivity

In order to improve students' achievement in science, the cognitive processes involved in learning need to be considered. Science learning tasks, especially in physics, are often so complex that students find it difficult to excel, resulting in low achievement. According to cognitive load theory, complexity of learning is associated with high levels of interactions among learning elements (i.e., element interactivity). In this thesis, element interactivity was used to analyze the complexity of students' learning tasks, as well as to describe students' cognitive processes. Results from Studies 3, 4, and 5 showed that element interactivity is related to student achievement, which in turn affects other educational outcomes such as academic self-concept and motivation. When element interactivity is so high that it overloads the working memory (which is known to have limited capacity and duration), learning is impeded, which negatively affects achievement. Managing element interactivity is thus a very important process that should not be neglected. It is important to assess students' prior knowledge or existing knowledge base as it affects the level of element interactivity that they are able to manage. Students with a substantial knowledge base in the domain are not novices, so they are able to recall large amounts of information from their long-term memory as a single schema to interact with the new information being taught, without overloading their working memory. These students are developing expertise in the domain and are able to handle high element interactivity tasks. In contrast, students who are novices and lack pre-existing knowledge in the domain do not possess such schemas, so their working memory gets overloaded more easily as they deal with new information. For these students, the level of element interactivity should be reduced at the early stages of learning and gradually increased as they gain expertise. In this thesis, this strategy was implemented using the isolating-elements strategy, and it was shown to improve student achievement and sense of competence. Getting students to complete pre-tests before lessons on a new topic will help teachers gauge students' pre-existing knowledge in terms of concepts and procedural skills, which will help in designing and delivering instruction with manageable element interactivity.

8.3.1.2. Non-Cognitive Process: Basic Psychological Needs

Cognitive processes can only begin when attention is given to learning tasks. Instructional processes that cater to students' cognitive needs and are well-designed and implemented will not be effective if students are so unmotivated that they do not pay attention to the instruction. Therefore, non-cognitive processes must also be in place in the learning environment in order to nurture student motivation for cognitive engagement. According to Self-Determination Theory (SDT), an effective way of nurturing student motivation is by supporting students' basic psychological needs: their sense of competence, autonomy, and relatedness (Niemiec & Ryan, 2009). Students are motivated to engage in learning tasks if they have a sense that they (1) have the ability to excel in the learning tasks (competence), (2) have a choice in the learning tasks (autonomy), and (3) belong to the learning community, which includes peers and teachers (relatedness). In this thesis, I have shown that when students' basic psychological needs are supported in an intervention, students' achievement and motivation were positively affected. Apart from making sure that students' cognitive needs are met through cognitive processes, students' basic psychological needs must also be supported for optimal educational outcomes.

8.3.2. Educational Outcomes

If both the cognitive and non-cognitive processes of student learning are well-implemented, students will experience dual-outcomes: cognitive (achievement) and non-cognitive (motivation) gains. In this thesis, I addressed the cognitive outcomes in terms of cognitive processes and achievement and the non-cognitive outcomes in terms of motivation.

8.3.2.1. Cognitive Outcome: Achievement

Achievement is a common educational outcome measure in school. Student achievement in a subject domain, such as science, is a measure of how well students have learned the materials in science and is reflected in terms of test scores from science learning tasks. Students with high achievement in science are assumed to have mastered most of the science materials. As seen from the results of the studies in this thesis, achievement does more to a student than give them an indication of their cognitive ability. Achievement predicts students' sense of competence in the domain. If students have high achievement in a subject domain, they believe more in their ability, and will continue to do well in the domain (Marsh & Craven, 2006). The correlation analysis shows that achievement is also related to motivation. Students with high achievement tend to have high motivation, which will drive them to be more engaged in the domain, leading to higher achievement. Therefore, making sure that students achieve success during everyday lessons is very important. In this thesis, it was shown that one way of doing this is by managing students' cognitive processes in the form of element interactivity. The success of the intervention indicates that managing element interactivity increases students' achievement and satisfying students' basic psychological needs not only increases achievement but also motivation. In sum, both cognitive and motivational processes influence student achievement.

8.3.2.2. Non-Cognitive Outcome: Motivation

For many decades, the focus of schools has been student achievement as an educational outcome (cognitive). In recent years, more research has shown that motivation (non-cognitive educational outcomes) is related to achievement and plays a crucial role in influencing future educational and career choices (Wang & Eccles, 2012). In this thesis, I focused on a few motivational outcomes that are in accordance with self-concept and SDT: *sense of competence, interest, task goal, educational aspiration, career aspiration, self-regulation, engagement* and *ego.* The first two (i.e., *sense of competence, interest*) are components of academic self-concept, which are important predictors of achievement and other motivational outcomes, respectively. Students with a high sense of competence in science tend to have high achievement, and students with high interest in science are more likely to aspire to further their education in science and thereafter pursue careers related to science. According to SDT, students who are autonomously motivated tend to have “more effective performance on heuristic types of activities” and “long term persistence” (Deci & Ryan, 2008, p. 183), contributing to many important outcomes. A *task goal* outcome was selected to find out if students’ reasons for learning science were autonomously motivated, and due to the declining rate of students’ enrolment in future science courses and careers, *educational aspiration,* and *career aspiration* were also included as motivational outcomes. Basically, students who rated themselves highly in *interest, task goal, educational aspiration,* and *career aspiration* are autonomously motivated. *Self-regulation* and *engagement* were selected because they are behavioral outcomes of motivation. Students who are autonomously motivated in science will most likely exhibit positive behaviors such as self-regulating in their learning and paying careful attention to science lessons. Since students learn in a class community, *ego-involvement* was chosen as a controlled motivation outcome to determine if students’ desire to do science correlates with their ego of appearing smart in front of their classmates or otherwise. As seen from the results of the final study (Study 5), supporting students’ basic psychological needs can help nurture their autonomous motivation and had no effect on controlled motivation. The consistent relations found between achievement and motivational outcomes suggested that the cognitive and non-cognitive processes leading to achievement and motivation should not be taken lightly in daily lessons. Every lesson should be designed to help students learn effectively in a learning environment which also nurtures student motivation.

8.4. Strengths of this Thesis

The main strength of this thesis is that it addresses both the cognitive and motivational aspects of science learning, which leads to the development of an instructional approach that incorporates both aspects of learning. Achievement and motivational factors were measured by multiple items and possessed strong psychometric properties in the studies. The thesis also extended past research by making several theoretical and methodological contributions to the field, leading to practical implications for policy makers and practitioners, as well as opening up paths for future research.

8.4.1. Theoretical and Methodological Contribution

This thesis has provided several theoretical and methodological contributions. First, it has incorporated academic self-concept findings from several decades of self-concept studies and tested their replicability in a sample of students in Singapore. The findings were consistent with past research and supported the replicability and robustness of self-concept theories. Past research was extended by testing both components (i.e., cognitive and affective) of academic self-concept for each of the five hypotheses. The results showed that the distinction between each component of self-concept for each hypothesis allows researchers and practitioners to gain novel insights about each component of self-concept, which assists in deciding the particular component that should be enhanced when targeting a specific educational outcome. Also, the interrelatedness between physics and mathematics achievement and self-concept found in this thesis highlights the importance of mathematics as a tool to learn physics, and how achievement in mathematics can influence students' self-concept in physics. Thus, students' mathematical skills should not be ignored by physics educators.

Second, in this thesis, I compared the relations between motivation and achievement between two consecutive school years, during the transition between primary and secondary schools (i.e., Grades 6 and 7). While past research normally used achievement scores from national data, this thesis not only used the achievement scores of a national local examination in Singapore (i.e., Grade 6 PSLE scores), but also the achievement scores of school-based tests as an outcome measure. The main reason for using school-based tests was to investigate whether students' achievement in these school-based tests had similar associations with students' motivation in school when compared with their achievement in the national examinations. As shown in the studies, students' attitudes and motivation were also related to their test scores from school-based achievement within the same subject domain. The stronger relations between motivation and achievement in Grade 7 (first year of secondary school), rather than Grade 6 achievement, identified that Grade 7 is the best place to begin educational interventions focused on changing students' attitudes towards learning (Anderman, Maehr, & Midgley, 1999).

Third, this thesis is the first to extend previous research using the concept of element interactivity to analyze problem tasks (Leahy, Hanham, & Sweller, 2015; Sweller, 2010) by using it to determine students' level of expertise in problem solving. The results align with cognitive load theory (Ayres, 2013) and demonstrate that students who were able to manage high element interactivity in their solutions were of higher expertise than those who used low element interactivity. Therefore, this thesis has shown that students' level of element interactivity in problem solving processes informs educators about their level of expertise beyond test scores. I also found that there were students who tried to solve problems using high element interactivity in their solutions got the answer wrong because of a science misconception. Such students should receive instruction that focuses on the development of science conceptual knowledge before acquiring procedural skills for problem solving, since focusing on the latter only will introduce extraneous cognitive load due to the expertise reversal effect (Kalyuga, 2007). Therefore, this thesis has contributed to evidence about the importance of element interactivity as a construct not only for task analysis, but also for student problem solving processes to determine their expertise in conceptual or procedural knowledge, in order to tailor instruction to suit their cognitive needs.

Fourth, this thesis is the first to extend previous research using the isolating-elements strategy when studying worked examples and information sheets (Ayres, 2013; Pollock et al., 2002). Student learning of science concepts was sequenced to reduce science instruction element interactivity by gradually introducing simple-to-complex activities as students gained expertise. The positive results of the intervention showed that the isolating-element strategy also worked for science instruction beyond studying worked examples and information sheets or manual. This thesis found that when learning tasks or activities were designed and presented such that the element interactivity at each stage of learning was within the cognitive capacities of the students, students had higher achievement and a positive self-concept.

Drawing on the strong interplay of student cognitive processes, achievement and motivation from the studies within this thesis as well as past research, this thesis is the first to design a dual-approach instruction which encompasses both the cognitive and motivational processes of learning in one instructional environment. The isolated-element strategy was used to manage element interactivity at every stage of learning and SDT strategies were used to support students' basic psychological needs of competence, autonomy, and relatedness (Deci & Ryan, 2008; Ryan & Deci, 2017). The success of the intervention showed that when both the cognitive and motivational aspects of learning are well-addressed in an instructional environment, students will not only have higher achievement, but also more positive attitudes and higher motivation towards learning.

In summary, in this thesis the strong interplay between the cognitive and non-cognitive aspects of science learning was evident. The findings not only provide a better understanding of the processes of science learning, but also model how to implement the various strategies to improve students' educational outcomes, which include both achievement and motivational factors.

8.5. Implications for Policy and Practice

This research has expanded previous research on the cognitive and non-cognitive aspects of learning, showing the interplay of both aspects and providing a heuristic guide for future research and intervention designs. The distinctiveness of the cognitive and affective components of self-concept found in Study 1 indicates that these components need to be treated separately because they influence different educational outcomes. In addition, the domain specificity of self-concept means that students' self-concept is influenced by the achievement of that domain, and not by other unrelated domains. Therefore, if the intended educational outcome is to improve student achievement in, for instance, chemistry, then intervention strategies need to focus on enhancing students' sense of competence (cognitive component of self-concept) in chemistry. Yet, if the intended educational outcome is to nurture students' long-term goals such as future academic choices and career aspirations in a specific domain, then intervention strategies need to focus on enhancing students' enjoyment and interest (affective component of self-concept) in that domain. Academic self-concept has been shown to contribute to positive educational outcomes, so schools should look into enhancing both the cognitive and affective components of students' self-concept for optimal results.

The correlations found in Study 2 between achievement and motivation showed strong positive associations. To maximize learners' motivation, educators need to plan instruction according to students' cognitive abilities to advance their chances of achievement. Conversely, if students' learning environments fail to nurture motivation, achievement is likely to be negatively affected. Educators should consider both students' cognitive processes and motivation when designing instruction. Study 1 and Study 2 demonstrate the interrelatedness between math and physics (the domain of science focused in this study), so instruction in physics should take account of students' achievement and motivation in mathematics as well.

The effectiveness of element interactivity as a construct to guide instruction as shown in Studies 3, 4, and 5 suggests that educators could use element interactivity as a construct to analyze students' learning processes as well as to assess learning tasks for their level of complexity. The results in Study 4 demonstrated the effectiveness of an intervention, which manages element interactivity in terms of student achievement and their sense of competence, indicating that educators should ensure that every learning activity is tailored according to students' cognitive needs. Additionally, as shown from the positive results of the intervention in Study 5, instruction that manages element interactivity can be further enhanced by nurturing student motivation in a learning climate that supports students' basic psychological needs of competence, autonomy, and relatedness. Educators could support students' basic psychological needs by: (1) inspiring and giving students the opportunities to excel in tasks that match their competencies while providing them with constructive feedback (competence), (2) setting a positive learning climate with minimal evaluative pressure and coercion, explaining the rationale behind learning activities, providing students with opportunities to investigate, ask questions, share ideas, make decisions and being attentive to what they have to say (autonomy), and (3) maximizing friendly interactions with each student, making sure that no student is isolated, respecting and valuing their contribution to the learning community (relatedness).

All teachers should be trained to facilitate a dual-approach instruction that supports both the cognitive and non-cognitive processes of learning in order to optimize student learning. Gone are the days when fear of teachers was advocated as a means for classroom management. When both the cognitive and motivational processes are both in place in a learning environment, students' innate desire to be involved in the learning activities will be effective classroom management in itself. Apart from academic achievement, students' joy of learning and their self-belief that they are capable of success are valuable educational outcomes in their own right.

8.6. Limitations and Directions for Future Research

As with all research, this thesis has its share of limitations, which also suggest several prospects for further research in the future. Data for this thesis were collected from Grade 7 students of similar academic ability, aged 12 to 13 years, attending school in Singapore. This limits the generalizability of study results to other students of different age groups and ability levels, nationally or internationally. Future research can look into extending the studies to include a diversified group of students of different academic abilities, age group, nationality, and race, to study the extent to which those variables may affect the results of the studies.

Additionally, due to the tight time schedule and constraints of the school curriculum, the motivational data of each study were collected at only two time-points, once before and once after physics instruction. No data were collected after every lesson to assess students' perceptions of the extent to which their basic psychological needs of competence, autonomy, and relatedness were fulfilled. There were no data collected to measure students' mental effort during problem solving or when completing the learning activities – the complexity of the task was only measured by the element interactivity of the task. While this thesis has provided preliminary evidence showing that the intervention improved student achievement and motivation, the causal links between the fulfilments of basic psychological needs, motivation and achievement could not be determined and reverse causality could not be explored due to this lack of information. Future research could look into: (1) collecting motivational data at various time-points in between the science achievement tests to provide more information about the relations between achievement and motivation and whether the relations vary with time, or with the instructional methods of the science topics being taught and, (2) collecting student perception data after every lesson or module to determine the extent to which their basic psychological needs were met, the status of their motivation level at the end of the lesson, and a mental effort rating by students to determine whether the element interactivity sequencing matched their cognitive capabilities, so that the relations between these factors could be studied more thoroughly.

Another limitation of this thesis is the measurement scale for element interactivity of the learning activities and problem solving tasks, which is rated as high or low, similar to past research. Future research can look into rating element interactivity on a continuous scale, based on the number of interacting elements of each task. Quantifying element interactivity would facilitate statistical analysis to investigate the relations between element interactivity (or cognitive load), achievement, and motivation.

Although this thesis adds to the current literature regarding the interplay between the cognitive and motivational aspects of science learning, due to the self-report nature of the motivation measures, the data collected are partially dependent on how well the students read and understood the survey items and responded honestly to each item. Future research could look into interviewing the students in small groups at various stages of learning to triangulate their opinions and perspectives related to their learning experiences. Lesson observations could also be conducted in both the intervention and control groups to observe certain behaviors such as lesson engagement. Finally, the studies in this thesis could also be extended across several disciplines to investigate if the relations between the cognitive and non-cognitive processes change over time and across different domains.

8.7. Conclusion

This thesis involved five studies that aimed to provide a more comprehensive understanding of students' learning of science. The results from the studies showed an interplay between the cognitive and non-cognitive aspects of science learning. Learning environments that focus on just one of these two aspects of learning will neither optimize student learning nor lead to long-term educational outcomes such as having aspirations to learn science in the future. Science instruction should not only provide opportunities for the students to be involved in interesting and meaningful investigations but should also be designed to suit the cognitive abilities of the students to ensure that they do not experience cognitive overload. In conclusion, efforts should be made to incorporate both the cognitive and motivational learning processes into the learning environment and everyday instruction for students to have positive cognitive and non-cognitive gains.

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APPENDICES

SUPPLEMENTARY MATERIALS:

CHAPTER 3

Appendix 3A

Academic Self-Concept Variables Used in the Study

Factor/Sample Items		Maximal Reliability
Physics Competence		.94
PC1	I am good at PHYSICS	
PC2	I have always done well in PHYSICS	
PC3	PHYSICS is one of my best school subjects	
PC4	I learn things quickly in PHYSICS	
Physics Affect		.92
PA1	I enjoy doing PHYSICS	
PA2	I am really interested in PHYSICS	
PA3	I think it's great that I learn all sorts of things in PHYSICS	
PA4	I find PHYSICS interesting	
English Competence		.90
EC1	I learn things quickly in ENGLISH classes	
EC2	I get good marks in ENGLISH	
EC3	Work in ENGLISH classes is easy for me	
EC4	ENGLISH is one of my best school subjects	
English Affect		.93
EA1	I like ENGLISH	
EA2	I enjoy ENGLISH classes	
EA3	I am interested in ENGLISH	
EA4	Work in ENGLISH classes is interesting	
Math Competence		.93
MC1	MATHEMATICS is one of my best subjects	
MC2	I get good marks in MATHEMATICS	
MC3	I do badly in tests in MATHEMATICS (-)	
MC4	I have always done well in MATHEMATICS	
Math Affect		.94
MA1	I like MATHEMATICS	
MA2	I enjoy MATHEMATICS classes	
MA3	I hate MATHEMATICS (-)	
MA4	I do not like to learn MATHEMATICS (-)	

Note. N = 275. The items were randomized in the survey. Items were coded such that higher scores reflected more favorable perceptions. (-) = reverse coded item.

Appendix 3B

Solution of Path Model (Factor Loadings and Uniquenesses)

	Physics competence	Physics affect	English competence	English affect	Math competence	Math affect	Uniquenesses
Factor Loadings							
PC1	.94***						.10***
PC2	.87***						.24***
PC3	.93***						.14***
PC4	.81***						.34***
PA1		.92***					.15***
PA2		.91***					.17***
PA3		.69***					.52***
PA4		.83***					.30***
EC1			.89***				.22***
EC2			.80***				.36***
EC3			.83***				.32***
EC4			.74***				.46***
EA1				.92***			.16***
EA2				.79***			.38***
EA3				.95***			.10***
EA4				.80***			.37***
MC1					.88***		.23***
MC2					.92***		.17***
MC3					.77***		.41***
MC4					.89***		.18***
MA1						.96***	.09***
MA2						.86***	.26***
MA3						.87***	.23***
MA4						.81***	.34***

Note. N = 275. Competence and Affect components of academic self-concept were measured in the curriculum domains of physics, English, and math. The model had a χ^2 (234) = 464.84, 90% CI (.05, .07), CFI = .96, TLI = .95, RMSEA = .06. ***p < .001.

SUPPLEMENTARY MATERIALS:

CHAPTER 4

Appendix 4A

Variables and Items Used in the Study to Measure Students' Attitudes (N=272)

Factors/Example Items of Attitudes towards physics	**Cronbach's Alpha**	**Mean**	**SD**
Self-concept : 4 items	0.93	3.42	1.19
I am good at PHYSICS.			
I have always done well in PHYSICS.			
PHYSICS is one of my best school subjects.			
I learn things quickly in PHYSICS.			
Self-efficacy: 5 items	0.85	4.30	0.78
I am sure I can learn PHYSICS well.			
I can do the hardest work in PHYSICS if I try hard enough.			
I can do almost all the work in PHYSICS if I do not give up.			
Even if the work in PHYSICS is difficult, I can learn it.			
I am capable of doing difficult work in PHYSICS.			
Interest: 4 items	0.91	4.16	1.06
I enjoy doing PHYSICS.			
I am really interested in PHYSICS.			
I think it's great that I learn all sorts of things in PHYSICS.			
I find PHYSICS interesting.			
Inquiry: 3 items	0.75	4.37	0.88
I would rather be given the right answer to a PHYSICS problem than to work it out myself. (-)			
If I don't see how to do a PHYSICS problem right away, I will not even try. (-)			
I do not like to be told answers to PHYSICS problems; I prefer to work through the answers myself.			
Engagement: 5 items	0.87	4.71	0.69
I pay attention during PHYSICS lessons.			
I am attentive to my work during PHYSICS lessons.			
I listen carefully when the teacher explains something about PHYSICS.			
I try my best to complete my work in PHYSICS.			
I try my best to answer PHYSICS questions.			
Educational Aspiration: 4 items	0.85	3.69	1.02
If I could do exactly what I wanted, I would like to study PHYSICS in future.			
We can't always do what we want to, but I think I can actually learn PHYSICS in college/university.			
My parents believe that I can take a PHYSICS course in future.			
If I can choose after secondary school, I will study PHYSICS in college /university.			

SUPPLEMENTARY MATERIALS:

CHAPTER 7

Appendix 7A

Sample of Eight Learning Activities used in the Intervention topic of Density

Objective: Measuring volume using the water displacement method

Activity 1: Is 1.0 cm^3 equivalent to 1.0 ml? (10 min)

Materials for each group of four: (Use the electronic balance on the teacher's bench.)

• 2 measuring cylinders (100-ml) • plastic cuboid tied with wire • small metal cube • small plastic cube	• string • wooden stick • floating object • plastic dropper	• pendulum bob tied with string • plastic ruler • displacement can

1. Measure the dimensions of the plastic cuboid (tied with wire).

   length: ………………… breadth: ………………… height: …………………

2. Using the dimensions you found above (Q1.), calculate the volume of the plastic cuboid.

Volume:

3. Fill a measuring cylinder with 70.0 ml of water. *(Use the dropper to help you get accurate volume.)* Submerge the plastic cuboid (tied with wire) gently into the water.

   a. How much does the water level rise? ________ml

   b. What does the rise in water level represent?

   ……………………………………………………………………………………………………

   c. What do your results indicate about the relationship between 1 cm^3 and 1 ml? Explain.

   ……………………………………………………………………………………………………

   ……………………………………………………………………………………………………

Activity 2: Does the depth at which an object is submerged in a liquid affect the amount of liquid the object displaced? (10 min).

1. **Imagine** a measuring cylinder filled with 70.0 ml of water. A brass pendulum bob tied to a string is then submerged into the water.

2. **Predict** what happens to the **water level** as the **submerged** pendulum bob is lowered deeper into the water such that the bottom of the bob aligns with the 55-ml mark, 25-ml mark and the 15-ml mark of the measuring cylinder:

   2.1
   Water level is lowest when the bob is at ☐15-ml mark. ☐25-ml mark. ☐55-ml mark. **or**
   ☐ Water level stays the same when the bob is at each depth.

Reason:……………………………………………………………………………………………………

   2.2
   Water level is highest when the bob is at ☐15-ml mark. ☐25-ml mark. ☐55-ml mark. **or**
   ☐ Water level stays the same when the bob is at each depth.

Reason:……………………………………………………………………………………………………

3. Carry out the experiment to check your prediction. How much does the water level rise for each position of the bob in water? Record your findings in the table:

Position of bob in water	Rise in water level (cm^3)
55-ml mark	
25-ml mark	
15-ml mark	

4. Does the **depth** at which the bob is submerged in the water affect the amount of water it displaced? ☐ Yes ☐ No

Reason:……………………………………………………………………………………………………

5. What is the volume of the bob? ………………………………………………

Activity 3: When submerged, does the object with more mass displace a larger volume of liquid? (10 min)

1. Collect 2 small cubes from the plastic box, one **metal** and the other **plastic**.
   By observation only - do not make any measurement - answer parts a & b.

   a. Are the two cubes about the same size? ☐ Yes ☐ No

   b. Do the two cubes have about the same volume? ☐ Yes ☐ No

Appendix 7A (continued)

Activity 3 (continued from previous page)

a. Place each cube on your palm and feel its weight. Which cube is heavier?
☐ metal cube ☐ plastic cube

b. i. Find the mass of each cube using the electronic balance on the teacher's bench.
mass of small metal cube = ………………… **mass of small plastic cube** = …………………
ii. Do the two cubes have the same mass? ☐ Yes ☐ No

c. Is the object with more mass also heavier? ☐ Yes ☐ No

d. Fill two measuring cylinders with 80.0 ml of water each. Gently release one cube into each separate cylinder such that water does not splash out.

Make sure that each cube is completely submerged in each cylinder.
Complete Table 3 below and find the volume of water displaced by each cube.

	Metal cube	**Plastic cube**
Initial water level	80.0 ml	80.0 ml
Final water level		
Volume of water displaced		

Table 3

e. Does each cube displace the same volume of water? ☐ Yes ☐ No

f. What is the volume of each cube? Volume of metal cube: …………………………………
Volume of plastic cube: …………………………………

2. If two objects, one heavier than the other, are of the same volume and fully submerged, tick the correct statements below:
☐ The heavier object displaces more water.
☐ The lighter object displaces more water.
☐ The object with more mass displaces more water.
☐ The object with less mass displaces more water.
☐ Both objects displace an equal volume of water.

3. The amount of water displaced by a fully submerged object is determined by its ……………………

Activity 4 (15 min)

- In your team, determine the **volume** of the **floating object** given to you.
- Describe your procedure in the space below.
- Tick the apparatus you used and draw your experimental set-up.
- Carry out your procedure and record the volume of each object in each of the table.

Apparatus used:	Procedure:	Drawing:
☐ displacement can ☐ measuring cylinder ☐ string ☐ pendulum bob (tied with string) ☐ wooden stick Others:	 Findings / Calculations:	
Volume of floating object:		

✓CLASS CHECKOUT (10 min)

Appendix 7A (continued)

Conduct all the activities by the sink of your laboratory bench.

Activity 5 (10 min): Do objects made of the same material have the same ratio of mass/volume?
Materials: plasticine, 100-ml measuring cylinders (2), dropper, electronic balance

Break your plasticine block into 2 pieces – one about double the size of the other.

Predict whether each piece floats or sinks in water. My prediction:
- ☐ Both float.
- ☐ Both sink.
- ☐ The larger one floats but the smaller sinks.
- ☐ The smaller one floats but the larger sinks.

Split your team into two groups.

Group A: Take measurements of the smaller piece of plasticine.
Group B: Take measurements of the bigger piece.

Objects	Mass	Volume	Mass /Volume (Divide its mass with its volume)	Floats or Sinks in Water?
Group A: SMALLER Plasticine piece				
Group B: BIGGER Plasticine piece				

Table 5

2. Is the value of mass/volume about the same for both the pieces of plasticine?
   ☐ yes ☐ no

3. a. Roll a very **tiny** piece of plasticine into a very tiny ball.

   b. What do you think is the **value of mass/volume** of this tiny plasticine ball? It is
   ☐ **less than** ☐ **about the same as** ☐ **more than**
   the value of mass/volume obtained earlier in Table 5.

b. **Predict** whether the **tiny plasticine ball** floats or sinks in water.

My prediction:	The tiny plasticine ball ☐ floats in water. ☐ sinks in water.	Reason for prediction:

c. Test out your prediction.

My prediction is: ☐ correct. ☐ wrong.

✓CLASS CHECKOUT (5 min)

Notes:

The result obtained when two numbers are divided is called the ratio of the two numbers.

When we calculate mass/volume, we are finding out how much mass is in one unit of volume.

The density of distilled water is found to be 1.0 **g/cm^3** (or 1000 **kg/m^3**). This means that the mass of 1.0 **cm^3** of distilled water is 1.0 **g**.

The ratio of **mass to volume is the same for objects made of the same material**, regardless of the size of the object.

Density is the name given to this ratio of mass/volume.

Density = mass / volume

Common units for density are **g/cm^3** and **kg/m^3**. The **S.I unit** of density is **kg/m^3**.

Appendix 7A (continued)

Activity 6 (10min)
Objective: Investigating the density of water
Materials: Two 100-ml measuring cylinders, tap water, dropper, electronic balance

Group A: Find the density of 25.0 ml of tap water.

Group B: Find the density of 50.0 ml of tap water.

1. Place a dry measuring cylinder on an electronic balance to measure its mass. Record it in Table 6 below (Column A).
2. Fill the measuring cylinder with 25.0 ml / 50.0 ml of tap water. Determine the **total mass**. Record it in Table 6 below (Column C). *(Leave the water in the measuring cylinder for the Activity 7.)*
3. Calculate the (1) mass & (2) density of 25.0 ml / 50.0 ml of tap water.

A	B	C	D	E	F
Mass of dry measuring cylinder / g	**Volume of water/ ml**	**Mass of cylinder with water/ g**	**Mass of water/g**	**Volume of water/cm^3**	**Density of water g/cm^3**
	25.0				
	50.0				

Table 6

4. Is the density about the same for both volumes of water?
☐ yes ☐ no

5. Do you think **different volumes** of the **same type of water** will have the same density?
☐ yes ☐ no

Reason: ....

....

6. You may draw a diagram to illustrate your reasoning:

Activity 7 (15min)
Objective: Investigating the density of saltwater
Materials: Small Beaker, glass rod, dropper, 15 g of salt

1. Use the same measuring cylinder you used in Activity 6 to contain the 50.0 ml of water. Record the mass of that measuring cylinder (when it was empty and dry) in the space below (based on Activity 6 results).

   Mass of dry measuring cylinder = ____________________

2. Dissolve 15 g of salt in the 50.0 ml water in the measuring cylinder.
   - *Stir with the glass rod until the salt dissolves completely.*
   - ***Leave the saltwater in the measuring cylinder for Activity 8.***

3. What is the **volume of the saltwater**? Complete Table 7 below.

Volume of water/ml	Volume of saltwater/ml	**Difference in volumes/ml**
50.0		

Table 7

4. What is the density of the **saltwater**?

   Mass of the **saltwater** = ... g

   Volume of **saltwater** = ... cm^3

   Density of **saltwater** = ... g/cm^3

Use this saltwater in the measuring cylinder for Activity 8 (next page).

Appendix 7A (continued)

Activity 8 (20min)
Objective: Investigating Density and Relative Density
Materials: 100-ml measuring cylinders (2), 2 small plastics beakers, tap water, saltwater, 2 plastic cylinders marked “1” and “2”, electronic balance

1. Write down, in the **heading** of column **e** and **f** of Table 8 (below), the **density of water** and **saltwater** as found in **Activity 6 and Activity 7** earlier.
2. There are 2 plastic cylinders in your tray. One is marked “1” and the other, marked “2”.
3. **Predict whether each cylinder sinks / floats in water. Circle** your prediction in column **a**.
4. Test your prediction and record your findings in columns **e** and **f**.
5. Collect data to **find out whether these cylinders are made from the same type of plastic.**
6. Record your findings in Table 8.

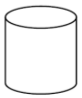
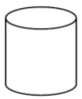
		a	b	C	d	e	f
Object	***Do both cylinders look alike?***	***My Predictions:***	Cylinders			**Density of water= ....g/cm^3**	**Density of saltwater= ....g/cm^3**
		Float/sink	mass g	volume cm^3	**Density g/cm^3**	Float / Sink in **water**	Float / Sink in **saltwater**
 Cylinder 1	☐ yes	*Floats/sinks in **water** *Floats/sinks in **saltwater**					
 Cylinder 2	☐ no	*Floats/sinks in **water** *Floats/sinks in **saltwater**					

Table 8

✓CLASS CHECKOUT

Secondary 1 Science – Physics
Density Package
FOLLOW-UP to LABORATORY SESSION 2
Density

Exercises: You need not carry out any experiment.
Use your knowledge from Laboratory Session 2 on Density to complete these exercises.

From Activity 5:

1. Do both the plasticine pieces (large and small) have the same **density**?
☐ yes ☐ no

Evidence from experiment:...

....

From Activity 8: Refer to **Table 8** to answer the following questions.

1. Are both cylinders 1 and 2 made from the same type of plastic material?
☐ yes ☐ no
Evidence from experiment:...

....

2. a) Rank the densities of cylinder 1, water and saltwater in ascending order.

____________________ < __________________< _________________

b) Why do you think that cylinder 1 floats in water and in the saltwater you prepared?

....

3. a) Rank the densities of cylinder 2, water and saltwater in ascending order.

____________________ < __________________< _________________

b) Why do you think that cylinder 2 sinks in water but float in the saltwater you prepared?

....

✓CLASS CHECKOUT (30 min)

Appendix 7B

Examples of How the Learning Activities in the Topic of Density were designed to Reduce Cognitive Load and Support Students' Basic Psychological Needs

The following Tables 7B1, 7B2 and 7B3 elaborate on how each science activity (Activities 1 to 8) shown in Appendix 7A was designed to:

- establish the concept of density using the isolating-elements strategy to **reduce cognitive load** by:
  1. introducing simpler learning activities before complex activities;
  2. establishing conceptual knowledge before procedural knowledge;
  3. providing step-by-step instructions and probing questions to guide students' thinking processes to establish each concept;
  4. providing several possible answers for students to choose from to guide their learning;
  5. providing structured worksheets with labelled tables and spaces for answers and diagrams; and
- support students' **basic psychological needs**:
  A. competence;
  B. autonomy; and
  C. relatedness.

Note. The superscript (i.e., 1-4; A-C) at the end of the description in Tables 7B1, 7B2 and 7B3 indicates how it maps onto the respective theoretical framework as described above. Students' Basic Psychological needs for C: relatedness is supported in all activities, in a learning environment where students worked together towards common goals, with their teacher as facilitator, interacting with every student (see Appendix 7C for more details), and will not be described in detail for each activity. Other needs were not only met by the activities but also through the learning environment and teacher facilitation.

Appendix 7B (continued)

Table 7B1

Hands-On Session	Details of Activity (Establishing Conceptual Knowledge of *Volume*[2])	Cognitive load was reduced by providing students with	Difficulty Level[1] (low, medium, high)	Supporting basic psychological needs A. competence, B. autonomy & C. relatedness
Activity 1	▪ Making simple length measurements and using the volume formula (pre-existing knowledge) to calculate volume of cuboid ▪ Relating calculated volume with finding volume using the water displacement method	▪ a simple activity that they can easily relate to as a first activity[1] ▪ step-by-step instructions and questions to establish concept of volume[3]	low	▪ challenges students to explain their observations[A] ▪ students selected instruments of measure[B]
Activity 2	▪ Observing the water level as object is submerged at different levels in the water ▪ Establishing the concept that water displaced by an object represents the volume of the object	▪ step-by-step guidance and questions to establish concept of volume[3] ▪ options of answers to guide their thinking processes[4]	low	▪ challenges students to explain their observations[A] ▪ students choose instruments of measure[B]
Activity 3	▪ Measuring mass and relating it to weight ▪ Observing if a heavier object of the same volume will displace more water when submerged ▪ Reinforcing the concept that water displaced by an object represents the volume of the object, regardless of its weight	▪ step-by-step guidance and questions to establish concept of volume[3] ▪ options of answers to guide their thinking processes[4] and relate experimental observations to theory	medium	▪ challenges students to relate observations to theory[A] ▪ students establish own understanding of volume[B]
Activity 4	▪ Design experiment to find out the volume of a floating object ▪ Choose necessary materials to carry out the experiment	▪ a list materials were given for students to choose for experiment[4] ▪ Labelling of procedure, space for drawing of experimental set-up and report the calculations that leads to the object's volume were provided in fragments to guide students[5]	high	▪ challenges students to apply concept of volume to finding volume of floating object[A] ▪ students design on materials and design own experiment and their shared ideas with peers and teachers[B]

Appendix 7B (continued)

Table 7B2

Hands-On Session	Details of Activity (Establishing Conceptual Knowledge of *Density*)	Cognitive load was reduced by providing students with	Difficulty Level (low, medium, high)	SDT Traits
Activity 5	1. Making predictions about floating and sinking 2. Making measurements of mass 3. Using the knowledge from Laboratory Session 1 to make measurements of volume 4. Calculating mass/volume 5. Observing whether each object floats or sinks in water 6. Think about whether the same material will have the same value of mass/volume, and will float/sink in water regardless of its size	▪ introducing procedural knowledge on density (i.e., formula) after establishing the conceptual knowledge to help consolidate their learning and as a precursor for the following activities[2] ▪ step-by-step guidance and probing questions to establish concept of density[3] ▪ options of answers to guide their thinking[4] ▪ a table of values to help students record their measurements[5]	medium	▪ challenges students to think and predict[A] ▪ students choose instruments of measure & decide on procedures to find volume[B] ▪ chance to reflect on learning and complete follow-up activities autonomously[B]
Activity 6	1. Measuring mass of cylinder and deriving the mass of water 2. Applying the formula introduced in the previous lesson to calculate the density of water 3. Comparing density of water, given varying volumes 4. Establish the concept that ‘density’ is the characteristic of a substance and remains the same regardless of volume (if volume changes, mass changes proportionally, making density the same).	▪ step-by-step instructions for measurements of mass[3] ▪ guiding / probing questions to establish the concept of density as a characteristic of a substance by reflecting on their findings[3] ▪ options of answers to guide their thinking[4] ▪ a table of values to help students record their measurements[5] ▪ the flexibility of representing their conceptual understanding in the form of a diagram[5]	medium -high	▪ challenges students to explain their observations, and establish links between experimental findings and theoretical knowledge[A] ▪ students did division of roles to complete task[B]
Activity 7	1. Applying similar methods in Activity 6 to measure volume of saltwater, derive the mass of saltwater and calculate the density of saltwater	▪ prompts and step by step guidance to establish the concept of density[3] ▪ a table of values to guide students to record the necessary measurements[5]	medium - high	▪ challenges students to derive density of saltwater[A] ▪ students used past experience to decide on methods of finding mass of saltwater[B]

Appendix 7B (continued)

Table 7B3

Hands-On Session	Details of Activity (Establishing Conceptual Knowledge of *Density*)	Cognitive load was reduced by providing students with	Difficulty Level (low, medium, high)	SDT Traits
Activity 8	1. Making predictions about floating and sinking of two objects of similar size 2. Making measurements of mass and volume of the objects, and calculating the density of each object 3. Establish the concept of density: Two objects of the same size (same volume) but different mass have different density and may have different floating / sinking nature when placed in water / saltwater 4. Making observations whether each object floats or sinks in water and saltwater 5. Comparing the density of object with the density of water and density of saltwater and relating the density magnitudes to the floating or sinking of the objects in water and saltwater 6. Establish the concept of relative density: An object sinks if it has a higher density than the liquid it is in and an object floats if it has a lower density than the liquid it is in	▪ selective instructions to guide them in the activity[3] ▪ guiding questions to establish concept was done by teachers during facilitation and class discussion[3] ▪ a table of values to help students record the necessary measurements[5]	high	▪ challenges students to think and predict, using past knowledge to decide on procedures and using the findings to establish whether or not the two similar cylinders are made from the same type of plastic[A] ▪ students choose instruments of measure & decide on procedures to find volume of the two cylinders, and draw conclusions from the data collected[B] ▪ chance to reflect on learning and complete follow-up activities autonomously[B]

Appendix 7C

How the Dual-Approach Instruction Supports Students' Basic Psychological Needs

Basic Psychological Needs	Lesson Design and Learning Activities	Observed Teacher Behaviors	Observed Student Behaviors
Competence	▪ Activities were optimally challenging to expand students' capabilities but were not beyond their cognitive abilities ▪ To support learning, isolating-elements strategy were implemented by introducing - conceptual knowledge before procedural knowledge - simpler activities before complex activities	▪ Provided relevant information for the learning activities so that students had enough knowledge to master the learning activities ▪ Facilitated students learning by encouraging, guiding and giving constructive feedback for students to excel at learning ▪ Praised students' efforts to nurture students' feelings of efficacy	▪ Worked in teams, shared knowledge and provided encouragement and guidance to each other to help everyone excel at learning ▪ Engaged in activities ▪ Called for teacher's assistance when all team members were unable to accomplish the tasks ▪ Homework related to the activities were provided to give students the opportunities to work independently and test their abilities
Autonomy	▪ Some activities were left open ended to give students the autonomy to design their own procedures for experiments, and to make own choices for apparatus and	▪ Explained the rationale for the learning activities ▪ Encouraged students to share their ideas and make decisions during the learning activities ▪ Listened to students' ideas ▪ Evaluative pressure and coercion was minimized	▪ Independently assigned roles to one another (timekeeper, leader, presenter, etc.) and took turns to observe and carry out the activities ▪ Made choices during learning tasks ▪ Asked questions ▪ Shared ideas and findings with peers and teachers during group and whole-class discussions
Relatedness	▪ Lessons were designed for students to work on activities in teams and teachers as facilitators to increase interaction and nurture a sense of belonging to a science community where students and teachers have a role to play in the learning of science	▪ Treated students with respect and valued the contribution of each student ▪ Went around to each group and interacted with every student with kindness and in a friendly demeanor ▪ Teachers ensured no student was isolated	▪ Got along and worked well with teachers and fellow team mates ▪ Students reported their preference to work in teams with teachers as facilitators, than *regular instruction* where teacher delivered information and there was no interaction with classmates ▪ No student was isolated

Appendix 7D

Key Differences in the Attributes of 'Dual-approach instruction' vs regular instruction

	Dual-Approach Instruction	***Regular Instruction***
Principle Learning Theory	Constructivism	Behaviorism
Learning Processes	<u>Cognitive Processes</u> Cognitive Load Theory was used to manage element interactivity at each stage of learning to support learning and increase episodes of success and achievement. <u>Non-Cognitive Processes</u> Self-Determination Theory was used to design learning climate to ensure that students' basic psychological needs of competence, autonomy and relatedness were met in order to enhance student motivation	<u>Cognitive Processes</u> Instruction involves high element interactivity which easily overload students' working memory. <u>Non-Cognitive Processes</u> Instruction does not focus on student motivation
Outcomes	Achievement (Cognitive) and Motivation (Non-Cognitive)	Achievement (Cognitive)
Student Participation	Active - Working and discussing in teams - Working on worksheets individually and in teams	Passive - Listening to teacher - Working on worksheets individually
Student's Role	Solves Problems and make observations to deduce scientific findings and concepts	Following Directions
Curriculum Goals	Both Process- and Product-Oriented	Product-Oriented
Teacher's Role	Guide / Facilitator of Learning	Director / Transmitter of Information

Appendix 7E

Cognitive and Non-Cognitive Measures used in the Study to Measure the Effectiveness of the Intervention

Pre-test measures	INSTRUCTION on science topics	Post-test measures
*Cognitive Pre-Test: 1. Heat 2. Forces 3. Speed 4. Density *5-mark Test for each topic comprises 5 test questions of low element interactivity, administered before instruction commencement of each topic	Control group: ▪ *Regular instruction* on all topics: Heat, Forces, Speed, and Density, Intervention group: ▪ *Regular instruction* on Heat and Forces ▪ *Dual-approach instruction* intervention on Speed and Density	**Cognitive Post-Test: 1. Heat 2. Forces 3. Speed 4. Density **10-mark Test for each topic comprises 5-marks test questions of high element interactivity and 5-marks test questions of low element interactivity, administered after instruction completion of each topic
Motivational factors assessed at time 1 ▪ Self-Regulation ▪ Engagement ▪ Sense of Competence ▪ Interest ▪ Task Goal Orientation ▪ Education aspiration ▪ Career aspiration ▪ Ego Involvement		Motivational factors assessed at time 2 ▪ Self-Regulation ▪ Engagement ▪ Sense of Competence ▪ Interest ▪ Task Goal Orientation ▪ Education aspiration ▪ Career aspiration ▪ Ego Involvement

Appendix 7F

Examples of Post-Test Items of Low Element Interactivity

F.1. Example of ***low*** element interactivity question used in the post-test taken from the topic Density

A solid wooden rod with a density of 0.70 g/cm^3 is placed in water of density 1.00 g/cm^3. Does it float or sink? Explain. ☐ The wooden rod floats in water. ☐ The wooden rod sinks in water. Reason: ……………………………………………………………………………………… ..……………………………………………………………………………………………… …

Elements involved:

1. Recall the concept of relative density: objects will float in liquid of higher density that itself and select the answer
2. Compare densities of wooden rod and water
3. Explain using the concept recalled in #2

   (i.e., The wooden rod is of lower density than water, so it floats.)

The question is categorized as low element interactivity, assuming that #1 is established (i.e., students have knowledge of relative density and its relation to floating and sinking).

F.2. Example of ***low*** element interactivity question used in the post-test taken from the topic Speed

If a cyclist travels at an average speed of 10 km/h, how long will the cyclist take to travel 20 km?

Elements involved:

1. Recall the concept of average speed: that 10 km/h means travelling 10 km in one hour
2. Identify that 20 km is twice the distance of 10km, so it should take twice the time; i.e., 2 hours; Alternatively, apply the formula: average speed = total distance ÷ total time, so by algebraic manipulation, total time=total distance average÷speed = 20 km ÷ 10km/h = 2 h

The question is categorized as low element interactivity, assuming that #1 is established (i.e., students have knowledge of average speed and knows how to interpret 10km/h).

Appendix 7G

Examples of Post-Test Items of High Element Interactivity

1. Example of ***high*** element interactivity question used in the post-test taken from the topic Density

Figure A shows three measuring cylinders having equal amount of water in them. Three solid cylindrical blocks are having the same base area of 1.0 cm^2 and height of 3.0 cm and labelled as Block A, B, C are made of aluminium, steel and plastic respectively. Their masses are 7.2 g, 23.4 g, and 2.4 g respectively. Density of water = 1.0 g/cm^3.

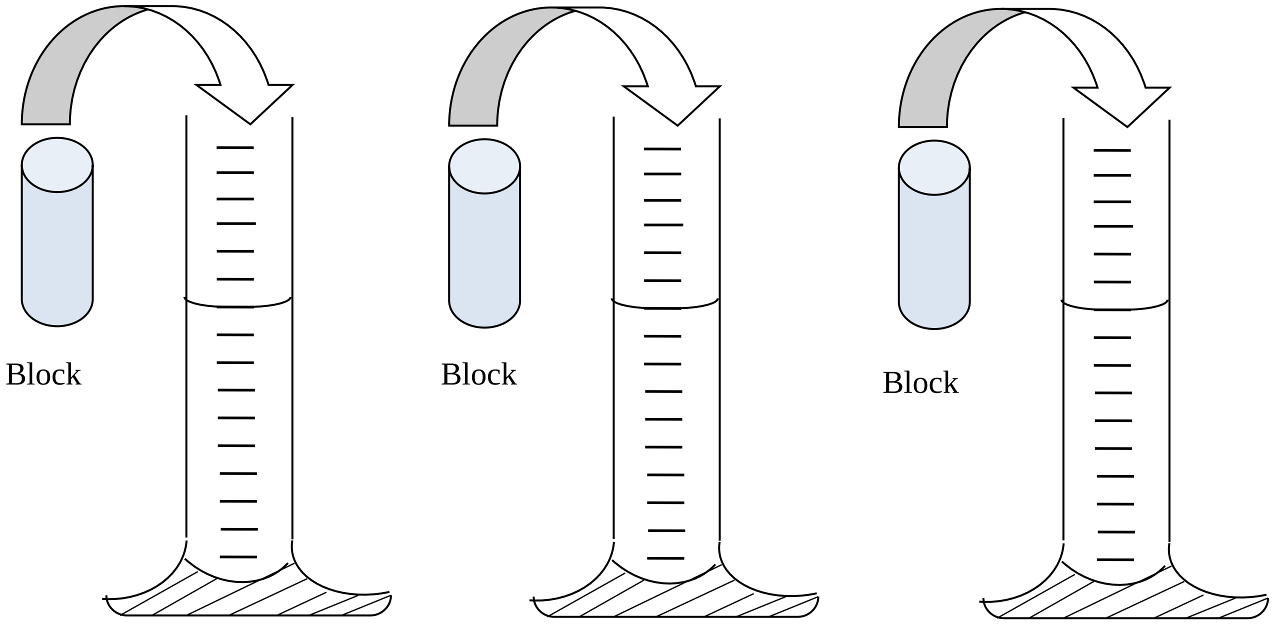


Figure A

a. Can you find out the densities of the 3 solid blocks?

☐ Yes, density of block A =…………………………………

density of block B =…………………………………

density of block C =…………………………………

☐ No, there is not enough information.

b. The 3 solid blocks are then placed into the cylinders as shown by the arrows in Figure A. Each division on the measuring cylinder indicates 1.0 ml.

For each solid block, **draw** in Figure A, showing whether it ***floats or sinks*** and the ***final water level*** in each cylinder.

Appendix 7G (continued)

Elements involved in solving the high element interactivity item taken from the Density topic:

Part a.

1. Recall formula for density (mass ÷ volume) and search for the quantities required to calculate density in the information given in the problem description
2. Identify the mass of each block
3. Locate measurements required for the calculation of volume
4. Calculate volume of block using the formula "volume = base area x height"
5. Calculate the density of each block by applying the formula "density = mass ÷ volume" and substituting the mass and volume quantities of each block

Part b.

6. Recall knowledge of relative density and compare the density of each block with the density of water: The block(s) with higher density than that of water will sink in water and the block(s) with lower density than the density of water will float in water
7. Represent the floating and sinking of the blocks in terms of drawing
    a. the block fully submerged in water if it sinks
    b. part of the block in the water, and the rest above water if it floats
    c. the final water level in the measuring cylinder for each case of floating and sinking
8. For the block that sinks, the rise of the water level represents the volume of the block, so divisions on the measuring cylinder needs to be counted to correctly mark the new water level.
9. For the block that floats, if half of the body of the block is in the water, and half is above water, then the rise in the water level represents half the volume of the block, so divisions on the measuring cylinder needs to be counted to correctly mark the new water level.

Appendix 7G (continued)

2. Example of ***high*** element interactivity question used in the post-test taken from the topic Speed

a. A van leaking oil at 1 drop per second was moving at a constant speed of 10 m/s. In the space below, mark the locations of the oil marks on the road with a '**X**'. Label the distance and time between the marks that you draw.

Oil marks made on the ground by van

b. A truck leaking water at 1 drop per second was moving at a constant speed of 20 m/s. In the space below, mark, with a '**X',** the locations of the water marks on the ground. Label the distance and time between the marks that you draw, using the same scale used in question a. above.

Water marks made on the ground by truck

Elements involved:

Part a.

1. Recall the concept of constant speed (same distance covered in each unit of time) and plan on illustrating the concept
2. Visualize that the marks made must be of equal distance apart to represent equal distance per unit time
3. Decide on a scale (e.g., 2 cm to represent 10 m)
4. Use a ruler to measure intervals of 2 cm and make a mark X between those intervals
5. Use a ruler to make interval markings and label the distance of 10 m and time of 1 s

Part b.

6. Recall the concept of constant speed (same distance covered in each unit of time) and visualize the diagram to be similar with that of part a.
7. Using the same scale, 20 m must be represented by 4 cm.
8. Use a ruler to measure intervals of 4 cm and make a mark X between those intervals
9. Use a ruler to make interval markings and label the distance of 20 m and time of 1 s

Appendix 7H

Factors and Items used in the Motivation Survey and the Maximal Reliability for the Pre-test and Post-test of each Variable

	Factors/Items of Motivation towards Science	*Maximal Reliability*	
ITEM		Pre	Post
	Self-Regulation (4 items)	0.86	0.83
Sre1	If I do not understand a SCIENCE concept, I ask my teacher.		
Sre2	When I'm reading my SCIENCE materials and do not understand something, I stop and think it over.		
Sre3	If I do not understand a SCIENCE concept, I'll read the information again.		
Sre4	If I do not understand a SCIENCE concept, I'll try to find some information on it.		
	Engagement (5 items)	0.88	0.90
Eng1	I pay attention during SCIENCE lessons.		
Eng2	I am attentive to my work in SCIENCE.		
Eng3	I listen carefully when the teacher explains something about SCIENCE.		
Eng4	I complete my work in SCIENCE diligently.		
Eng5	I try my best to answer SCIENCE questions.		
Eng1			
	Sense of Competence (4 items)	0.90	0.86
Com1	I am good at SCIENCE.		
Com2	I have always done well in SCIENCE.		
Com3	SCIENCE is one of my best school subjects.		
Com4	I learn things quickly in SCIENCE.		
	Interest (4 items)	0.90	0.88
Int1	I enjoy doing SCIENCE.		
Int2	I am really interested in SCIENCE.		
Int3	I think it's great that I learn all sorts of things in SCIENCE.		
Int4	I find SCIENCE interesting.		
	Task Goal Orientation (4 items)	0.90	0.80
Tgo1	An important reason I do my work in SCIENCE is that I like to learn new things.		
Tgo2	An important reason I do my work in SCIENCE class is that I want to get better at it.		
Tgo3	An important reason I do my work in SCIENCE is because it is important to me to do my work well.		
Tgo4	An important reason I do my work in SCIENCE is that I enjoy figuring things out.		

Appendix 7H (continued)

	Factors/Items of Motivation towards Science (continued)	*Maximal Reliability*	
ITEM		Pre	Post
	Educational Aspiration (4 items)	0.83	0.84
Eda1	It is important to me that I get to study SCIENCE in future.		
Eda2	I would like to study SCIENCE in college/ university.		
Eda3	I will be satisfied if I can take a SCIENCE course in future.		
Eda4	I want to study SCIENCE after secondary school.		
	Career Aspiration (4 items)	0.89	0.88
Caa1	It is important to me to have a job related to SCIENCE in future.		
Caa2	In the future, I would like to have a career in SCIENCE.		
Caa3	I want to have a career that applies SCIENCE to solve real life problems.		
Caa4	I will be satisfied if I have a job that has to do with SCIENCE.		
	Ego Involvement (4 items)	0.82	0.86
Ego1	I want to show others that I am smart in SCIENCE.		
Ego2	It is important that the teacher in my SCIENCE thinks I am smart.		
Ego3	I do not want my classmates to think I am weak in SCIENCE.		
Ego4	It is important that I do not look stupid in front of my classmates during SCIENCE classes.		

Note. N = 430. Maximal reliability was computed using CFA.

Appendix 7I

Standardized Factor Loadings for the Model at Pre-test and Post-test

		Pre-Test		Post-Test	
Factor	Indicator	Standardized Loadings	Residual invariances	Standardized loadings	Residual invariances
Self-Regulation	Sre1	0.70***	0.51	0.72***	0.49
	Sre2	0.85***	0.28	0.78***	0.39
	Sre3	0.74***	0.45	0.73***	0.47
	Sre4	0.83***	0.31	0.76***	0.42
Engagement	Eng1	0.79***	0.38	0.80***	0.37
	Eng2	0.82***	0.33	0.86***	0.27
	Eng3	0.72***	0.49	0.76***	0.42
	Eng4	0.72***	0.49	0.78***	0.40
	Eng5	0.79***	0.38	0.81***	0.35
Competence	Com1	0.88***	0.23	0.78***	0.40
	Com2	0.78***	0.39	0.74***	0.45
	Com3	0.84***	0.30	0.82***	0.34
	Com4	0.81***	0.34	0.76***	0.43
Interest	Int1	0.89***	0.22	0.82***	0.34
	Int2	0.89***	0.22	0.86***	0.26
	Int3	0.75***	0.44	0.81***	0.35
	Int4	0.75***	0.43	0.75***	0.44
Task Goal Orientation	Tgo1	0.86***	0.27	0.76***	0.42
	Tgo2	0.75***	0.44	0.72***	0.49
	Tgo3	0.87***	0.24	0.78***	0.40
	Tgo4	0.85***	0.29	0.75***	0.44
Educational Aspiration	Eda1	0.79***	0.38	0.82***	0.34
	Eda2	0.77***	0.41	0.76***	0.42
	Eda3	0.70***	0.51	0.72***	0.49
	Eda4	0.80***	0.36	0.84***	0.30
Career Aspiration	Caa1	0.73***	0.46	0.75***	0.44
	Caa2	0.89***	0.21	0.86***	0.26
	Caa3	0.87***	0.24	0.84***	0.29
	Caa4	0.76***	0.42	0.76***	0.42
Ego Involvement	Ego1	0.78***	0.39	0.80***	0.36
	Ego2	0.79***	0.38	0.80***	0.36
	Ego3	0.70***	0.51	0.78***	0.39
	Ego4	0.75***	0.44	0.72***	0.49

Note. N = 430. ***p < .001. The goodness-of-fit indices for the model are: χ^2 (467) = 934.78, p < 0.001, CFI = .94, TLI = .93, RMSEA = 0.05, 90% CI = [0.04, 0.05] at pre-test and χ^2 (467) = 812.16, p < 0.001, CFI = .95, TLI = .94, RMSEA = 0.04, 90% CI = [0.04, 0.05] at post-test.

Appendix 7J

Results of Longitudinal Measurement Invariance for Latent Motivation Constructs

		χ^2	*df*	*p*	CFI	TLI	RMSEA	90% CI	|ΔCFI|	|ΔTLI|	|ΔRMSEA|
Self-Regulation											
Model 1	Baseline model	25.67	19	0.140	0.99	0.99	0.03	0.00 to 0.06			
Model 2	Factor Loadings	30.98	23	0.123	0.99	0.99	0.03	0.00 to 0.05	0.00	0.00	0.00
Model 3	Intercepts	74.81	27	<0.001	0.95	0.95	0.07	0.05 to 0.08	0.04	0.03	0.04
Model 4	Partial intercepts	47.55	24	0.003	0.98	0.97	0.05	0.03 to 0.07	0.02	0.02	0.02
Engagement											
Model 1	Baseline model	106.58	33	<0.001	0.96	0.94	0.07	0.06 to 0.09			
Model 2	Factor Loadings	126.85	38	<0.001	0.95	0.94	0.07	0.06 to 0.09	0.01	0.00	0.00
Model 3	Intercepts	204.42	43	<0.001	0.91	0.90	0.09	0.08 to 0.11	0.04	0.04	0.02
Model 4	Partial intercepts	67.69	24	<0.001	0.97	0.96	0.07	0.05 to 0.08	0.02	0.02	0.01
Competence											
Model 1	Baseline model	28.87	19	0.068	0.99	0.99	0.04	0.00 to 0.06			
Model 2	Factor Loadings	35.20	23	0.050	0.99	0.99	0.04	0.00 to 0.06	0.00	0.00	0.00
Model 3	Intercepts	68.73	27	<0.001	0.97	0.96	0.06	0.04 to 0.08	0.03	0.03	0.03
Model 4	Partial intercepts	43.09	24	0.001	0.98	0.98	0.04	0.02 to 0.06	0.01	0.01	0.01
Interest											
Model 1	Baseline model	34.44	19	0.016	0.99	0.98	0.04	0.02 to 0.07			
Model 2	Factor Loadings	45.87	23	0.003	0.98	0.98	0.05	0.03 to 0.07	0.01	0.00	0.00
Model 3	Intercepts	106.91	27	<0.001	0.94	0.93	0.08	0.07 to 0.10	0.04	0.05	0.04
Model 4	Partial intercepts	79.31	24	<0.001	0.96	0.95	0.07	0.06 to 0.09	0.02	0.03	0.03

Appendix 7J (continued)

		χ^2	*df*	*p*	CFI	TLI	RMSEA	90% CI	|ΔCFI|	|ΔTLI|	|ΔRMSEA|
Task Goal Orientation											
Model 1	Baseline model	27.16	19	0.101	0.99	0.99	0.03	0.00 to 0.06			
Model 2	Factor Loadings	34.60	23	0.057	0.99	0.99	0.03	0.00 to 0.06	0.00	0.00	0.00
Model 3	Intercepts	83.88	27	<0.001	0.95	0.95	0.07	0.05 to 0.09	0.04	0.04	0.04
Model 4	Partial intercepts	37.09	24	0.043	0.99	0.99	0.04	0.01 to 0.06	0.00	0.00	0.00
Educational Aspiration											
Model 1	Baseline model	77.03	19	<0.001	0.94	0.92	0.09	0.07 to 0.11			
Model 2	Factor Loadings	80.39	23	<0.001	0.94	0.93	0.08	0.06 to 0.10	0.00	0.02	0.01
Model 3	Intercepts	109.52	27	<0.001	0.92	0.92	0.09	0.07 to 0.10	0.03	0.02	0.01
Model 4	Partial intercepts	89.65	24	<0.001	0.94	0.92	0.08	0.06 to 0.10	0.01	0.01	0.00
Career Aspiration											
Model 1	Baseline model	45.96	19	0.001	0.98	0.97	0.06	0.04 to 0.08			
Model 2	Factor Loadings	54.79	23	<0.001	0.98	0.97	0.06	0.04 to 0.08	0.00	0.00	0.00
Model 3	Intercepts	112.00	27	<0.001	0.94	0.93	0.09	0.07 to 0.10	0.04	0.04	0.03
Model 4	Partial intercepts	67.69	24	<0.001	0.97	0.96	0.07	0.05 to 0.08	0.01	0.01	0.01
Ego Involvement											
Model 1	Baseline model	33.06	19	0.024	0.99	0.98	0.04	0.02 to 0.07			
Model 2	Factor Loadings	46.42	23	0.003	0.98	0.97	0.05	0.03 to 0.07	0.01	0.01	0.01
Model 3	Intercepts	93.58	27	<0.001	0.94	0.93	0.08	0.06 to 0.09	0.04	0.04	0.03
Model 4	Partial intercepts	65.26	24	<0.001	0.96	0.95	0.06	0.05 to 0.08	0.02	0.02	0.02

Note. N = 430. χ^2 = chi-squared test, *df* = degree of freedom, p = p-value, CFI = Comparative Fit Index, TLI = Tucker-Lewis Index, RMSEA = Root Mean Square of Approximation, CI = confidence interval, |Δ| = absolute value of the difference between nested models.