The Role of Self-Regulation on Students’ Learning in an Undergraduate Flipped Math Class

DISSertation

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Abstract

Flipped classroom, a newly emerged instructional model, has attracted increasing attention in all grade levels, particularly at the higher education level in recent years. With a growth trend of implementing the flipped classroom in STEM introductory courses in large public colleges and universities, researchers and instructors desire to know “Does the flipped classroom work?” A synthesized review of literature revealed inconsistent findings regarding this question and suggested further research in the direction of examining “How can we make the flipped classroom work?”

This study adopted Winne and Hadwin’s self-regulated learning theory as the theoretical framework and aims to examine how students succeed in a flipped class. Specifically, the purpose of this study is twofold: (a) first, to conceptualize a self-regulated learning model to explain the relationships of three key self-regulatory constructs (i.e. prior domain knowledge, self-efficacy, and the use of learning strategies) with math achievement in the context of the flipped math class; and (b) second, to investigate the relationships among these three constructs and academic achievement in both pre-class Internet-based and in-class collaborative learning environments of the flipped math class.

In the spring of 2015, a total of 151 undergraduate students who enrolled in Introductory to Calculus I and II flipped courses in a large Midwest public university participated in this study through taking two online surveys during the semester. Using
Structural Equation Modeling (SEM) as the primary method, this study analyzed the relationships among self-regulatory constructs and achievement in the flipped math class.

The study found that all domain-specific self-efficacy had a positive effect on math achievement, especially math self-efficacy. Additionally, the study found that prior math knowledge had a positive indirect effect on math achievement through the mediating effect of math self-efficacy. Moreover, this study also found that help-seeking was positively related to math achievement. These results suggest that the students who are more likely to succeed in the flipped math class are those who hold high level confidence in learning math and using the Internet to learn math, who are skilled at seeking help from others in the face of challenges, and who are prepared for in-class collaborative learning. The implications of theory and instructional design are presented in Chapter 5.
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Chapter 1: INTRODUCTION

Background

During the fall of 2010, approximately 21 million people were enrolled in undergraduate studies in the United States (Knapp, Kelly-Reid, & Ginder, 2012), an increase of 32% from the fall of 2000 enrollment data (Snyder & Dillow, 2012). Despite the increasing enrollment, public funding for higher education continues to shrink. Over the past five years, 48 states have cut funding to higher education, which has resulted in an average 28% funding cut for higher education per state (Oliff, Palacios, Johnson, & Leachman, 2013). In response, large public colleges and universities across the United States have to offer courses, especially STEM (science, technology, engineering, and mathematics) introductory courses, in a large lecture format to accommodate the high student-faculty ratios (Barber & Njus, 2007; Schullery, Reck, & Schullery, 2011).

A large lecture course normally refers to a class taught in a large lecture hall with at least 75 students enrolled in a class (Revell & Curry, 2010). It is a teacher-centered instruction where the teacher’s role is to present the knowledge to students and direct their learning process. Students in a large lecture course are mainly involved in tasks such as listening to the lecture, taking notes, sometimes asking questions during class, and doing assignments after class on their own (Cooper, 1995). This large lecture course format normally raises concerns including incompatibility with different learning characteristics.
(Lage, Platt, & Treglia, 2000), little or no individualized attention and instruction to students, limited interactions among peers and with instructors (Schullery, Reck, & Schullery, 2011), and an achievement gap between students with different knowledge and social backgrounds (Hakk, HilleRisLambers, Pitre, & Freeman, 2011).

In the past decade, instructors and education researchers have been exploring new instructional methods to enhance students’ learning experience in large lecture courses. Active learning method has been identified as a promising alternative solution to address the concerns in various disciplines (Freeman et al., 2013). Active learning method is generally defined as an instructional method that involves students in various active learning activities (e.g. reading, discussing, problem solving) and provides opportunities for students to reflect on their performances in these activities (Bonwell & Eison, 1991). It comprises three major forms: collaborative learning, cooperative learning, and problem-based learning (Prince, 2004). Regarding collaborative learning, it refers to “any instructional method in which students work together in small groups towards a common goal” (Prince, 2004, p.223). A meta-analytic review shows that collaborative learning promotes a broad range of positive learning outcomes including enhanced academic achievement (Johnson, Johnson, & Smith, 1998), increased class engagement (Peterson & Miller, 2004), as well as improved critical thinking and social skills (Gokhale, 1995). In addition, active learning combined with intensive practices and a highly structured course design has also demonstrated a profound impact on reducing the achievement gap between disadvantaged and nondisadvantage students in a college-level introductory class (Hakk et al., 2011).
The development of learning technologies further facilitates the practice of the active learning method in large lecture courses (Revell & Curry, 2010). Personal Response System (PRS) or “Clickers,” as they are commonly called, is the most popular technology widely incorporated in large-enrollment classes (Caldwell, 2007). This technology allows students in the room to respond to a question simultaneously by using a handled device and presents the collective students’ responses immediately via the LCD projector (Kenwright, 2009). Serving as an assessment tool, PRS provides students immediate feedback regarding their responses in order to help them clarify misunderstood or challenging concepts. Moreover, the collective students’ responses displayed by PRS also gives faculty a practical means to vary and adjust their instructions in order to better meet students’ learning needs (Kenwright, 2009). Extensive research has demonstrated that implementing PRS in large lecture courses is effective in the improvement of students’ engagement in active learning (Moredich & Moore, 2007), the enhancement of student-faculty interaction (Skiba, 2006), and the increase of students’ course participation and satisfaction (Vernaza, 2007).

Since the practice of active learning method and the incorporation of innovative learning technologies have been proven to optimize students’ learning in large lecture courses, why does the traditional lecturing method (e.g. professor talks and students listen) continue to be the most prevalent model of instruction in large enrollment classes? Caldwell (2007) tried to answer this question by explaining two common dilemmas instructors had when teaching in large-size classes. One is that instructors in large lecture classes always feel that they have an obligation to “cover” all materials, which leaves little time for active learning during class. The other is that because of instructors’
common lecturing practices, students have become used to disregarding preparations before class because they believe the important materials will be covered in class. In order to provide a solution to these dilemmas, the flipped classroom approach, empowered by the active learning method and learning technologies, was introduced to higher education and started to attract attention among educators (Berrett, 2012; Tucker, 2012).

The flipped classroom approach tends to create a learning environment in which basic content knowledge is covered largely through text readings and lecture videos prior to class, and students are engaged in active learning through collaborative activities during class (Herreid & Schiller, 2013). Flipped classroom practitioners in large lecture courses believe that moving basic content delivery to pre-class work frees up in-class time for professors to guide students to focus on challenging tasks and provide real-time feedback to individual students (Brame, 2013). In essence, the implementation of the flipped learning model in large lecture courses aims to address the “2 Sigma Problem”: design teaching-learning conditions that could allow students under group instruction to achieve at the level that they would under individual tutoring conditions (Bloom, 1984; Guskey, 2007).

Overview of the Flipped Classroom

Definition, History, and Characteristics of the Flipped Classroom

A commonly accepted description of “Flipped Classroom” is “school work at home, home work at school” (Yarbro, Arfstrom, McKnight, & McKnight, 2014). This overly simplistic definition implies that the flipped classroom merely represents a rearrangement of class time and activities. However, this is not the case (Lage, Platt, &
Grounded in active learning theory, the flipped classroom, also called an inverted classroom, is an instructional model or approach that involves moving lectures outside of the classroom, typically in the form of online lectures, and using the in-class time for engaging students in work that is associated with the application of the online materials (Bergmann & Sams, 2012). More specifically, the flipped classroom commonly consists of two parts: pre-class Internet-based learning and in-class collaborative learning. In a flipped class, students first get exposure to content prior to class through text readings, instructional videos, individual or collaborative activities, or a combination of these. Then they gather together in person and are required to be involved in collaborative learning in class through problem-based and group-based activities (Yarbro et al., 2014). Since the in-class activities are normally associated with pre-class instructional materials, students’ in-class learning is heavily dependent on their pre-class preparation (Schell, 2013). Additionally, the design of the flipped classroom aims to push the lower cognitive-level content of Bloom’s Taxonomy such as remembering, understanding, and sometimes applying to pre-class so students could be able to learn on their own. Students can then focus on the higher cognitive-level skills such as analyzing, evaluating, and creating in class with the assistance of instructors and peers (Bormann, 2014).

The “Flipped Classroom” term was coined in 2007 and has gained great popularity since then. Jonathan Bergmann and Aaron Sams, two science teachers in Woodland Park High School in Colorado, are the pioneers who have been practicing the flipped classroom teaching approach in their classes since 2007. Originally they used this approach to help students who missed classes due to sports and activities to catch up with
the content by watching their recorded lessons at home. Then they observed that in addition to this group of students, those who had difficulty in understanding content during class also benefited from the recorded lessons. Therefore, they decided to promote this approach to the entire class and published the first flipped classroom book based on their flipping experiences (Bergmann & Sams, 2012). Salman Khan is another prominent driving force of the flipped concept. He started with creating tutorial videos for his niece, and discovered his niece enjoyed these videos because she could pause, rewind, or watch the videos multiple times if necessary. Then he began to rethink the formal education in 21st century, and decided to launch Kahn Academy in 2008. The videos in the Khan Academy website have been widely used as the major source of the pre-class learning materials in many flipped classes (Thompson, 2011).

Four prominent characteristics of flipped classroom are documented in the literature (Flipped Learning Network, 2014). First, a flipped classroom provides flexible time and space frames for students to learn content and demonstrate mastery of knowledge. It also allows educators to conduct formative assessments and provide instant feedback to students during their learning process. Second, different from the teacher-centered traditional learning model, a flipped classroom focuses on student-centered learning, which creates rich learning opportunities to involve students in active knowledge construction and personal learning evaluation inside and outside of a flipped class. Third, teachers in a flipped class determine which materials students should explore on their own and the concepts where they might need guidance or collaborative work. Then they intentionally design the flipped course accordingly. Last, the role of a professional educator is even more important in a flipped class. He or she is no longer the
“sage on the stage,” but the “guide on the side.” During the in-class time of a flipped
class, educators are expected to continually provide personal feedback and encourage
students to reflect on their own learning.

With eight years of development, the flipped classroom now has formed its own
community including conferences (e.g. FlipCon), websites (e.g. Flipteaching,
Vodcasting, and Flipped Classroom), and a professional learning network of more than
3,000 teachers (i.e The Flipped Learning Network). It has also been implemented in a
variety of disciplines such as economics (Lage. Platt, & Treglia, 2000; Lage & Platt,
2000), chemistry (Bergmann & Sams, 2012), physics (Riendeau, 2013), math (Fulton,
2012; Strayer, 2012), medical (Ferreri & O’Connor, 2013; Pierce & Fox, 2012), as well
as information system (Davies, Dean, & Ball, 2013). With an ever-growing interest in the
practice of the flipped classroom, educators understandably want to know “does it
work?”

Limitations in the Flipped Classroom Literature

A review of literatures concerning the flipped classroom topic has been conducted
on peer-reviewed articles dating back to 2000. The synthesized review of the literatures
revealed two major categories of flipped classroom research studies, which I named
“comparative studies” and “examination studies.” The “comparative studies” are the
research studies that compare the flipped classroom with the traditional face-to-face
classroom in terms of students’ achievement and engagement (e.g. Baepler, Walker, &
Driessen, 2014; Davies, Dean, & Ball, 2013; Findlay-Thompson & Mombourquette,
2014; Lage, Platt, & Treglia, 2000). The “examination studies” are the research studies
that focus on examining students’ attitudes towards studying in the flipped class (e.g. Bate & Galloway, 2012; Strayer, 2012).

Conflicting results have been observed in both research categories. With respect to comparative studies, some research concluded that students had higher achievement and more engagement in the flipped classroom than those in the traditional classroom, and also preferred learning in the flipped classroom (e.g. Baepler, Walker, & Driessen, 2014; Fulton, 2012). However, other research found no significant differences in students’ academic achievement and course engagement between these two types of learning models (e.g. Davies, Dean, & Ball, 2013; Findlay-Thompson & Mombourquette, 2014). With respect to examination studies, the majority of the studies found that students, on average, held positive attitudes towards flipped classroom learning at the end of the semester and engaged more in course learning (e.g. Bate & Galloway, 2012; Butt, 2014), whereas some studies found that students actually were not satisfied with their learning experiences in the flipped classroom and disliked how the flipped classroom structure oriented them to learning tasks (e.g. Strayer, 2012).

The mixed findings in the literature seem to not be helpful in answering the question “does it work?” Moreover, with an avoidable trend of implementing the flipped classroom model in large lecture courses (Goodwin & Miller, 2013), educators are no longer satisfied with the research concerning “Does it work?” They are more interested in “How can we make it work” and “How can students succeed in the flipped classroom?” Therefore, to accommodate educators’ current needs and further existing flipped classroom research, it is necessary for the research to move beyond the studies that examine the effectiveness of the flipped classroom and focus on studying how students
learn in the flipped classroom environment. The investigation of factors that can help students succeed in flipped learning would be beneficial for an effective design of a flipped class. However, the question of how students learn in a flipped class has rarely been answered in existing flipped classroom research studies. Therefore, the present study tries to fill this gap in the literature and aims at exploring factors that can help students succeed in a flipped class.

**Self-Regulated Learning Theory**

**Self-Regulated Learning in the Flipped Classroom**

The flipped classroom, as a newly emerging instructional approach, presents new challenges and problems to students (Horn, 2013). Especially, the flexible characteristic of the flipped classroom creates a student-centered learning environment in which students must recognize and demonstrate self-regulated learning skills to succeed in a flipped class (Sophia and Flipped Learning Network, 2014; Talbert, 2014). In a flipped class, rather than passively listening to a lecture, students are commonly required to learn content knowledge on their own prior to class and asked to work in groups to apply learned knowledge into practices during class (Bergmann & Sams, 2012). For the students who are new to this approach, they may be initially resistant, since it requires them to learn content knowledge alone at home instead of being taught by instructors in a classroom. Consequently, they may come unprepared for in-class learning activities, which can result in low performance in these classes (Herreid & Schiller, 2013). For the students who have already experienced flipped classroom, they might still feel frustrated when exposed to a great amount of content knowledge prior to class and feel confused when they find disconnections between pre-class materials and in-class activities.
Although the freedom of navigating through lectures at their own pace provides rich opportunities for students to personalize their instruction during pre-class learning, ubiquitous online resources make it difficult for them to regulate their efforts to focus on their individual needs. Sometimes the mismatch of knowledge between pre-class and in-class learning makes the situation even worse (Johnson, 2013).

Therefore, although the flipped classroom is prominent in providing flexible access to content knowledge and opportunities for students to take control or self-regulate their learning process (Fulton, 2012), not every student is capable of taking advantage of these opportunities (Herreid & Schiller, 2013; Johnson, 2013). In other words, not all students are skilled in being self-regulated learners to manage their own learning in terms of the pace of study, mastery of content, and responsibility for coming to class prepared. This potential weakness of students’ self-regulation may impede the learning process and lead to unsatisfactory learning outcomes. Giving students control over their learning process is indispensable and necessary in flipped classroom, and self-regulated learning becomes a crucial aspect for the success in flipped classroom learning. Therefore, the self-regulated learning theory naturally becomes the theoretical framework for the current study.

**Theoretical Framework: Winne and Hadwin’s Self-Regulated Learning Theory**

Self-regulated Learning (SRL) is defined as the degree to which students are motivationally, behaviorally, and metacognitively active in their own learning (Schunk & Zimmerman, 1994). Self-regulated learners are perceived to have a collection of adaptive beliefs and attitudes (e.g. self-efficacy), which drive them to engage in and persist at academic tasks (Pintrich & Zusho, 2007). They are thought to be proficient in deploying
self-regulated strategies such as rehearsal, organization and elaboration for basic tasks, critical thinking, effort regulation, and help seeking for advanced tasks (Pintrich, 2004). They are also viewed as skillful learners who are capable of monitoring their own cognitive behavior and feedback with regard to the learning process (Pintrich & De Groot, 1990). Overall, self-regulated learning is an integrated learning process guided by a set of motivations, behaviors, and metacognitive activities, planned and adapted to support the pursuit of personal goals (Schunk, 2001).

A number of self-regulated learning theories have been proposed to elaborate the self-regulation process that occur during learning (Pintrich, 2000; Winne & Hadwine, 1998, 2008; Zimmerman, 1998). Among these theories of SRL, Winne and Hadwin’s theory has been especially popular in research regarding technology-enhanced learning (Azevedo et al., 2004; Azevedo et al., 2008; Azevedo et al., 2011) because it complements the work of Pintrich and others by outlining a specific cognitive learning process and reconceptualization of some phases that is conducive for technology-enhanced research (Greene & Azevedo, 2007; Winne, 2001). Given that the flipped classroom is one type of technology-enhanced learning, Winne and Hadwin’s SRL theory, therefore, is chosen as the guiding theory for this study.

Winne and Hadwin (1998) posited in their SRL theory that learning occurs in four basic phases: task definition, goal setting and planning, studying tactics, and adaption to metacognition. In addition, they hypothesized that cognitive and metacognitive processes happen within each phase. Using the acronym COPES, they described that each of the four phases is an interaction of a person’s conditions, operations, products, evaluations, and standards. When a student is given a task, he or she creates a personalized definition
of the task (e.g. hard or easy task) and frames a profile of standards for the defined task based on certain task conditions (e.g. flipped classroom environment) and individual cognitive conditions (e.g. prior knowledge). After the task definition and standards setting, the student uses different learning strategies to produce learning outcomes and then evaluates the performance by comparing the outcomes with set standards (Winne & Hadwin, 2008).

Based on theoretical understanding and empirical research of SRL, three psychological constructs – prior domain knowledge, self-efficacy, and the use of learning strategies – have been presented as critical components of students’ self-regulated learning (Moos & Azevedo, 2008; Winne, 2001). First, prior domain knowledge refers to “… the knowledge, skills or ability that students bring to the learning process” (Jonassen & Grabowski, 2012, p.417). It is one of the cognitive conditions that plays a predicting role in the task-definition phase of self-regulated learning (Lodewyk & Winne, 2005). Students with low-level prior domain knowledge tend to be more likely to believe their academic capabilities are below the task’s difficulty, which further decreases their confidences in successfully completing the task (Moos & Azevedo, 2008), influences their choices of learning strategies to approach the task (Murphy & Alexander, 2002), and finally leads to low-level achievement (Song, 2010).

Second, self-efficacy is defined as “people’s judgments of their capabilities to organize and execute courses of action required to attain designated types of performances” (Bandura, 1986, p. 391). It is also one of the cognitive conditions that impacts students’ actions in the task definition phase of SRL model (Winne & Hadwin, 1998). Extensive research has shown that students’ academic self-efficacy has a positive
direct effect on their academic achievement (Bandura, 1997; Pintrich & Zusho, 2007) and also a significant indirect effect on the achievement through the mediating role of the use of learning strategies (Crede & Philips, 2011; Pintrich & De Groot, 1990). These suggest that students with a high level of self-efficacy tend to devote more efforts in tasks, are more motivated to accomplish set goals by mobilizing various resources and skills, and eventually achieve better performance (Bandura, 1997). Moreover, research has also suggested that to increase the accuracy of prediction, self-efficacy should be measured at a domain-specific level (Pajares & Barich, 2005). In the current study, three domain-specific self-efficacies are examined, including math self-efficacy (Pajares & Barich, 2005), Internet self-efficacy (Kim & Glassman, 2013), and collaborative-learning self-efficacy (Johnson & Johnson, 1999; Bandura, 2000).

Last, learning strategies are defined as “behaviors and thoughts in which a learner engages and which are intended to influence the learner’s encoding process” (Weinstein & Mayer, 1983, p.3). Use of learning strategies is considered to be an advanced action in the enactment phase of SRL model, and an effective use of learning strategies is believed to be the hallmark of sophisticated self-regulated learning (Winne, 2001). Pintrich and his colleagues have categorized learning strategies into three main areas: cognitive, metacognitive, and recourse management areas (Pintrich et al., 1993). A body of research has demonstrated that these three areas of learning strategies have significant impacts on students’ academic achievement (Duncan & McKeachie, 2005; Pintrich & De Groot, 1990). However, the significance of individual areas of learning strategies varies, and the difference of learning environments contributes to such variation (Azevedo, 2005; Azevedo & Cromley, 2004; Crede & Philips, 2011).
Purpose of the Study

The purpose of this dissertation is to examine the effects of prior domain knowledge, self-efficacy, and the use of learning strategies on students’ academic achievement in a large-enrollment flipped undergraduate math course. Specifically, the aim of this study is twofold: (a) first to conceptualize a self-regulated learning model to explain the relationships of prior domain knowledge, self-efficacy, and the use of learning strategies with academic achievement in the context of the flipped math class; and (b) second to investigate the relationships among prior domain knowledge, self-efficacy, the use of learning strategies, and academic achievement in both the pre-class Internet-based and in-class collaborative learning environments of the flipped math class.

Guided by Winne and Hadwin’s (1998) SRL theory and associated research, this model explains the essence of self-regulated learning theory and describes the relations of three relevant psychological constructs in the context of flipped classroom. The hypothesized relationships include: (a) the direct effect of prior domain knowledge on domain-specific self-efficacy, the use of learning strategies, and academic achievement; (b) the direct effect of self-efficacy on both the use of learning strategies and academic achievement; and (c) the direct effect of the use of learning strategies on academic achievement.

Since the flipped math class consists of the pre-class Internet-based and in-class collaborative learning environments, the proposed conceptual model is examined in these two environments respectively. During pre-class learning, students learn math content knowledge mainly through Internet-streamed lecture videos and online quizzes. During
in-class learning, students apply the knowledge learned prior to class through in-class collaborative learning activities.

**Research Questions**

The present study seeks to investigate students’ learning process in a large-size undergraduate flipped math class. Specifically, this study aims at examining the effects of prior domain knowledge, self-efficacy, and the use of learning strategies on academic achievement in both the pre-class Internet-based and in-class collaborative learning environments of the flipped math class. The following two research questions guided the design of this research.

Research Question 1: What are the relationships between prior math level, math self-efficacy, Internet self-efficacy, and the use of learning strategies on students’ online math achievement in the pre-class Internet-based learning environment?

Research Question 2: What are the relationships between online achievement, math self-efficacy, collaborative learning self-efficacy, and the use of learning strategies on students’ in-class math achievement in the in-class collaborative learning environment?

**Significance of the Study**

The findings of this study contribute to the existing body of literature in three significant ways. First, this study fills the gap in the flipped classroom literature by (a) dividing the flipped classroom into the pre-class Internet-based and in-class collaborative learning environments to conduct the research, and by (b) focusing on the examination of the factors that can help students succeed in both learning environments of the flipped
class. Through the research of these two perspectives, the present study furthers flipped classroom research into the field of investigating how students learn in a flipped class.

Second, this study extends the practice of Self-Regulated Learning (SRL) theory into the context of the flipped classroom. By a detailed examination of self-regulation factors in both the pre-class and in-class learning environments of the flipped math class, this study could provide evidence to support whether SRL theory is maintained in the context of flipped classroom.

Third, this study provides guidance in teaching and learning practices. Through examining the factors that can help students succeed in the flipped class, the results can serve as a learning guide for students who are interested in taking flipped courses, especially flipped math courses. Meanwhile, the results can also serve as a practical guideline for instructors and instructional designers to design an effective flipped class in order to motivate and engage them in flipped learning.

Summary

This dissertation is divided into five chapters. In this chapter, I provide an introduction to this study with research context, purpose, questions, and significance. In Chapter 2, I present a literature review regarding the flipped classroom within past decade, introduce Self-Regulation Learning (SRL) theory, particularly Winne and Hadwin’s (1998) SRL model, and elaborate on the relationships between the three psychological constructs in this model – prior domain knowledge, self-efficacy, and the use of learning strategies – in the context of the flipped classroom. Chapter 3 presents methodology including the data collection and analysis, the rationale of adopting the quantitative approach for this study, and also the measurements used in this study.
Chapter 4 depicts the procedures and results of the analysis, describes the issues of the data, and presents the solutions of dealing with missing data. In the last chapter, Chapter 5, I provide an understanding of the results in the context of the flipped classroom, point out the limitations of this study, and suggest the future directions of flipped classroom research.
Chapter 2: LITERATURE REVIEW

The flipped classroom, as a newly emerging instructional model, has attracted attention for use in all grade levels. This model aims to create a student-centered learning environment in which students complete pre-class learning via online lectures prior to class and engage in active learning activities to develop higher-order thinking skills during class. Existing flipped classroom research mainly focuses on answering the question “Does the flipped classroom work?” With an increasing interest in the practice of the flipped classroom model in large lecture courses, educators are no longer satisfied with the research that examines whether the flipped classroom works or not. They are more concerned with how can we make the flipped classroom work or what factors can help students succeed in a flipped class. However, the question – how students learn in a flipped class – remains unanswered in existing flipped classroom literature. The current study aims at filling this literature gap through the investigation of students’ learning process in a flipped class with the lens of self-regulated learning theory.

The purpose of this study is to examine the effects of three self-regulation key constructs – prior domain knowledge, self-efficacy, and the use of learning strategies – on students’ academic achievement in a large-enrollment undergraduate flipped math course. Specifically, this study first provides an overview of flipped classroom including the introduction of its history, generation of its definition, summary of its characteristics, and review of its literatures. Second, the study presents Self-regulated Learning (SRL)
theory as the theoretical framework and discusses Winne and Hadwin’s self-regulated learning theory in particular as the guiding theory for the current study. Third, the study conceptualizes a path model to explain the relationships between three key SRL constructs (i.e. prior domain knowledge, self-efficacy, and the use of learning strategies) and academic achievement based upon the review of relevant literatures. Last, the study applies the Winne and Hadwin’s self-regulated learning theory in the flipped classroom environment. Specifically, the three key constructs are discussed in both the pre-class Internet-based and in-class collaborative learning environments of the flipped math class, and two structural models are proposed to enrich the conceptual model and explain students’ self-regulated learning process in these two distinct learning environments of the flipped classroom.

Overview of the Flipped Classroom

History of the Flipped Classroom

The “Flipped Classroom” notion was coined in 2007, and has gained great popularity since then. The Flipped classroom approach was originally proposed by two science teachers, Jonathan Bergmann and Aaron Sams, in Woodland Park High School in Colorado to help students who missed class to catch up with the content through watching lecture videos. During the process, they realized this learning model could not only help students more prepared for class, but more importantly, it could also provide more opportunities for interactive activities and formative assessments during class while compared to the traditional lecture-based learning model. They then started to adapt this model in all their classes and wrote a book, *Flip Your Classroom*, to share their flipping experiences (Bergmann & Sams, 2012). Sal Kahn is another critical driving force in the
development of the flipped classroom. He started the idea by creating tutoring videos online for teaching his niece in 2004. Soon Khan discovered his niece enjoyed watching the videos since she could pause, rewind, or watch the video more than once if necessary. Then with the financial support of several benefactors, Khan began to provide more tutoring videos and create a large and prominent virtual classroom called Khan Academy (Thompson, 2011). As of June 2014, Khan Academy’s website has been translated into 23 languages and its videos into 65 languages (Khan Academy, 2014).

However, some educators criticized that the flipped classroom topic is not brand new. The idea of the flipped classroom has already been consistently practiced in various disciplines, notably in humanities and social science disciplines (Tucker, 2012; Walvoord & Anderson, 2011). For example, Barbara Walvoord and Virginia Johnson Anderson has started to promote the flipping idea since 1998 by introducing an assignment-based model in which students produce work (e.g. writing) prior to class and receive productive feedback through the processing activities that occurred during class. Moreover, professor Eric Mazur in Department of Physics and Applied Physics at Harvard University has also been flipping courses since the early 1990s by using a method he calls “peer instruction,” in which students work in groups to answer each other’s questions during lectures. Modeled on professor Mazur’s work, faculty members in the Math Department at the University of Michigan have also started to flip their teaching of introductory calculus since the mid-1990s. In their flipped courses, students are expected to finish readings before class. Then in class, the instructor first gave a brief lecture, and then let students work in groups to go through examples in the textbook (Berrett, 2012).
Since the idea of the flipped classroom has existed for decades, why has the flipped classroom become such a buzzword in academic circles at all levels in recent years? The convergence of several trends is suggested to contribute to the recent interest in flipped classroom. The first trend is technological innovation and information infrastructural development, which have made it easier for instructors to create enriched learning materials and distribute them to students (Berrett, 2012). These developments have also made access to information abundant. Students no longer need to memorize information in order to retrieve it, instead, they can easily and quickly find information on the Internet (Roehl, Reddy, & Shannon, 2013). The second trend is that policy makers, scholars and others want to reform schools in order to meet the vision of the future school in the 21st century. For instance, Darling-Hammond (2010) advocates altering schools to the point that “will enable students to learn how to learn, create, and invent the new world they are entering” (p.3). Also, the National Science Foundation (2008) calls for the use of cyberlearning to transform schools by providing students with “a mix of diverse content via the combined technological capabilities of the Internet, high performance computing, advanced networking, in-home electronics, and mobile communications” (p. 6). The last trend is the economic reality. Strained budgets make it difficult for schools, especially large public universities, to decrease class sizes and provide personalized instructions for students (Berrett, 2012). Therefore, since the large lecture class with one professor and hundreds of students is not going away in near future due to its cost-effective for colleges and universities, these trends are coming together to create an urgency to seek alternative instructional models to make the lecture more productive and meaningful for students. In response, the flipped classroom was
introduced and has gained an increasing popularity at all grade levels (Yarbro, Arfstrom, McKnight, & McKnight, 2014).

**Definition of the Flipped Classroom**

Despite the popularity of the flipped classroom in education practices, a lack of consensus exists on what exactly the flipped classroom is. In this section, I will review some widely accepted definitions and attempt to provide my definition of the flipped classroom. One of the most commonly accepted definitions of “Flipped Classroom” is “school work at home, home work at school” (Yarbro et al., 2014, p.1). This overly simplistic definition indicates that the flipped classroom merely means rearrangements of class time and activities. This definition echoes with the “Inverted Classroom” definition given by Lage and his colleagues (2000): “Inverting the classroom means that events that have traditionally taken place inside the classroom now take place outside the classroom and vice versa” (p.32). Although these two definitions capture the structure of the classroom and the rationale of flipping or inverting, they do not adequately cover the practices in a flipped classroom.

In the recent flipped classroom work, the definition of the flipped classroom starts to incorporate class activities and learning theories in different parts of the flipped classroom structure. For instance, Bergmann and Sams (2012) defined flipped classroom as an instructional model that involves moving lectures outside of the classroom, typically in the form of online lectures, and using the in-class time for engaging students in work associated with applications of the online materials. Bishop and Verleger (2013) defined the flipped classroom as “an educational technique that consists of two parts: interactive group learning activities inside the classroom, and direct computer-based
individual instruction outside the classroom” (p. 4). While these definitions cover the essential practices of the flipped classroom, they ignore the importance of the link between pre-class and in-class learning and fail to elaborate roles of instructors and students as well as characteristics of activities in the flipped classroom.

As for the link between pre-class and in-class learning in the flipped classroom, educators have been highly aware of the importance of the link by consistently asking questions such as “How can I get my students to do pre-class work” or, in more advanced perspective, “How can I get my students to best learn from doing pre-class work” (Schell, 2013). Since the in-class active learning activities heavily depend on students’ preparation in pre-class learning in the flipped classroom, education researchers and practitioners have been exploring various techniques to help students engage in pre-class learning such as incentives for completing pre-class work (Brame, 2013), a mechanism to assess students’ understanding of pre-class materials (Schell, 2013), and interpolated memory tests embedded in online lecture videos (Szpunar, Khan, & Schacter, 2013).

As for roles of instructors and students, the flipped classroom approach creates a student-centered learning environment in which the ownership of the learning is transferred to students. Students take control of their own learning process by being held accountable for the preparation prior to class and the engagement during class (Bergmann & Sams, 2012). The role of instructors in the flipped classroom changes from “sage on the stage” to the “guide on the side,” which means besides necessary lecturing, the major responsibilities of instructors are to distribute learning resources prior to class and to provide in-time personalized feedback during class (Herreid & Schiller, 2013).
As for characteristics of activities, Bloom’s Taxonomy provides a framework to explain the characteristics. It is believed that the flipped classroom pushes lower cognitive level work of Bloom’s Taxonomy, including remembering, understanding, and sometimes applying, outside of class where students mainly learn on their own, and focuses on higher cognitive level work, including analyzing, evaluating, and creating in class, where they have the support from peers and instructors (Brame, 2013; Bormann, 2014; Honeycutt & Garrett, 2014).

By incorporating these three features in existing flipped classroom definitions, my definition of flipped classroom is:

*Flipped classroom is an instructional model that creates a student-centered learning environment mainly consisting of two parts: (a) exposure to lower level cognitive knowledge through the leverage of technologies prior to a face-to-face class; and (b) application of higher level cognitive knowledge through active learning activities in a face-to-face class. Specifically, prior to the face-to-face class, instructors assemble learning resources and distribute instructions through online lecture videos, text readings, and assessment tools. Students personalize the instructions based on their needs to cover lower level cognitive knowledge. During the face-to-face class, students are engaged in group-based active learning activities to apply higher-order cognitive skills. At the same time, instructors facilitate group learning by providing instant and individualized instructions and feedback.*
Characteristics of the Flipped Classroom

As a unique instructional model, the flipped classroom has its own distinct characteristics. Flipped Learning Network (2014) describes the characteristics by proposing “four pillars” that teachers must incorporate in practice to design a successful and effective flipped class. They are flexible environment, learning culture, intentional content, and professional educator. First, flexible environment means that the flipped classroom allows for flexible time and space for students’ interaction and reflection on their learning as needed and provides different ways for students to learn content and demonstrate their mastery. Second, the flipped classroom model creates a student-centered learning culture in which students take control of their own learning process and are actively involved in knowledge construction as they engage in personally meaningful activities. Third, instructors intentionally rearrange course materials to better utilize the time in the flipped classroom. They prioritize lower level cognitive knowledge prior to class for students’ direct instruction and maximize class time in order to practice active learning strategies to deepen students’ understanding of content and improve their higher level cognitive skills. Last, the flipped classroom places higher demands on professional educators because the in-class active learning activities require teachers to continuously observe students, assessing their performances and providing in-time personalized feedback to help students engage in flipped learning.

Overall, the flipped classroom is prominent for its re-allocation of learning time and task, as well as its change of roles for teachers and students. The flipped classroom creates a flexible student-centered learning environment in which students become the owners of their learning. They are responsible for demonstrating their mastery of
knowledge in pre-class Internet-based learning and being prepared for in-class collaborative learning. With a growing interest in practicing the flipped classroom methods at all levels of education, the flipped classroom becomes an exciting new topic in educational research. Much of the research regarding this instructional model has sprung up in the past decade. In the following section, I will review relevant flipped classroom research studies and identify the limitation of the research.

Review of the Flipped Classroom Research

Literature Search Technique and Executive Summary

In order to summarize the literature in a more systematic way, I conducted the initial search through the EBSCO database and Google Scholar. In addition to these two primary sources, reviewing the bibliography of existing articles—the snowball technique—was also used to discover other relevant studies. The key words I used for searching include “flipped classroom,” “flipped learning,” “inverted classroom,” and “inverted learning.” In total, 17 papers regarding the topics of flipped classroom or inverted classroom were identified as peer-reviewed articles and are included in this review.

Figure 1 provides a visual summary of the synthesized review. Overall, there is an increasing trend in flipped classroom research, especially after 2013. One paper was published in 2000, 4 were published in 2011, and 14 were published during 2013-14.

These research studies vary in terms of the level of education, research methodology, and research topics. With respect to the level of education, the majority of the papers (88.2%) were conducted at the undergraduate level in various disciplines, with 2 (11.8%) conducted in K-12 and at the graduate level respectively. With respect to the research methodology, the K-12 level studies all employed the case study method, whereas the
higher education level studies used both quantitative and mixed methods. With respect to the research topic, I summarized studies into two categories including a comparative study and an examination study. The comparative study refers to the research that compares the flipped classroom with the traditional classroom in terms of students’ achievement and engagement. The examination study refers to the research that examines whether a specific flipped design is effective or not. Based on the review, I found that all K-12 level research focused on the comparative study, while the higher education level research focused on both the comparative study (53.3%) and the examination study (46.7%).

During the process of the literature review, I noticed that research findings were not consistent in both research categories. In the following section, I elaborate the inconsistency by describing research findings of both categories in detail.

Figure 1. Visual summary of synthesized review of the flipped classroom literature
**Comparative Study: Flipped Learning vs. Traditional Learning**

With respect to the comparative study category, a great number of studies have been conducted to compare the flipped classroom with the traditional classroom in terms of students’ achievement and engagement. Before describing specific studies, it is important to analyze what constitutes flipped and traditional classrooms and what the differences are between these two learning models.

According to Bormann (2014), both learning models are designed based on Blooms’ Taxonomy for Learning model (Bloom, 1956). The traditional classroom often addresses lower levels of Bloom’s Taxonomy – *remembering*, *understanding*, and sometimes even *applying* – within the classroom through lecturing, worksheets, or reading textbooks. The higher levels, including *analyzing*, *evaluating*, and *creating*, are then left for students to do on their own after class without teachers’ on-the-spot assistance. By comparison, the flipped classroom inverted the learning process of the traditional classroom. A truly flipped environment delivers lower levels of Bloom’s Taxonomy prior to class and requires students to learn the content on their own, in most cases, through watching online lessons. During class, students are involved in higher levels of Bloom’s Taxonomy through problem-based collaborative learning activities or other active learning activities.

The reviewed comparative studies result in mixed research findings. Some research concluded that students had higher achievement in the flipped classroom than those in the traditional classroom, and also preferred flipped classroom learning than traditional classroom learning (Baepler, Walker, & Driessen, 2014; Fulton, 2012; Lage, Platt, & Treglia, 2000; Mason, Shuman, & Cook, 2013; Riendeau, 2012; Talley &
Scherer, 2013). For example, Mason and his colleagues (2013) adopted the “Inverted Classroom” concept to redesign their control system course. They created online video lectures for students to watch prior to class and used in-class time for learner-centered activities. To examine the effectiveness of the inverted classroom, they compared the inverted class to a traditional class offered during the previous year in terms of students’ performance on traditional quizzes and exam problems, as well as their perceptions of teaching, learning, and the class format. Twenty students were in each class format, who were all senior students in Department of Mechanical Engineering. T-test analysis showed that students in the inverted classroom performed significantly better than those in the traditional classroom on design problems and some exam problems. Moreover, students in the inverted classroom gave a higher rating of teaching at the end of the quarter than those in the traditional classroom and felt that the inverted classroom was better in usage of time and preparation of engineering practice by the 4th week of the quarter. Overall, their results are encouraging with students demonstrating equal or better academic performance in an inverted class and showing greater satisfaction in the class format. Additionally, Talley and Scherer (2013) also conducted an empirical study to compare the effectiveness of a flipped class to a traditional class. They integrated the flipped classroom format along with learning techniques, self-explanation, and practice testing into an undergraduate psychology course and assessed the effectiveness of the class format by testing students’ knowledge retention at the end of the semester. The results showed that the flipped format along with other learning techniques increased students’ study time and led to higher exam grades.
Contrary to the positive findings, some studies found no significant differences in academic achievement between students in the flipped classroom and those in the traditional classroom. They also found that students were actually unsatisfied with their flipped experiences (Davies, Dean, & Ball, 2013; Findlay-Thompson & Mombourquette, 2014; Jaster, 2013; McLaughlin et al., 2013; Strayer, 2012). For example, McLaughlin and his colleagues flipped their basic pharmaceutical course by requiring students to watch recorded lectures prior to class and engaging students in active-learning exercises during class. The flipped class, similar to a previous year’s traditional class, was delivered to 22 satellite students in 2 different campuses. To determine the effectiveness of the flipped design, they employed the quantitative method to compare the flipped class with the previous year’s traditional class in terms of students’ academic performance. The results showed that final achievement did not differ significantly between these two class formats. The same result was also observed in Davies, Dean, and Ball’s (2013) study. They integrated the flipped classroom model in an introductory-level college course on spreadsheets and examined what benefits the flipping design could bring to student in terms of academic achievement and satisfaction of the course. An ANOVA comparison of means between the flipped and regular classrooms revealed no significant differences between these two formats for student evaluations of the course and instructor, self-reported how much they learned in the class, and their final achievement.

Examination Study: Students’ Experiences in the Flipped Classroom

Besides the comparative study category, the other major category that emerged from the flipped classroom literature review was examination. These studies did not compare flipped classroom with the traditional classroom; instead, they were focused on
examining the flipped learning environment in terms of students’ attitudes towards the class format and their engagement in a flipped class. However, the findings of these studies are also inconsistent.

Among these studies, the majority of them found that students, on average, held positive attitudes towards the flipped classroom format at the end of the semester and engaged more in course learning (Bate & Galloway, 2012; Butt, 2014; Chen, Wang, & Chen, 2014; Enfield, 2013; Lemmer, 2013; Schullery, Reck, & Schullery, 2011). For example, Butt (2014) presented a report on an introduction of a flipped lecture in a final-year actuarial course. He flipped the large lecture actuarial course by moving the “delivery” of material outside of formal class time and using formal class time to help students undertake collaborative and active activities relevant to the materials. By conducting a survey research at the start and end of the semester, he found that students, on average, became more positive towards the flipped approach after experiencing the entire course. His study suggests that a flipped approach could be perceived as a positive approach for a large lecture course. In addition, Schullery, Reck, and Schullery (2011) also adopted the flipped classroom model in a large-size introductory business course attempting to address the high enrollment and low engagement dilemma. They reformed the introductory course delivery to a flipped classroom model, which devoted class time to active learning and assigned reading and videotaped lectures for completion outside class. Factor and content analyses of student surveys (N=868) supported the expectations of engagement and learning as well as satisfaction with the flipped format. The results also showed that the pre-class engagement with materials and satisfactions of the course format were positively related with in-class engagement in interactive activities. Overall,
the study indicates that flipped classroom has successfully addressed the dilemma presented in the high-enrollment course.

In contrast to the positive findings, some studies, however, found students were not satisfied with their learning experiences in the flipped class and disliked how the classroom structure oriented them to the learning tasks (Jaster, 2013; Strayer, 2012). For example, Jaster (2013) conducted a mixed method dissertation study on an inverted college algebra class, in which students viewed videos and took notes outside class and solved problems in class. One of his major findings was that the majority of students preferred a lecture-based class over the inverted class. The qualitative analysis of students’ feedback indicated that students felt more work was required in the inverted class and that pre-class watching videos or taking notes was very time consuming.

Strayer (2012) also conducted a mixed method dissertation study on a flipped college level introductory statistics course in which the lectures were delivered outside class via technology and homework and practices with concepts were moved inside class via learning activities. He employed the College and University Classroom Environment Inventory (CUCEI) to measure both students’ learning environment preferences and their learning environment experiences. He collected both quantitative data (e.g. survey responses, grades) and qualitative data (e.g. field notes, student interviews) for this study. One of his major findings was that students in the flipped class were less satisfied with how the structure the classroom oriented them to the learning tasks in the class because students felt less unsettled in the flipped class due to the variety of learning activities in the class.
With a growing interest in practicing flipped classroom in all levels of education (Goodwin & Miller, 2013), educators, on one hand, are interested in investigating whether the flipped classroom works or not and in examining what elements in a flipped class can improve students’ achievement and engagement. On the other hand, they are also concerned with how students learn in a flipped class, where students need help, and how they can help their learning process. Based upon the literature review, the existing research studies mainly focus on addressing whether the flipped classroom works or not. How students learn in a flipped class is rarely studied. To further flipped classroom research, there is a need to move beyond the studies that examine “Does the flipped classroom work” to the studies that investigate “How we can make the flipped classroom work?” Specifically, this study investigates how students learn in a flipped class and explores what factors can help students succeed in a flipped class.

While the flipped classroom holds promise for helping students to nurture active learning, it also demands more of students (Berrett, 2012; Zhang, Wang, & Zhang, 2012). Especially, the flexible characteristic of the flipped classroom creates a student-centered learning environment in which students must recognize and demonstrate self-regulated learning skills to succeed in flipped learning (Sophia and Flipped Learning Network, 2014; Talbert, 2014). To fully take advantage of the opportunities that flipping offers, students must possess self-regulated learning skills to self-direct, monitor, and evaluate their learning processes in order to achieve active learning outcomes (Estes, Ingram, & Liu, 2014; Talbert, 2014). Therefore, the present study adopts self-regulated learning theory as the theoretical framework to examine how students learn in the flipped classroom environment. In the following sections, I first introduce the self-regulated
learning theory in general and then describe the guiding theory – Winne and Hadwin’s Self-regulated Learning Theory – in detail.

**Theoretical Framework: Self-Regulated Learning (SRL)**

At one time or another, we have observed students who are confident, diligent, and resourceful in approaching educational tasks; who are proactive in exploring information when needed and use strategies to master it; who are persistent in the face of challenges and obstacles; and who are aware when they know a fact or possess a skill and when they do not. These students are called self-regulated learners (Zimmerman, 1998, 2002, 2008). People often ask how one becomes a self-regulated learner. What are the psychological mechanisms that enable these students to become masters of their own learning? Over the past two decades, Self-Regulated Learning (SRL) theory has been developed and promoted to address this question (Pintrich, 2004; Winne & Hadwin, 1998, 2008; Zimmerman, 1998). Self-regulation theorists view academic self-regulation neither as a mental ability such as intelligence nor an academic skill such as reading proficiency. Instead, they view self-regulated learning as the self-directive process through which learners transform mental abilities into academic skills (Zimmerman, 1998). Self-regulatory activities play mediating roles between personal or contextual condition and task performance (Pintrich, 2004). Not only does SRL focus on the learners’ personal condition that initiated the learning process, but more importantly, it also has profound implications for academic achievement (Zimmerman, 1990; Zimmerman & Schunk, 2001). SRL perspective shifts the focus of educational research from the learners’ ability and learning environment as “fixed” entities to “changeable” factors that can be mediated to improve learners’ academic achievement in both

**Definition and Theories of SRL**

Many SRL definitions differ in sometimes subtle and sometimes significant ways. Boekaerts and Cascallar offered a comprehensive overview of SRL in 2006 and defined SRL as “multi-component, iterative, self-steering processes that target one’s own cognitions, feelings, and actions, as well as features of the environment for modulation in the service of one’s own goal” (p. 199). In short, self-regulated learning is an integrated learning process guided by a set of motivations, behaviors, and metacognitive activities to support the pursuit of personal goals and finally improve the achievement (Schunk, 2001; Zimmerman & Schunk, 2001; Zimmerman, 1998).

The definitions of SRL reflect three key features of SRL theories. First, systematic use of metacognitive, motivational, and behavioral strategies is the fundamental feature of defining SRL (Zimmerman, 1989a). All learners use regulatory processes to some degree; however, self-regulated learners are distinguished by their systematic use of strategies to achieve academic goals and awareness of the relation between the strategy use and learning outcomes. Second, SRL is prominent as a “self-oriented feedback” loop (Zimmerman, 1989b). This loop is a cyclic process in which learners monitor the effectiveness of their learning strategies and adapt their following behaviors based on the feedback, such as covertly changing self-perception of the learning tasks or overtly altering the use of learning strategies (Zimmerman, 1990). Self-regulated learning theorists believe that feedback of learning effectiveness is a paramount determinant of self-regulated learning (Winne & Hadwin, 2008). Third, self-regulated
learning is the interdependent relationship between learning and motivation. For instance, the learner’s perception of self-efficacy is both a motive to learn and also an outcome of learning (Schunk, 2001). Self-regulated learning involves more than the capability to use self-control in the learning process and have the capability to adapt behaviors based on learning feedback. Self-regulated learners continue to set higher learning goals when previous goals are achieved and proactively put efforts into learning to meet the challenges.

A number of prominent self-regulated learning theories have been proposed attempting to elaborate how the self-regulated behaviors occur during the learning, such as Zimmerman’s three-phase cyclical SRL theory (Zimmerman, 1998; Zimmerman & Campillo, 2003), Pintrich’s four-phase × four-area SRL theory (Pintrich, 2000, 2004), and Winne and Hadwin’s four-phase × five-process SRL theory (Winne & Hadwin, 1998, 2008). Specifically, Zimmerman’s SRL theory consists of three phases, which include the *foreshotth thought phase, performance phase, and self-reflection phase*. It integrates motivational, behavioral, and metacognitive constructs attempting to explain the students’ problem-solving process in both formal and informal contexts. The three constructs are often measured through the Self-Regulated Learning Interview Scale (SRLIS; Zimmerman & Martinez-Pons, 1986, 1988). Compared to Zimmerman’s SRL theory, Pintrich’s theory is slightly complex because he and his colleagues not only included four phases of learning, but they also incorporated four areas of regulation. The four phases are highly consistent with the phases in Zimmerman’s model, which can be summarized as *Phase 1* – planning, goal setting, and activation of domain knowledge, *Phase 2* – monitoring process, *Phase 3* – self-controlling and self-regulation, and *Phase 4*
– self-reflection. The four areas are comprised of cognitive, motivation and affect, behavior, and external environment or context. Pintrich’s SRL model specifies the self-regulated learning process by providing taxonomy of the components that can be involved in self-regulated learning.

As for Winne and Hadwin’s SRL theory, it was adopted as the guiding theoretical framework in this study. In the following sections, I explain why this theory was adopted and describe how the model works.

**Guiding Theory of SRL: Winne and Hadwin’s SRL Theory**

Winne and Hadwin’s (1998) self-regulated learning theory was chosen as the foundational theory for this study for two major reasons: first, based on the Information Processing (IP) theory, their model builds a cognitive architecture or system by incorporating recursive information processing elements in each phase (see Figure 2). This architecture enriches previous SRL theories, explicitly models how the work of each phase is done, and provides a more detailed look at the interaction among information processing elements; second, their model is widely applied in both the traditional and computer-supported learning contexts (Azevedo et al., 2004; Azevedo et al., 2008; Azevedo et al., 2011), which are aligned with the flipped classroom context examined in this study.

Winne and Hadwin (2008) explained that “the construct of SRL emerges from an assumption that students exercise agency by consciously controlling and intervening in their learning” (p. 297). They postulated that all the learning is goal-oriented. Given the limits and constraints of both the individual and the learning environment, the student exercises agency by setting goals as well as making choices to achieve the goals such as
selecting study strategies, deciding how much effort and time to put into the task, and whether to persist in the task in face of adversity. They believe that self-regulation occurs when students metacognitively monitor their engagement in the goal-oriented tasks.

Winne and Hadwin (2008) distinguished self-regulation behavior from nonself-regulation behavior by introducing a design called “If-Then-Else.” If refers to the condition of the task; Then refers to a collection of operations or strategies to achieve learning goals; and Else refers to another collection of operations or strategies to achieve the goals when the first collection of operations or strategies did not meet the goals. They claimed that self-regulation behaviors only occur when students switch from a Then to an Else. This switch represents that students metacognitively recognize the discrepancies between learning product and feedback by comparing to desired goals and consciously take actions to change the discrepancies within the context (Winne & Hadwin, 1998, 2008). Overall, they postulated “the hallmark of SRL is adaption or change” (Winne & Hadwin, 2008, p. 303).

**Four Stages**

Through the lens of metacognition and goal-oriented learning, Winne and Hadwin (1998) posited a SRL model with four cyclical stages: task definition, goal setting and planning, enactment, and adaption (see Figure 2). They proposed that this four-stage model is a “recursive and weakly sequenced system” (Winne & Hadwin, 1998, p. 281). The operation of the current stage depends on the products of the previous stage, and learning does not necessarily follow the order from Stages 1 to 4, instead, learning might skip Stage 1, oscillates between Stages 2 and 3, and makes adaption (Stage 4) at any point. Below is the detailed explanation of each stage of the model.
**Stage 1: Task definition.** This stage is the first notable difference between Winne and Hadwin’s model and other SRL models because they separated the task definition process from the process of goal setting and planning. The primary product of this stage for the student is to develop a perception of a goal for a task. The goal is a set of standards by which the task can be judged.

*Figure 2. Winne and Hadwin’s (1998) model of self-regulated learning*
The student’s perceived goal might be the same with the teacher’s goal, or it might be different. When the student’s perceived goal does not match with the teacher’s goal, he or she might reframe the goal of the task. For example, if the instruction of a math task or the goal of the teacher for the math task is “Read Chapter 2, and finish the exercise Questions 1-5. If you have time, try the Question 6”. The students who agree with the teacher’s goal would strictly follow the instruction, while the students who are not confident in their math ability might think the “try the Question 6” is unnecessary and directly interpret the instruction as “Read Chapter 2, and do Exercises 1-5”. In another situation, if the time for completing the given task is limited, the “Read Chapter 2” and “Try the Question 6” might be skipped by a lot of students. Thus, both individual and task differences ensure that perceptions will vary about what a “given” task is.

*Stage 2: Goal Setting and Planning.* In this stage, the student’s personal goals start to play a role and might reframe the perceived task goal formed in Stage 1 if the student’s personal goal or standards differ from those perceived task goals. Continue with the example in Stage 1, and take the students whose task goals are the teacher’s goal as an example. If their personal goals are to learn the knowledge, then the perceived task goal would be reinforced since both goals aim at mastering the knowledge. In view of the reinforced goal, relevant plans would be built to approach this mastery goal such as carefully reviewing the chapter, memorizing the formula for doing the homework, and seeking help from the instructor when encountering problems. However, if their personal goals view the task just as a job to complete, they may judge their perceived task goals are set at too high a level or require too much effort, and then readjust or alter the original perceived task goal into “finish exercise Questions 1-5”. In light of this reframed goal,
students now build a new set of plans to approach this goal, such as go back to the book searching for formulas if needed, ask for help immediately when meeting difficult problems. Overall, Winne and Hadwin (1998) postulated that the student reinforces or reframes the perceived task goals and assembles a plan to approach these goals in this stage.

**Stage 3: Enactment.** The enactment of study tactics and strategies planned in Stage 2 marks the transition to Stage 3. The student employs certain study tactics, such as memorizing, reviewing the content knowledge, and seeking help from others, to achieve the goals identified in Stages 1 and 2. As part of the operation of enacting study tactics, evaluations, or feedback are generated internally. For example, students in the previous example may find the math problems are too difficult to start. Monitoring this deficiency, the students may generate attributions: some who hold an incremental belief about ability would think the task is too difficult and the identified goal in Stage 2 is at too high a level, while others who hold the belief about ability would attribute this to their lack of ability. As Winne mentioned (2001), it is common to see the frequent oscillation between Stages 2 and 3, since monitoring the products of the study tactics may result in dynamic changes to the identified goal in Stage 2 and the according plans in Stage 3.

**Stage 4: Adaption.** Adaption here means adapting studying through self-monitoring and external feedback. According to Winne and Hadwin (1998), decisions made in this stage are not about fine-tuning the process within only Stages 1 to 3; rather, they take two forms. In one form, the decisions can help coordinate the process of Stages 1 to 3 as a whole, which could result in a large-scale adjustment to the student’s understanding about task, goals, plans, and study tactics. For example, the adaption in
Stage 4 can make the student set more appropriate goals and standards and use time in a more effective way. In the other form, the decisions can serve as the cognitive condition for future studying tasks. For example, the adaption in this stage might reshape student’s motivation orientation from performance-based to mastery-based. Alternatively, students might lower his or her standards for a similar task in future.

**Five Processes**

Besides the four stages, Winne and Hadwin (1998) also hypothesized that five processes occur within each stage. Using the acronym COPES, they described that each stage is the interaction of a student’s conditions (C), operations (O), products (P), evaluations (E), and standards (S) (see Figure 1). The work of each stage is completed within the cognitive system composed of COPES. By introducing the COPES of each stage, Winne and Hadwin’s (1998) model complements other SRL models and provides a detailed look at the cognitive processes that occur during learning (Green & Azevedo, 2007).

**Conditions (C).** Conditions are resources available to a student and constraints embedded in a task or environment, which affect how the task is defined and engaged (Green & Azevedo, 2007). Conditions consist of two types: task condition and cognitive condition. Task conditions refer to external factors inherent in a task or environment, which mainly comprise learning subject, studying environment, and instructional cues (Winne & Hadwin, 1998). Take a flipped math class as an example. Based on the characteristics of the flipped classroom described in the previous section, task conditions for pre-class learning of the flipped math class include the math subject, Internet-based learning environment, and personalized or self-paced instruction, while task conditions
for in-class learning of the flipped math class include the math subject, collaborative learning environment, and personalized feedback.

Cognitive conditions refer to a student’s personal characteristics and experiences, which often consist of students’ prior domain knowledge and perceived confidence of completing the task (Moos & Azevedo, 2008, 2009). Cognitive conditions oftentimes are associated with task conditions (Winne & Hadwin, 2008). For example, within the pre-class Internet-based learning environment of a flipped math class, students’ perceived confidence of learning math is not only influenced by their confidence of learning math; it is also affected by their confidence of using Internet to learn math. Therefore, the interaction between task and cognitive conditions help students identify the task.

Standards (S). Standards are multifaceted or multivariate profiles that a student believes as the optimal criteria for completing a task, which include both metrics and beliefs (Green & Azevedo, 2007). Students might set different standards for a given task based on their own metrics and beliefs. After reviewing the instruction of the task, the student might develop their own task standards such as what needs to be done for the task (metrics) and how much effort should be put into the task (belief). In Figure 1, Winne and Hadwin (1998) used a bar chart to illustrate how a student defines the criteria of “success”, with each bar representing a different standard with the varying quality of a task. These overall profiles of standards define student’s goals. These goals and standards are used to compare with the products of each stage in order to determine the “success” of the operations in that stage and adapt accordingly.

Operations (O). Operations are the information manipulation process. As Winne (2001) stated, learning is a set of processes by which the student acquires information.
Based on Information Processing (IP) Theory, he proposed that five fundamental types of information processes occurred during operations, which include Searching, Monitoring, Assembling, Rehearsing, and Translating, abbreviated as SMART. He believes students are practicing various combinations of SMART in their everyday learning, such as searching information from memory, monitoring deficiency between produced information and target standards, assembling or encoding new information into long-term memory through useful cognitive links, rehearsing the acquisition of the information through taking notes or rereading, and translating information through cognitive representation. Besides the cognitive process, students also experience the motivational process, which is directly reflected on their affect such as anxiety towards the task or the test and satisfaction towards the performance or the evaluation. Thus, operations produce both cognitive and motivational products.

**Products (P).** Products are the results of operations process. For example, the product of operations in Stage 1 is the perceptions of the task, the product in Stage 2 is the reframed goals of the task and the plan for approaching the goals, the product in Stage 3 is the traces of studying tactics and reorganized knowledge, and the product in Stage 4 could be an overall update of the COPES processes, or a change of motivation and beliefs, or an improvement of the conditional knowledge and study tactics. As illustrated in Figure 1, Winne and Hadwin (1998) also used a bar chart to illustrate the “success” of the product in each stage in terms of their quality. Winne and Hadwin (1998) emphasized that their SRL model is a recursive system indicating the product in the previous stage always has an influence on the operational process in the subsequent stage.
**Evaluations (E).** Evaluations are essentially feedback about products generated internally by students themselves or provided by external sources such as the teacher’s feedback. This process is also called the monitoring process (Green & Azevedo, 2007). Through monitoring or comparing products with standards, the student tries to discover whether or not products meet standards. If products meet standards, no further work is needed and the student can move on to the next task. If products do not meet standards, further work remains to be done. Students may update the COPES processes such as revising the conditions and standards or enacting other study tactics to approach the set goals. After a few iterations of updates in Stage 3, if learning products are consistently not matching up with standards, then at this point the metacognitive strategy is initiated and the standards set in Stage 2 might be changed such as from “the task is easy” to “the task is hard” or vice versa. Also, the study tactics are updated based on reframed standards.

Overall, this SRL model depicts the self-regulated learning that occurs in four recursive and weakly sequenced stages: *defining the task, goal setting and planning, enacting study tactics and strategies, and metacognitively adapting studying for the future.* Each stage is modeled by a single cognitive architecture in which a personalized profile of a task is first created by considering both task factors and individual differences *(conditions)*, and then a profile of standards *(standards)* is framed to achieve the perceived task. The student engages in activities *(operations)* that produce both cognitive and motivational outcomes *(products)* and then compares such outcomes with set standards to obtain internal feedback *(evaluations)* and be provided with external feedback *(evaluations).* At each stage, evaluations update the students’ understanding of
the task, standards, and plan they created, as well as the study tactics they applied, then he or she initiates the metacognitive monitoring and control to current task operations and future learning.

This SRL model emphasizes three areas. (1) Conditions, as the initial process of self-regulated learning, serve as the foundation that have a direct impact on standards, operations, and products processes (Green & Azevedo, 2007). (2) Operations, as the critical process of manipulating information, play a mediating role of transforming set goals or plans to learning products (Winne, 2001). (3) Final products or learning achievements are the results of recursive processes in each stage, and they guide the update and alternation of previous processes, especially operations process (Green & Azevedo, 2007; Winne, 2005; Winne & Hadwin, 1998).

Consistent with the emphases of Winne and Hadwin’s SRL model, a great amount of SRL research has demonstrated that academic achievement is significantly associated with constructs in conditions and operations processes. Specifically, research has shown that learning achievement is related to prior domain knowledge (e.g. Moos & Azevedo, 2008; Murphy & Alexander, 2002) and self-efficacy (e.g. Pajares, 2008; Pintrich & Zusho, 2007), which are two constructs in the conditions process. In addition, the use of learning strategies, a construct in the operations process, has also been proven to have a significant influence on academic achievement (e.g. Berger & Karabenick, 2011; Duncan & McKeachie, 2005).

The synthesized review of the flipped classroom literature has suggested that theoretical or systematic understanding of how students learn in the flipped classroom should be the focus of current flipped classroom research. Current theoretical and
empirical advances about self-regulated learning provide an appropriate framework for such research. In order to further advance the understanding of the learning process in a flipped class within the SRL framework, research is needed to empirically examine factors repeatedly proven to be related to academic achievement in the SRL research, such as previously mentioned prior domain knowledge, self-efficacy, and the use of learning strategies. Therefore, in the following sections, I first describe research studies related to these three constructs and discuss their relationships with academic achievement as well as their interrelationships. Then, I apply SRL theory in the flipped classroom environment, particularly the application of three constructs in the context of the flipped classroom. Last, I propose two SRL structural models for the pre-class Internet-based and in-class collaborative learning environments of the flipped math class respectively.

Three Key Constructs of SRL Theory

Prior Domain Knowledge

Definition

Prior domain knowledge refers to “… the knowledge, skills or ability that students bring to the learning process” (Jonassen & Grabowski, 2012, p.417), and it integrates declarative, procedural, and inferential knowledge (Chi, 2000, 2006). It is a factor in the cognitive conditions process that plays a predicting role in the task definition phase of self-regulated learning (Lodewyk & Winne, 2005) and is considered as an important factor in explaining the variability of domain learning (Alexander, 2003). Individuals with greater prior domain knowledge tend to understand and remember more
than those with less prior domain knowledge (Committee on Developments in the Science of Learning, National Research Council, 1999).

**Relationship between Prior Domain Knowledge and Academic Achievement**

Prior domain knowledge benefits students’ learning and achievement within that specific domain (Alexander, 2003). This conclusion has been supported by studies of a variety of content domains, including reading comprehension (McNamara, Kintsch, Songer, & Kintsch, 1996), psychology (Murphy & Alexander, 2002), mathematics (Clarke, Ayres, & Sweller, 2005), medical (Song, 2011), and computer science (Yu, Jan, Simoff, & Debenham, 2007) with students ranging from elementary grades to graduate level (Thompson & Zamboanga, 2004).

For example, in the field of reading comprehension, grounded in the Construction Integration model (CI model; Kintsch, 2005), McNamara et al. (1996) conducted two experiments to examine the role of prior knowledge on comprehension of biology texts among junior high students. They first measured 36 students’ prior knowledge about the traits of mammals – the topic of biology texts – by means of a sorting task and a set of questions about the text. Then they examined their comprehensions of both coherent and incoherent texts regarding mammals via free recall, written questions, and a key-word sorting task. The experimental results indicated that the students with more knowledge of mammals were more capable of understanding incoherent or challenging texts, while the students with less knowledge about mammals were more capable of learning from the coherent texts. This study provides evidence that students with higher prior knowledge are better equipped to reconstruct the content relevant knowledge.
In addition, Thompson and Zamboanga (2004) conducted an empirical study investigating both domain-specific knowledge and general learning aptitude on students’ achievement in an undergraduate psychology course. In total, 353 students participated in their study. Student ACT scores served as an indicator of general ability, and two pretests on the second day of the class served as an indicator of prior psychological knowledge. Regression analyses showed that the pretest of psychological knowledge had a positive impact on final exam scores of the course even with the influence of ACT being controlled. Their study furthers earlier prior knowledge research by demonstrating that beyond general ability, domain-specific knowledge is a critical factor that assists students learning in introductory psychology.

Based upon the understanding of prior knowledge, a general research hypothesis is generated, which is:

_Hypothesis A: Prior domain knowledge has a direct effect on academic achievement._

**Self-efficacy**

**Definition**

Self-efficacy is defined as “people’s judgments of their capabilities to organize and execute courses of action required to attain designated types of performances” (Bandura, 1986, p. 391). This core belief touches almost every aspect of people’s lives and is considered as the foundation of human agency (Bandura, 2002). It determines whether coping action will be initiated, how much effort will be devoted, and how long to persevere in the face of adversity and failure (Bandura, 1997). People with high self-efficacy have strong belief in their coping capabilities, and tend to set higher-level or
challenging goals, be more motivated to accomplish the goals by mobilizing various resources, skills, and efforts, and be more persistent in the face of difficulty than those with low self-efficacy.

**Relationship between Self-efficacy and Academic Achievement**

Since the construct of self-efficacy was introduced by Bandura in 1977, educational researchers have examined the role this construct can play on academic lives of students. The cumulative findings have confirmed that students’ academic self-efficacy beliefs powerfully influence students’ academic achievement across grade levels and learning environments (e.g. Finney & Schraw, 2003; Pajares, 2008; Pajares & Johnson, 1996; Pintrich & Zusho, 2007; Schunk & Pajares, 2005; Zimmerman & Bandura, 1994; Zimmerman, Bandura, & Martinez-Pons, 1992).

In regard to academic self-efficacy research at different grade levels, Caprara et al. (2011) did a longitudinal study examining the contribution of academic self-efficacy on academic achievement at the high-school level. The results showed that academic self-efficacy was constantly a significant predictor of students’ final achievement in both their junior and senior years. Robbins et al. (2004) performed a meta-analysis on the relation between psychological and study skill factors and academic outcomes at the college level. The meta-analyses indicated that academic self-efficacy was the best predictor for college GPA and the second strongest predictor for the knowledge retention among college students. Thus, a collection of previous findings has suggested that academic self-efficacy is a significantly positive predictor of students’ academic achievement regardless of the grade level.
In regard to academic self-efficacy research in various learning environments, an extensive study has shown the significant effect of academic self-efficacy on academic achievement in a face-to-face learning environment (e.g. Caprara et al., 2011; Pintrich & Zusho, 2007; Robbins et al., 2004). With the advance of technology and the growth trend of online and blended learning, the effect of self-efficacy on students’ learning has also been examined in an Internet-based learning environment (e.g. Azevedo & Cromley; 2004; Wang & Wu, 2008). The findings are consistent with the findings in traditional face-to-face environment. For example, Wadsworth et al. (2007) examined the effects of academic self-efficacy on students’ math achievement in an undergraduate online math course. The results revealed that academic self-efficacy was one of the significant predictors of college students’ math achievement. Lynch and Dembo (2004) conducted a similar study in a blended undergraduate marketing course and concluded that the academic self-efficacy significantly predicted academic performance in the course.

**Domain-specific Self-efficacy**

Above all, a variety of research studies have proven the robust and consistent effect of academic self-efficacy on corresponding academic achievement across grade levels and learning environments. However, some self-efficacy research studies do not agree with the major finding. For example, Wilhite (1990) found that college students’ self-assessment of memory ability was the strongest predictor of their GPA, followed by the locus of control. The academic self-efficacy only had a weak relationship with college students’ GPA. Cooper and Robinson (1991) reported a low correlation between math self-efficacy and the Missouri Mathematics Placement Test. Wang and Wu (2008) did
not find a significant direct relationship between self-efficacy and academic performance either. So what causes such an inconsistent finding?

One possible reason for the incongruous results lies in the measurement of the self-efficacy. As noted by Pajares (1996), self-efficacy researchers sometimes used a generalized, global, or composite scale to measure self-efficacy belief. Use of such measurement could confuse respondents and lead to a nonsignificant relationship between self-efficacy and academic achievement. According to Bandura (1986) and Pajares (1996), if self-efficacy was globally assessed or did not correspond with the outcome criterion, the predictive value could be decreased or even nullified. For example, a researcher aimed at examining whether students’ perceived math self-efficacy had an impact on their final math achievement in a flipped math class. Instead of using a specific item to measure math self-efficacy such as “I expect to do well on learning math in this flipped class,” he used a generalized self-efficacy item such as “I expect to do well in the class” to measure students’ perceived math self-efficacy on a Agree-Disagree Likert scale. The respondent who answered “agree” with such a generalized item could mean he agreed that he expected to do well in learning math or he agreed that he expected to do well in learning in a flipped class. Therefore, the responses to the generalized item might not reflect what the researcher really wanted to measure and led to nonsignificant findings. The majority of nonsignificant self-efficacy studies have been evidenced to use such generalized self-efficacy items to measure students’ academic self-efficacy (Cooper & Robinson, 1991; Wang & Wu, 2008; Wilhite, 1990).

Since the global or generally defined self-efficacy measure weakens the effect of academic self-efficacy on academic achievement, the self-efficacy belief should be
measured at the task- or domain-specific level to enhance the accuracy of the effect research (Finney & Schraw, 2003; Pajares, 1996; Schunk, Pintrich, & Meece, 2008). Pajares and Miller’s study (1995) provided a good example of tailoring the measures of self-efficacy to the outcome criterion. In their study, they developed three domain-specific math self-efficacy scales – the confidence to solve mathematics problems, confidence to succeed in math-related courses, and confidence to perform math-related tasks – to measure three facets of the math self-efficacy and map with the interested outcome criterions - solution of math problems and choice of math-related majors. The results of the study showed that students’ perceived confidence to solve math problems was a stronger predictor of math problem-solving performance than the other two facets of math self-efficacy. Students’ reported confidence to succeed in math-related courses was a more powerful predictor of students’ choice of math-related majors than the other two facets of math self-efficacy.

Based upon the understanding of the relationship between domain-specific self-efficacy and academic achievement, a general research hypothesis is generated for current study, which is:

_Hypothesis B: Domain-specific self-efficacy has a direct effect on academic achievement._

**Relationships between Prior Domain Knowledge and Domain-Specific Self-efficacy**

Besides the direct effect of prior domain knowledge on academic achievement discussed above, some research has also shown that prior domain knowledge has a direct effect on domain-specific self-efficacy, which, in turn, influences academic achievement (Ferla, Valcke, & Cai, 2009; Pajares & Miller, 1994; Rimal, 2001; Song, 2011). For
example, Pajares and Miller (1994) conducted an empirical study examining the effects of prior math experience and math self-efficacy in mathematical problem solving. Participants consisted of 350 undergraduate students who were enrolled in education classes. Prior math experience was assessed by a composite score of maximum math level attained in high school courses and earned semester math credits in college courses. Math self-efficacy was measured through the Mathematics Confidence Scales (MCS). Path analyses revealed that prior math experience had a direct effect on math self-efficacy and math self-efficacy, in turn, had a direct impact on mathematics performance. The results support the social cognitive theory (Bandura, 1986), which argues that people are more influenced by how they interpret their experience rather than by their achievements. For this reason, domain-specific self-efficacy beliefs are always a powerful predictor for future behaviors in the content domain, while prior experience influences subsequent behavior largely through its effect on self-efficacy beliefs.

Moreover, Song (2011) also examined the relationship between prior domain knowledge and domain-specific self-efficacy in a multimedia learning environment. In total, 386 medical clerkship students from six medical schools participated in his study. Students’ prior domain knowledge was measured using a multiple-choice knowledge test, and their self-efficacy belief was assessed by adapted self-efficacy scale from Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1993). The results from structural equation modeling indicated that students’ prior domain knowledge was significantly associated with their domain-specific self-efficacy.
Based upon the understanding of the relationship between prior domain knowledge and domain-specific self-efficacy, a general research hypothesis is generated for current study, which is:

_Hypothesis C: Prior domain knowledge has a direct effect on domain-specific self-efficacy._

**Learning Strategy**

**Definition**

Learning strategies are introduced as “behaviors and thoughts in which a learner engages and which are intended to influence the learner’s encoding process” (Weinstein & Mayer, 1983, p1). In SRL, learning strategies are the actions that learners take in the enactment stage to meet the goals and standards set in the goal setting and planning stage. The goal of using any particular learning strategy is to either affect learners’ motivational or affective state or to help learners actively process information such as select, acquire, organize, or integrate new knowledge (Entwistle, 1988). For example, before taking an exam, a learner may use the emotional arousal strategy such as self-talk to get through the task: “I can do this. Just go one step at a time” to reduce feelings of anxiety. When learning a new topic, a learner may use the note-taking strategy to help him memorize and organize the knowledge. When doing group activity, a learner may use the peer learning and help seeking strategy to effectively acquire the knowledge.

Based on the early work of learning strategies (Weinstein & Mayer, 1983, 1986), Pintrich and his colleagues divided the learning strategies construct into three categories of individual learning strategy, which include cognitive, metacognitive, and resource management strategy (Pintrich et al., 1993). Specifically, cognitive strategy involves
students’ use of basic and complex strategies to process information from texts and lectures such as repeating words, paraphrasing, summarizing, outlining, and critical thinking. Metacognitive strategy concerns students’ use of strategies to control and regulate their cognitive behaviors such as setting goals, monitoring the comprehension, and regulating their learning behaviors. Resource management strategy refers to learners’ regulatory strategies for controlling other resources besides one’s own cognition such as effectively using time, regulating efforts in the face of obstacles, and seeking help from peers or instructors when needed (Pintrich et al., 1993). These three categories of learning strategy constitute the learning strategies scale that is a part of prominent Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1993).

**Relationship between the Use of Learning Strategies and Academic Achievement**

A great body of empirical research has demonstrated the significant relationship between the use of learning strategies and academic achievement (Berger & Karabenick, 2011; Diseth, 2011; Duncan & McKeachie, 2005; Elliot et al., 1999; Greene et al., 2004; Pintrich & De Groot, 1990; Sins et al., 2008; Zimmerman & Martinez-Pons, 1986, 1988). For example, Duncan and McKeachie (2005) reviewed research studies from 2000 to 2004 that have used MSLQ and concluded that the link between the use of learning strategies and academic achievement has been empirically established. Moreover, Crede and Philips (2011) conducted a meta-analytic review on 59 research articles that have used MSLQ and observed the moderate to strong relationships between class grades, self-efficacy, effort regulation, and resource management strategy. They also found that the relationship between some strategies and class grades were weaker and even unrelated. For instance, peer learning and help seeking strategies appeared to be largely unrelated to academic
achievement. They postulated that these two types of learning strategies exhibited curvilinear relationship with grades, which means neither very high performing nor very low performing students are likely to engage in peer-learning or help-seeking activities. In contrast, some studies, especially the ones conducted in the online or computer-supported collaborative learning environments, found that effective use of help seeking strategy in fact could substantially improve students learning process and achievement (Aleven et al., 2003; Taplin et al., 2001).

Based upon the understanding of the use of learning strategies, a general research hypothesis is generated for current study, which is:

*Hypothesis D: Use of learning strategies has a direct effect on academic achievement.*

**Relationship between Prior Domain Knowledge and the Use of Learning Strategies**

Research indicates that prior domain knowledge is related to how students process the information, particularly how they enact different learning strategies to achieve learning goals (Moos & Azevedo, 2005, 2008; Murphy & Alexander, 2002; Song, 2011). For example, grounded in Model of Domain Learning (MDL model: Alexander, 2003), Murphy and Alexander (2002) conducted an exploratory study in an undergraduate psychology course to examine the relationship between subject-matter knowledge and use of strategies during learning. The results showed that the students with higher domain knowledge before entering the educational psychology course tended to use deeper-level processing strategies (e.g. building a mental image, entail a personalization or transformation of the printed message) and seemed better equipped to gain from the instruction than those with lower prior domain knowledge. Therefore, they concluded that
it was the interaction between prior domain knowledge and the enactment of learning strategies that helped students obtain final achievement.

This relationship is even more important in an Internet-based learning environment, particularly within a hypermedia learning environment, because these learning environments provide ubiquitous learning resources and allow students to choose which resource to access to. Such freedom of getting access to a wide range of information requires students to manage a high degree of control in order to effectively navigate through such learning environments. For instance, Moos and Azevedo (2008) conducted pre-post research within a hypermedia learning environment. Based upon Winne and Hadwin’s (1998) SRL model, they used the think-aloud method to investigate the relationship between prior domain knowledge and self-regulated learning in a hypermedia-based undergraduate biology course. The content analysis revealed that prior domain knowledge was positively related to students’ monitoring and planning activities but negatively related to their use of cognitive strategies such as memorizing and summarizing content during the hypermedia learning tasks. This line of prior domain knowledge research provides valuable insights for the understanding of the relationship between prior domain knowledge and students’ self-regulated learning behaviors in the context of an Internet-based learning environment.

Based upon the understanding of the relationship between prior domain knowledge and the use of learning strategies, a general research hypothesis is generated, which is:

\textit{Hypothesis E: Prior domain knowledge has a direct effect on the use of learning strategies.}
Relationship between Self-efficacy and the Use of Learning Strategies

Students’ perceived self-efficacy plays a critical role of affecting their use of learning strategy (Crede & Philips, 2011; Diseth, 2011; Greene et al., 2004; Liem, Lau, & Nie, 2008). This conclusion has been supported by various studies that examined the relationships among academic self-efficacy, the use of learning strategies, and academic achievement. Research studies have consistently shown that the perceived self-efficacy influences students’ choices of learning strategies, and the use of learning strategies, in turn, influences academic achievement (Pintrich & Garcia, 1991; Pintrich et al., 1993; Zimmerman & Bandura, 1994; Zimmerman & Martinez-Pons, 1990, 1992; VanderStoep, Pintrich, & Fagerlin, 1996). For example, Pintrich and De Groot (1990) performed a correlational study among self-efficacy, self-regulated learning strategies, and classroom academic performance on 173 seventh-grade students. The regression analysis showed that self-efficacy was one strong predictor of academic performance and was highly correlated with the use of cognitive and metacognitive self-regulated learning strategies.

Based upon the understanding of the relationship between self-efficacy and the use of learning strategies, a general research hypothesis is generated, which is:

*Hypothesis F: Self-efficacy has a direct effect on the use of learning strategies.*

Overall, the review of literatures regarding three key constructs – prior domain knowledge, self-efficacy, and the use of learning strategies – within Self-Regulated Learning (SRL) theoretical framework indicates that (1) all three constructs have direct effects on academic achievement; and (2) interrelationships exist between these three constructs. Based on SRL theoretical foundation and general hypotheses A – F, a conceptual model is proposed in order to explain the self-regulated learning process.
Apply SRL Theory in the Flipped Classroom Environment

The flipped classroom consists of two major learning environments: the pre-class Internet-based and in-class collaborative learning environments (Bergmann & Sams, 2012; Herreid & Schiller, 2013). Each learning environment presents its distinctive features that students have to cope with in order to succeed in a flipped classroom. For example, as for the pre-class learning environment, it allows for flexible time, space, and pace for students’ engagement in learning resources and reflection on their performances. Such flexibility of content learning offers a certain degree of control to students on their learning process. Students are expected to regulate their time and efforts during pre-class learning in order to personalize online instructions to meet their personal needs and interests. As for the in-class learning environment, it provides collaborative opportunities

Figure 3. Conceptual self-regulated learning model in a flipped classroom
for students demonstrating the mastery of pre-class knowledge and collaborating with others in groups to apply higher-order thinking skills. It is anticipated that students will regulate their learning behaviors and efforts to work in groups in order to further pre-class learning and obtain higher level cognitive knowledge.

Moreover, both learning environments create a student-centered learning culture, in which students take control of their own learning process and are actively engaged in knowledge construction that is meaningful to them in person (FL Network, 2014). Such a learning culture demands more of students. For example, when learning in the pre-class environment, students are required to complete online lectures on their own. Such a task requires that students self-regulate their learning in order to achieve personalized learning outcomes (Estes, Ingram, & Liu, 2014; Talbert, 2014). Meanwhile, when learning in the in-class environment, students are expected to collaborate with peers to implement higher level cognitive knowledge and skills. Such collaboration requires that students exert self-regulated learning to monitor and evaluate their learning processes in order to achieve active learning outcomes (Herreid & Schiller, 2013).

With growing interest of the flipped classroom model in higher education, the investigation of how students learn and what factors can contribute to their success in a flipped class has emerged as a necessary and meaningful research topic. Self-regulated learning has provided an appropriate theoretical framework for the understanding of students’ learning process in the flipped classroom environment. Particularly, empirical research has suggested that the success of learning in a flipped class may be mediated by three essential constructs in self-regulated learning theory, including prior domain knowledge (e.g. Murphy & Alexander, 2002, Thompson & Zamboanga, 2004), self-
efficacy (e.g. Caprara et al., 2011; Pintrich & Zusho, 2007), and the use of learning strategies (e.g. Aleven et al., 2003; Crede and Philips, 2011).

Three Key Constructs in the Flipped Classroom Environment

Prior Domain Knowledge in the Flipped Classroom Environment

When taking a flipped class, it is common that student first complete online lectures on their own prior to class and then apply learned knowledge through collaborative activities during class (Bergmann & Sams, 2012; Herreid & Schiller, 2013). Thus, students’ success of in-class activities heavily relies on their preparation prior to class. According to the research finding that prior domain knowledge is a crucial variable that contributes to learning outcomes (e.g. Murphy & Alexander, 2002), students’ preparation or obtained knowledge in pre-class learning, therefore, directly influence their in-class achievement. In addition, due to the flexibility of pre-class learning environment, students need to manage a high degree of control in order to effectively learn through online lectures (Talbert, 2014). According to the research finding that prior domain knowledge is a critical component of learning in an Internet-based learning environment, particularly a hypermedia environment (Moos & Azevedo, 2007; Chen, Fan, & Macredie, 2006), students’ prior knowledge of a specific content domain, thus, contribute to their navigation in the pre-class Internet-based learning environment and understanding of online lecture materials.

Based upon the understanding of the characteristics and structure of the flipped classroom, as well as the prior domain knowledge research, the following two implications apply to the current study:
• In the pre-class Internet-based learning environment of a flipped math class, prior knowledge that students have in the math domain has a direct impact on pre-class domain-specific self-efficacy, the use of learning strategies, and pre-class math achievement.

• In the in-class collaborative learning environment of a flipped math class, the knowledge obtained in pre-class learning has a direct impact on pre-class domain-specific self-efficacy, the use of learning strategies, and pre-class math achievement.

**Domain-specific Self-efficacy in the Flipped Classroom Environment**

Self-efficacy has been consistently shown as one of the essential factors affecting students’ learning outcomes (e.g. Caprara et al., 2011; Pintrich & Zusho, 2007). In order to investigate how students learn in the flipped classroom environment, it is meaningful to empirically examine the effect of self-efficacy on students’ learning in a flipped class. Moreover, research has also suggested that to increase accuracy of prediction, self-efficacy should be measured at the optimal level of specialty that corresponds to the outcome criterion being compared (Bandura, 1986; Pajares, 1996). For example, to accurately examine the effect of the self-efficacy belief on students’ math problem-solving performance, the self-efficacy belief scale should be developed to specifically measure students’ confidence of solving math problems (Pajares & Miller, 1995).

The current study was conducted in an undergraduate flipped math class. Therefore, a general flipped classroom environment is narrowed down to a flipped math classroom environment. Based on the characteristics and the structure of flipped classroom, three major outcome criterions emerge from a flipped math class, which
include the *math learning outcome*, the *pre-class Internet-based learning outcome*, and the *in-class collaborative learning outcome*. Specifically, the math learning outcome refers to the math achievement students obtain during pre-class and in-class learning of the flipped math class. Pre-class math achievement consists of a lecture-embedded quiz score, a final online-quiz score, completeness of online lectures, or a combination of these; while in-class achievement consists of a class participation score, an in-class quiz score, a take-home assignment score, or a combination of these.

In terms of the Internet-based learning outcome, this occurs in the pre-class Internet-based learning environment and refers to students’ obtained achievements through using the Internet. Since during pre-class learning students are using the Internet to learn math knowledge, elements of pre-class math achievements can also be considered as components of the pre-class Internet-based learning outcomes. To understand how students learn in the pre-class learning environment, it is necessary to examine the relationship between students’ pre-class achievements and the beliefs of their capabilities to use the Internet to find useful information, differentiate the usefulness of the information, and answer questions or post comments on online discussion boards (Kim & Glassman, 2013).

The in-class collaborative learning outcome is a reflection of students’ collaborative performances in group-based activities, which is normally comprised of a class participation score, a take-home assignment score, or a combination of these. In order to understand how students learn in the in-class learning environment, it is necessary to examine the relationship between students’ collaborative achievements and the beliefs of their capabilities to learn through collaborative activities such as the
capability to take a lead in group work, provide and receive explanations, and elaborate thinking (Johnson & Johnson, 1999; Webb & Palincsar, 1996).

To effectively and accurately examine the effects of self-efficacy beliefs on three outcome criterions in the flipped math class, self-efficacy beliefs were measured in three corresponding domains, including math self-efficacy, Internet self-efficacy, and collaborative learning self-efficacy. In the following sections, I introduce the concept of each domain-specific self-efficacy and its relevant research studies.

**Mathematics Self-efficacy (MSE).** The concept of mathematics self-efficacy (MSE) has existed for more than two decades (Pajares & Miller, 1994). It is defined as “a situational or problem-specific assessment of an individual’s confidence in her or his ability to successfully perform or accomplish a particular [mathematical] task or problem” (Hackett & Betz, 1989, p. 262). Students with higher MSE persist longer while facing difficult math problems and are more accurate in math computation than those with low MSE (Hoffman & Schraw, 2009). The main research topic related to MSE is its effect on individuals’ mathematical performance in a variety of grade levels and learning environments.

With respect to the MSE research in different grade levels, the effect of MSE on math achievement has been examined from elementary grades to undergraduate level (Finney and Schraw; 2003; Pajares & Barich, 2005; Pajares & Miller, 1994, 1995; Spence & Usher, 2007). For example, Fast et al. (2010) conducted a longitudinal study of fourth, fifth, and sixth graders regarding the relationship between their confidence in learning math (i.e. MSE) and their performance in California Standard Test for Mathematics. Results showed that MSE had a positive effect on students’ achievements
in the test, indicating the higher level of MSE students perceive, the higher grades they would obtain on the test. Finney and Schraw (2003) found a similar result in their study that was conducted in an undergraduate level. They implemented a self-developed statistic self-efficacy scale in an introductory statistical method course to examine the effect of the scale on students’ statistical performance. In total, 103 students responded the scale, and analysis showed a significant relationship between students’ perceived statistic self-efficacy and their final achievement.

With respect to the MSE research in various learning environments, MSE has been widely studied in a face-to-face learning environment, and its positive effect on math achievement has been consistently supported by extensive studies (Fast et al., 2010; Finney & Schraw, 2003; Pajares & Barich, 2005; Pajares & Miller, 1994, 1995). With an increasing number of math courses being offered in online or blended learning environments, examining this relationship in these learning environments becomes an emerging area of study (Spence & Usher, 2007). For example, Spence and Usher (2007) conducted a comparative study on the effect of MSE on math achievement between traditional and online courses. They concluded that MSE was the primary predictor of math achievement regardless of learning environments. Altogether, MSE has been evident as a robust predictor of math achievement in math-subject courses.

Internet Self-efficacy (ISE). Internet self-efficacy (ISE) is denoted as students’ perceived capability of organizing and executing courses of Internet actions required to produce given attainments (Tsai et al., 2011). It is a relatively new concept whose history can be traced through the last decade (Kim & Glassman, 2013). Prior to this, research was mainly focused on the computer self-efficacy (CSE) concept, studying its effect on
individuals’ computer use (Compeau & Higgins, 1995; Eastin & LaRose, 2000). With the development and prevalence of the Internet in recent years, Internet or Web-based learning activities have widely integrated into a variety of curriculums (Kim & Glassman, 2013). ISE has become popular and appeared in many research studies related to online or blended learning (Hsu & Chiu, 2004; Kim & Glassman, 2013; Tsai & Tsai, 2003; Tsai et al., 2011).

One major line of the ISE research is the examination of its relationship to the online or blended learning outcomes (Hsu & Chiu, 2004; Joo, Bong, & Choi, 2000; Kim & Glassman, 2013; Lynch & Dembo, 2004; Tsai & Tsai, 2003). In 2011, Tsai and his colleagues conducted a literature review regarding ISE in the Internet-based learning environments based on 46 relevant research papers published from 2000 to 2009. Through a comprehensive review, they conclude that 1) both the individual’s behavioral and psychological factors (i.e., perceived usefulness, anxiety, attitudes) were related to ISE; 2) ISE was positively related to individuals’ attitudes towards Internet-based learning; and 3) ISE was a strong predictor of individuals’ academic performance in Internet-based learning.

Furthermore, Kim and Glassman (2013) argued that to better understand a wide ranges of online activities under current development of the Internet, there was a need to update existing ISE scales that mainly focused on the measurement of students’ technical skills. Grounded in Internet and social cognitive theories, they developed a five-factor ISE scale that assesses a different complexity level of online activities including search, communication, organization, differentiation, and generation. A few research studies have been implemented this scale in their studies, and results suggested that some factors
have contributed to the change of ISE (Kim, Glassman, Bartholomew, & Hur, 2013; Shank & Scotten, 2014). For instance, Kim et al. (2013) compared the development of ISE in a blogged centered curriculum with the development in a traditional lecture curriculum. A pre-and-post analysis revealed that a blogcentric course had an impact on the increase in students’ ISE, particularly on the higher complex level of ISE – generative ISE.

Collaborative Learning Self-Efficacy (CLSE). The concept of collaborative learning self-efficacy has not been widely studied yet. Within Bandura’s (1997) self-efficacy framework, collaborative learning self-efficacy can be defined as an individual’s belief in his or her ability to be successful in collaborative learning activities. In other words, collaborative learning self-efficacy is concerned with the individual’s confidence of doing collaborative or group-based learning tasks.

In a review of collaborative learning, Johnson and Johnson (1999) suggested that collaborative learning had a positive effect on students’ academic performance. Webb and Palincsar (1996) suggested that heterogeneous groups that include members who are diverse in ability, motivation, gender, or race were more conducive for collaborative learning than the homogeneous groups. That is because heterogeneous groups exhibit greater degrees of elaborative thinking, providing and receiving explanations, and perspective taking in discussion material, which, in turn, lead to deeper understanding, better reasoning abilities, and accuracy in long-term retention (Johnson & Johnson, 1999; Webb & Palincsar, 1996).
Based upon the understanding of the characteristics and structure of flipped classroom, as well as the research in the three domain-specific self-efficacies – MSE, ISE, and CLSE, the following two implications apply to the current study:

- In the pre-class Internet-based learning environment of a flipped math class, math self-efficacy (MSE) and Internet self-efficacy (ISE) are two significant factors affecting students’ use of learning strategies and their pre-class math achievements.

- In the in-class collaborative learning environment of a flipped math class, math self-efficacy (MSE) and collaborative learning self-efficacy (CLSE) are two significant factors affecting students’ use of learning strategies and their in-class math achievements.

**The Use of Learning Strategy in the Flipped Classroom Environment**

Under the social-cognitive theoretical framework on which the MSLQ was developed, the use of learning strategies is assumed not to be the inherent trait of the learner, but rather that it can be learned and regulated by the learner (Duncan & McKeachie, 2005). Therefore, the use of learning strategies can vary, and the variation could be dependent on the nature of the academic task (e.g. multiple choices, essay writing) and the learning environment (e.g. traditional lecture-based learning environment, online learning environment) (Azevedo, 2005; Azevedo & Cromley, 2004; Azevedo, Guthrie, & Seibert, 2004). In terms of variation in using learning strategies in different academic tasks, Duncan and McKeachie (2005) pointed out in their synthesized review that there is potential variation in using learning strategies in different academic tasks. However, they provided limited supportive examples or arguments for backing up
this point. In terms of the variation in using learning strategies in different learning environments, research that was conducted in a traditional face-to-face learning environment has shown a significant relationship between students’ academic achievements and their use of cognitive strategy (Greene et al., 2004) as well as the use of self-regulation strategy (Pintrich & De Groot, 1990). Differently, research that was conducted in a hypermedia learning environment has demonstrated a significant relationship between students’ academic achievement and their use of metacognitive and effort regulation strategies (Azevedo, 2005; Azevedo & Cromley, 2004; Azevedo, Guthrie, & Seibert, 2004).

The flipped classroom provides a distinct learning environment to examine the relationship between students’ use of learning strategies and their academic achievement because the flipped classroom itself consists of both Internet-based/online and group-based/faceto-face learning environments. In a flipped math class, students commonly view math lecture videos and do associated quizzes in the online learning environment and solve problems in groups and take exams in the face-to-face learning environment. According to the learning strategy research, use of metacognitive and self-regulated strategies is assumed to be more closely related to the success of online learning (Azevedo, 2005; Azevedo & Cromley, 2004; Azevedo, Guthrie, & Seibert, 2004); while the help seeking strategy is assumed to play a more important role in the performance of collaborative activities during in-class face-to-face learning (Aleven et al., 2003, 2006).

Based upon the understanding of the characteristics and structure of flipped classroom, as well as the research regarding the use of learning strategies, the following two implications apply to the current study:
• In the pre-class Internet-based learning environment of a flipped math class, the use of learning strategy contributes to pre-class academic achievement. Particularly, the use of metacognitive and self-regulation strategy is more closely related to the pre-class math achievement.

• In the in-class face-to-face learning environment of a flipped math class, the use of learning strategy is related to in-class academic achievement. Particularly, the use of help seeking strategy might be more important for the success of in-class math achievement.

The Proposed Models of This Study

Overall, based on the above discussions of applying research findings of three SRL key constructs to the flipped classroom environment and the six implications for the current study, two structural models are proposed to enrich the conceptual model (see Figure 3). Each model was built based on the distinct characteristic of the pre-class and in-class learning environment. Below are the detailed descriptions of these two structural models.

Structural Model for Pre-class Internet-based Learning Environment

According to Winne and Hadwin’s (1998, 2008) SRL theory, when learning in the pre-class Internet-based environment of a flipped math class, the student first creates a personalized profile of the task based on their considerations of both task and cognitive conditions. The task conditions for pre-class learning refer to the Internet-based learning environment in which students take control of their own learning process and regulate their motivation, behavior, and metacognition to complete the defined task. The cognitive conditions consist of students’ personal characteristics and experiences of completing the
task, which include prior math knowledge, Internet self-efficacy, and math self-efficacy. After developing a sense of the task, students set goals and create relevant plans to complete the task. While putting plans into actions, the student employs various combinations of learning strategies to produce achievements. Metacognitive and self-regulation strategies are expected to be especially related to the achievements (e.g. Azevedo, 2005). Finally, the student compares the achievement with the previously set goal. If the achievement meets the goal, no further work is needed and the student can move on to the next task; otherwise, further work remains to be done such as updating goals and changing learning strategies.

Figure 4 demonstrates the self-regulated learning process in the pre-class Internet-based learning environment of the flipped math class. Specifically, prior math knowledge is expected to have a direct effect on students’ online learning achievement. In addition, it is also expected to have an indirect effect on achievement through students’ perceived math and Internet self-efficacy as well as the use of learning strategies. In terms of perceived self-efficacies, they are expected to have direct effects on online achievement and also indirect effects on achievement through the mediating factor – the use of learning strategies. As for the use of learning strategies, it is expected to have a direct effect on online achievement.
Structural Model for In-class Collaborative Learning Environment

The discussion of the structural model for the in-class collaborative learning environment is similar to the above discussion of the pre-class structural model. Based upon Winne and Hadwin’s (1998, 2008) SRL theory, when learning in the in-class collaborative environment of a flipped math class, the student also first creates a personalized profile of the task based on their considerations of both task and cognitive conditions. The task conditions for in-class learning refer to the face-to-face collaborative learning environment in which students engage in active learning activities, such as group-based problem solving or in-class presentation to complete the defined task. The cognitive conditions mean students’ personal characteristics and experiences of completing the in-class task, which include prior knowledge obtained in online learning, collaborative learning self-efficacy, and math self-efficacy. After developing a sense of the task, students set goals and create relevant plans to complete the task. While putting
plans into actions, the student employs various combinations of learning strategies to produce achievements. Help seeking strategy is expected to be especially related to the achievements (e.g. Aleven et al., 2003, 2006). Finally, the student compares the achievement to the previously set goal. If the achievement meets the goal, no further work is needed and the student can move on to the next task; otherwise, further work remains to be done, such as an update of goals and a change of learning strategy.

Figure 5 demonstrates the self-regulated learning process in the in-class collaborative learning environment of the flipped math class. Specifically, prior knowledge obtained in online learning is expected to have a direct effect on students’ in-class achievement. In addition, it is also expected to have an indirect effect on achievement through students’ perceived math and collaborative learning self-efficacy as well as the use of learning strategies. In terms of perceived self-efficacies, they are expected to have direct effects on the in-class achievement and also indirect effects on achievement through the mediating factor – the use of learning strategies. As for the use of learning strategies, it is expected to have a direct effect on in-class achievement.
Summary

In conclusion, the flipped classroom instructional model, normally consisting of pre-class Internet-base and in-class collaborative learning, presents distinct characteristics and creates a more complex and diverse environment for students’ learning. The research in this area has a relatively brief history and mainly focuses on examining the effectiveness of the flipped classroom by comparing it with the traditional face-to-face classroom. With a growing interest in practicing flipped classroom in all levels of education (Goodwin & Miller, 2013), educators are no longer satisfied with the research regarding whether or not the flipped classroom works. They are more concerned with what makes the flipped classroom work and how students learn in the flipped classroom. Moreover, since there are various confounding factors (e.g. instructor’s teaching styles, learning materials, peer interaction) between the flipped and traditional face-to-face classrooms, a lack of consideration of these factors raises concerns of the validity and interpretation of the results.
in those comparative studies. Therefore, to accommodate educators’ current needs and provide more valid results, it is necessary to focus the current flipped classroom research on the examination of how students learn in a flipped class or what factors contribute to students’ success in a flipped class.

While the flipped classroom holds promise for providing personalized learning experience, it also demands more of students (Berrett, 2012; Zhang, Wang, & Zhang, 2012). Especially, the student-centered learning environment requires students to exercise greater control over their learning (Talbert, 2014). To fully take advantage of the opportunities that the flipped classroom offers, students must possess self-regulated learning skills to self-direct, monitor, and evaluate their learning processes in order to achieve active learning outcomes (Estes, Ingram, & Liu, 2014; Talbert, 2014). To understand students’ self-regulated learning process in the flipped classroom environment, Self-regulated Learning (SRL) theory is adopted as the theoretical framework for the current study. In particular, Winne and Hadwin’s (1998, 2008) SRL theory serves as the guiding theory of this study. According to their SRL model, self-regulated learning occurs in four distinct stages: task definition, goal setting and planning, enactment, and adaption. Also, five processes, Condition (C), Operations (O), Products (P), Evaluations (E), and Standards (S), happen in each individual stage.

Winne and Hadwin’s (1998, 2008) SRL model emphasizes the significant effects of the condition and operation processes on the products process. This emphasis is supported by a large number of studies in the field of SRL. Specifically, research has shown that learning achievement is related to prior domain knowledge (e.g. Moos & Azevedo, 2008; Murphy & Alexander, 2002) and self-efficacy (e.g. Pajares, 2008;
Pintrich & Zusho, 2007), which are two constructs in the conditions process. In addition, the use of learning strategies, a construct in the operations process, has also been proven to have a significant influence on academic achievement (e.g. Berger & Karabenick, 2011; Duncan & McKeachie, 2005). Overall, three key constructs – prior domain knowledge, self-efficacy, and the use of learning strategies – have emerged from SRL research demonstrating substantial influences on academic achievement during self-regulated learning.

Besides the direct relationship between academic achievement and these three key constructs, interrelationships also exist among these constructs. First, research has shown that prior domain knowledge has a direct effect on domain-specific self-efficacy (Ferla, Valcke, & Cai, 2009; Rimal, 2001). For example, the more prior math experience a student has, the higher grade he or she would obtain in a math test (Pajares & Miller, 1994). In addition, prior domain knowledge has also been evidenced to influence the use of learning strategies (Moos & Azevedo, 2005, 2008; Murphy & Alexander, 2002; Song, 2011). For instance, students with a higher level prior domain knowledge tend to use more monitor and planning strategies, while students with a lower level prior domain knowledge are more likely to use self-regulation strategy in a hypermedia learning environment (Moos & Azevedo, 2008). Second, research has also shown that self-efficacy is a particularly critical factor affecting students’ use of learning strategy (Crede & Philips, 2011; Diseth, 2011; Greene et al., 2004; Liem, Lau, & Nie, 2008). For example, students’ academic self-efficacy was positively associated with their use of cognitive and metacognitive learning strategy in a correlational study (Pintrich & De Groot, 1990).
Based upon the understanding of the characteristic and structure of the flipped classroom as well as the research regarding the three key constructs, a conceptual model (see Figure 3) is built to investigate students’ self-regulated learning process in a flipped class. Specifically, by applying the conceptual model in the flipped classroom environment, two distinct structural models are proposed to examine the relationships among prior domain knowledge, domain-specific self-efficacy, the use of learning strategies, and academic achievement in both the pre-class Internet-based learning environment (Figure 4) and in-class collaborative learning environment (Figure 5).
Chapter 3: METHODOLOGY

In this chapter, I first present the methodological framework that guided the data collection and analysis in this study and explain the rationale of adopting the quantitative approach for this study. Second, I describe the research purpose and questions of this study. Third, I introduce the context of the research, including the target course, participants, and procedures, and depict each measurement adopted in this study. Last, I describe the process of data collection and data analysis.

Methodological Framework

The quantitative research approach was employed because it can achieve the goal of this study, which is to empirically examine the relationships between students’ self-regulatory constructs and their academic achievement in a flipped classroom, as well as to develop generalizations that contribute to the self-regulated learning theory. Among a variety of quantitative research approaches, survey research and mathematical modeling methods were conducted for the data collection and analysis (Krosnick, 1999).

Survey research refers to a method that “provides a quantitative or numeric description of trends, attitudes, or opinions of a population by studying a sample of that population” (Creswell, 2013, p.145). In reality, it is often impossible to conduct the study on the entire population of interest. Thus, researchers often enact the survey research method to choose a representative sample from the target population and generalize the finding based on the sample to the entire population (Lohr, 2009). In this study the target population are the
people who have experienced the flipped classroom model in higher education. A convenient sample of the population was selected as the representation of the target population, and the research findings based on the sample were generated to the entire population with limitations.

Mathematical modeling is a common method often utilized in the quantitative research approach to generate statistical results (Williams, 2007). Especially, the structural equation modeling method was employed as the primary mathematical modeling method in this study to examine the relationships among three key self-regulatory constructs and students’ academic achievement. More detailed information is described in the data analysis section.

**Research Purpose and Research Questions**

The purpose of this study is to examine the relationships between prior domain knowledge, students’ perceived self-efficacy, the use of learning strategies, and their academic achievement in a large-size undergraduate flipped math course. Specifically, the aim of this study is twofold: (a) first, to conceptualize a self-regulated learning model to explain the relationships of prior domain knowledge, self-efficacy, and the use of learning strategies with academic achievement in the context of the flipped math class; and (b) second, to investigate the relationships between prior domain knowledge, self-efficacy, the use of learning strategies, and academic achievement in both the pre-class Internet-based and in-class collaborative learning environments of the flipped math class.

The following two research questions guided the design of this research.
Question 1: What are the relationships between prior math level, math self-efficacy, Internet self-efficacy, the use of learning strategies, and online achievement in the pre-class Internet-based learning environment?

Question 2: What are the relationships between online achievement, math self-efficacy, collaborative learning self-efficacy, the use of learning strategies, and in-class achievement in the in-class collaborative learning environment?

Research Context

The Target Course

The target courses for this study are the undergraduate flipped Calculus I and Calculus II courses, which are delivered by the Math Department at The Ohio State University. These courses are mainly designed for first- and second-year undergraduate students. Calculus I is one of the largest courses at The Ohio State University because it introduces students from all academic backgrounds to the basic concepts of calculus such as differential and integral calculus. This is a 14-week course that consists of 3 online lessons and 2 recitation sessions per week, with a total 33 online lessons and 28 recitation sessions for the entire semester. The final grade of the course is comprised of six parts: online homework (6.16% of the total grade), recitation participation (3.08% of the total grade), quizzes (6.92% of the total grade), online lessons (6.92% of the final grade), three midterms (46.2% of the total grade), and a final exam (30.8% of the total grade).

Calculus II, the advanced level of Calculus I, promotes a deeper understanding of the theory of calculus and its applications such as the topic regarding sequences and series. The format of the Calculus II course is very similar to the Calculus I course, which is a 14-week course that consists of 35 online lessons and 28 recitation sessions for the entire
semester. The grading schema is exactly the same as the schema in the Calculus I course. Although these two courses focus on different levels of content, they share the same flipped format that includes two types of activities: 1) watching online lessons before attending the relevant recitation and 2) attending recitation by either going to the classroom in person or participating online.

**Prior to the Class – Online Lectures**

Both target courses have their designated course websites in Desire2Learn learning management system, which are open to all registered students. The sample course webpage is demonstrated in Figure 6. Tables of content are listed on the left side of the webpage, and the individual task is listed on the right side of the webpage. In addition, the desired course routine is shown in Figure 7. There are typically three online lessons per week. Students are expected to watch these online lessons and finish online homework on Mondays, Wednesdays, and Fridays and attend the relevant recitations on Tuesdays and Thursdays.
As for the pre-class online lessons, instead of attending lectures in a classroom, students in the target courses are required to watch online interactive lessons streamed...
from the Internet (see Figure 8) prior to class. The online lessons are created by using Articulate Storyline software, which include videos, slides, and questions to help assess students’ understanding of the concepts (see Figure 9). In some places, the lessons also include choices on how much help the student feels he or she needs with a particular topic (see Figure 10). To ensure students working through the assigned online lessons, they have to answer several questions embedded in the lessons (see Figure 11). The questions are automatically graded, and the grades contribute to their online interactive lesson score.

*Figure 8. The first page of an online lecture*
Figure 9. An online lecture slide with an embedded video clip

Figure 10. An online lecture slide with an interactive question
During the Class – Recitation Session

As for the recitation, there are eight sessions of recitation on each Tuesday or Thursday from 8:00 a.m. to 4:10 p.m. Each session lasts 55 minutes, and typically contains around 30 students per class. The recitation is group-work based. In each session, the instructor first spends approximately 10 minutes to go through one or two warm-up examples with the entire class and then breaks up the class into groups. Students form groups on their own, and each group receives a problem handout that group members can work on together to practice the knowledge learned in the previous online lessons. After group discussion on a certain problem, the instructor randomly chooses a group to present their solution to the entire class, provides feedback to the solution, and then moves on to the next problem. The sample group problem is
demonstrated in Figure 12. Students can choose to attend the recitation sessions either online or in person.

![Recitation #3 (September 4) - 2.2: Definition of Limits](image)

**Figure 12.** A sample question for the collaborative activity in a recitation session

Students attend the online recitation session through a program called Carmen Connect. The login page of Carmen Connect is demonstrated in Figure 13. This program is a web-conferencing tool that allows students to talk to other classmates through the computer headset microphone, chat in a text box, and work together on a common workspace on the computer. Students who use this program are also able to see the instructor’s writing on the white board in class and hear them talk as well.

Students attend the in-person recitation session by physically going to the classroom. The classroom setup is favorable for group work. The sample classroom is
demonstrated in Figure 14. The space is designed around pod seating and has three projectors that can allow for presentations or individual group display. Students in such a classroom are able to easily collaborate with peers on solving problems.

Figure 13. The login page of Carmen Connect
Participants

The population of interest for this study are the people who have experienced the flipped classroom instructional model in higher education. In the fall of 2014, two flipped math courses, Calculus I and II, were chosen as the target course for this study. All the registered students in Calculus I \(N=256\) and Calculus II \(N=240\) became the sample population. In the sample, 96 out of 256 students in Calculus I consented to participate in this study, and 76 out of 240 in Calculus II consented to participate, which resulted in 172 students who agreed to participate in this study. Among the consented students, 6 students in Calculus I and 4 students in Calculus II dropped out during the semester. Five students in Calculus I and 6 students in Calculus II consented but did not start the survey.
Therefore, these 21 students were deleted from the dataset, which resulted in total of 151 students who consented and fully or partially completed the survey.

The participants consisted of freshman through seniors who represent a variety of majors throughout the campus. Among the 151 participants, 37 of them missed one or more survey items. The Little Missing Completely Random (MCAR) test was conducted to examine the pattern of the missing data (Cohen et al., 2003). The test indicated that there was weak evidence to suggest an identifiable pattern existed in the missing data (chi-square=48.53, df=36, \( p=0.08 \)). That is, the nature of the missing data was completely random and not systematic. The demographic distribution of these 151 participants appears in Table 1. There were 2 students in Calculus I and 3 students in Calculus II who did not provide any demographic information, which resulted in 2.3% missing data rate for Calculus I and 4.6% missing data rate for Calculus II in the demographic distribution.

As shown in Table 1, genders were evenly distributed among all participants with more female students who participated in Calculus I and more male students who participated in the Calculus II. In terms of race/ethnicity, more than two thirds (68.9%) of the participants were white students, about one fourth (25.2%) were Asian students, and the rest were from other ethnic backgrounds. In terms of grade level, both courses were dominated by freshman and sophomore students. In total, about 85% of all participants were from these two grade levels, and the rest were junior or senior students. In terms of major or academic background, the majority of students were science or biology majors (35.1%), followed by business majors (21.2%) and engineer majors (10.6%). The other majors included agriculture, communication/liberal arts, computer science, and mathematics; undecided took up the rest.
<table>
<thead>
<tr>
<th>Category</th>
<th>Participants</th>
<th>Calculus I</th>
<th>Calculus II</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>%</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>N 86</td>
<td>57.6%</td>
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<td>76</td>
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<td>60.0%</td>
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<tr>
<td>Race</td>
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<td>73.8%</td>
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<tr>
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<td>23.1%</td>
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<td>Asian</td>
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<td>3.1%</td>
<td>9</td>
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<tr>
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<td>43.0%</td>
<td>57.0%</td>
<td>76</td>
</tr>
<tr>
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<td>41.5%</td>
<td>80</td>
</tr>
<tr>
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<td>25.6%</td>
<td>40.0%</td>
<td>48</td>
</tr>
<tr>
<td>Sophomore</td>
<td>N 3</td>
<td>3.5%</td>
<td>10.8%</td>
<td>10</td>
</tr>
<tr>
<td>Junior</td>
<td>N 8</td>
<td>9.3%</td>
<td>7.7%</td>
<td>13</td>
</tr>
<tr>
<td>Senior</td>
<td>N 3</td>
<td>3.5%</td>
<td>10.8%</td>
<td>13</td>
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<tr>
<td><strong>Major</strong></td>
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<td>0.0%</td>
<td>3</td>
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<td>26.7%</td>
<td>13.8%</td>
<td>32</td>
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<tr>
<td>Business</td>
<td>N 9</td>
<td>10.5%</td>
<td>3.1%</td>
<td>11</td>
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<tr>
<td>Communication/Liberal Arts</td>
<td>N 7</td>
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<td>6.2%</td>
<td>16</td>
</tr>
<tr>
<td>Computer Science</td>
<td>N 8</td>
<td>9.3%</td>
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</tr>
<tr>
<td>Engineer</td>
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<td>9.2%</td>
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<tr>
<td>Mathematics</td>
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<tr>
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<td>10.8%</td>
<td>13</td>
</tr>
<tr>
<td>Undecided</td>
<td>N 3</td>
<td>3.5%</td>
<td>0.0%</td>
<td>3</td>
</tr>
</tbody>
</table>
Procedures

Two major procedures were used to recruit participants and deliver surveys for data collection. One was conducted prior to the study, and the other was conducted during the study. Detailed processes are described as follows.

Prior to the study

Visits of the classrooms of Calculus I and II courses provided student recruits. Four approaches were employed to recruit participants in these two courses. First, on the 2nd week of the fall semester in 2014, a news item was posted on each course’s course website by the course instructor, which contained a brief introduction of the researcher and the research study, as well as an expression of gratitude for participation. Second, on the 3rd week, the researcher went into each flipped session of these two courses and spent 5 minutes at beginning of the class to briefly introduce the research purpose and recruit participants. Third, two recruitment emails were sent to all students at the 3rd and 10th week of the semester respectively. Last, the instructors helped to send two other reminder emails to encourage participation.

During the study

Two online survey links were sent to all registered students in Calculus I and II through OSU email at the 3rd and 10th weeks of the semester. Participants provided their consent by clicking the “Agree” button on an informed consent form that appeared on the first page of the online survey (see Appendix A). Each survey took students approximately 5 to 10 minutes to complete, and each survey was kept active for three weeks in order to provide enough time for students to participate in the study. The participation was completely voluntary. However, those who completed both surveys
would be entered into a raffle for winning a 16GB Apple iPad mini. The prize winner was notified the last week of the semester through OSU email.

Measurement Instruments

Prior Math Knowledge

Prior domain knowledge is defined as conceptual understanding of a certain domain, which integrates declarative, procedural, and inferential knowledge (Chi, 2000, 2005). Two measures of this construct are commonly seen among research studies. One is the pre-test measure (Moos & Azevedo, 2005; Murphy & Alexander, 2002). The other is the generic measure, such as prior social studies grade (Zimmerman, Bandura, & Martinez-Pons, 1992), prior math experience (Pajares & Miller, 1994), and previously assessed writing aptitude (Pajares & Johnson, 1996).

In terms of prior math knowledge for pre-class Internet-based learning, since this is a quasi-experimental study, the authentic research condition does not allow the researcher to do a pre-test to measure students’ prior math level before learning online lessons. Thus, the generic measure method is used to measure students’ prior math knowledge. Based on the experiences of the class instructor, the item “What was the highest level of mathematics you took prior to college?” is chosen as an appropriate survey item for measuring students’ prior math level, which serves as the indicator of prior math knowledge for pre-class learning. This item with other basic demographic information appeared at the beginning of the survey that was delivered at the 3rd week of the semester (see Appendix B).

In terms of prior math knowledge for in-class collaborative learning, the pre-class online homework score was chosen as the indicator of the prior domain knowledge for in-
class collaborative learning. Since students were required to complete online lessons and associated homework before attending relevant recitation sessions, students’ in-class achievements are, therefore, predicted by their pre-class achievements.

**Self-Efficacy Measures**

Self-efficacy is “people’s judgments of their capabilities to organize and execute courses of action required to attain designated types of performances” (Bandura, 1986, p. 391). This core belief is the foundation of human agency (Bandura, 2002). It determines whether coping action will be initiated, how much effort to be expended, how long to persevere in the face of adversity and failure, and how many accomplishments will be achieved (Bandura, 1977).

Research has shown that to increase accuracy of prediction, self-efficacy should be measured at the optimal level of specialty, which corresponds to the outcome criterion being compared with (Bandura, 1986; Pajares, 1996). The present study is interested in examining three learning outcomes: mathematical outcome, pre-class Internet-based learning outcome, and in-class collaborative learning outcome. Thus, corresponding domain-specific self-efficacies are measured.

**Math Self-Efficacy (MSE)**

Math Self-Efficacy (MSE) is “a situational or problem-specific assessment of an individual’s confidence in her or his ability to successfully perform or accomplish a particular [mathematical] task or problem” (Hackett & Betz, 1989, p. 262). Students with higher MSE persist longer facing difficult math problems and are more accurate in math computation than are those with low MSE (Hoffman & Schraw, 2009).
In this study, MSE is measured by 5 items, which are adjusted based on the self-efficacy subscale of Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991). The Self-efficacy subscale in MSLQ measures people’s expectancy for success in a certain domain, their judgments of one’s ability to accomplish a task, as well as their confidence in one’s skills to perform a task (Duncan & McKeachie, 2005). Previous research has shown this subscale is a highly valid and reliable scale for measuring students’ self-efficacy, and measured scores are significantly related to various learning outcomes such as writing (Zimmerman, & Bandura, 1994), statistics (Bandalos, Finney, & Geske, 2003), as well as science and English (Pintrich & De Groot, 1990). In this study, the original MSLQ self-efficacy items were modified to fit to the mathematical curriculum. The modified MSLQ asked participants to rate their agreement to 5 statements about the level of confidence of learning math on a 7-point Likert scale that ranges from 1 (not true at all) to 7(very true) (Appendix C). A Sample item is “I’m confident I can understand the basic concepts taught in math.” This scale was delivered in the first online survey at the 3rd week of the semester.

**Internet Self-Efficacy (ISE)**

Internet self-efficacy (ISE) is denoted as students’ perceived capability of organizing and executing courses of Internet actions required to produce given attainments (Tsai et al., 2011). In this study, we are interested in investigating individuals’ decision processes during pre-class Internet-based learning such as how to learn the assigned materials, how much to learn, how much time to spend on it, what extra materials need to learn, how to understand them, when to abandon or modify plans and strategies, and when to increase effort (Azevedo & Cromley, 2004; Moos &
Azevedo, 2009). According to Kim and Glassman (2013), these decision-making processes can be categorized into the knowledge differentiation domain of ISE. Therefore, the ISE measurement in this study is adjusted based on Kim and Glassman’s (2013) Internet Self-Efficacy (ISS) scale.

ISS scale published by Kim and Glassman (2013) measures the degree to which students view themselves as capable of using the Internet to learn content from five self-efficacy domains, including search, communication, organization, differentiation, and generation dimension. Since the ISS scale is closely aligned with Bandura’s self-efficacy theory, and all subscale of ISS have high reliability with Cronbach’s alpha .91, .88, .89, .82, and .89 respectively (Kim & Glassman, 2013), it serves as the main reference for creating the Internet Self-Efficacy (ISE) scale for this study. Since this study is interested in the students’ perception of using the Internet to organize and differentiate knowledge, the organization and differentiation subscales of the ISS were adopted form the original scale. The modified ISE asked participants to rate their agreement to 8 statements about the level of confidence of using the Internet to organize and differentiate knowledge on a 7-point Likert scale that ranges from 1 (not true at all) to 7 (very true) (Appendix C). A sample item is “I can improve my performance through information gained from Youtube or online videos.” This scale was delivered in the first online survey at the 3rd week of the semester.

**Collaborative Learning Self-Efficacy (CLES)**

The concept of Collaborative Learning Self-Efficacy (CLSE) has not been widely studied yet. Within Bandura’s (1997) self-efficacy framework, CLSE can be defined as an individual’s beliefs in his or her ability to succeed in collaborative learning activities.
As with MSE, the CLSE measurement in this study was modified based on the self-efficacy scale of MSLQ (Pintrich et al., 1991). The modified MSLQ asked participants to rate their agreement to 5 statements about the level of confidence in doing collaborative learning tasks on a 7-point Likert scale that ranges from 1 (not true at all) to 7(very true) (Appendix D). A sample item is “I believe I can do well in the in-class group learning.” This scale was delivered in the second online survey at the 10th week of the semester.

**Learning Strategies**

Self-regulated learning strategy has been defined as a set of metacognitive, motivational, and behavioral techniques that a learner can use to pursue knowledge and skills (Zimmerman, 1989, 1990; Zimmerman & Martinez-Pons, 1986). The goal of using any particular learning strategy is either to affect learners’ motivational or affective state or to help learners select, acquire, organize, or integrate new knowledge (Entwistle, 1988).

There is a 23-item learning strategy subscale included in MSLQ, which is divided into three categories: cognitive, metacognitive, and resource management strategy. Cognitive strategy involves learners’ use of basic and complex strategies for the processing of information from texts and lectures such as repeating words, paraphrasing, summarizing, outlining, and critical thinking. Metacognitive strategy is concerned with learners’ use of strategies to monitor and regulate their cognitive behaviors such as setting goals, monitoring the comprehension, and regulating their learning behaviors. Resource management strategy refers to learners’ regulatory strategies for controlling other resources besides their own cognition such as effectively using time, regulating efforts in the face of obstacles, and seeking help from peers or instructors when needed.
Extensive research has shown that the learning strategy subscale in MSLQ is a valid and reliable scale (i.e. Berger & Karabenick, 2011; Pintrich & De Groot, 1990). Therefore, this scale is adapted to measure students’ use of learning strategies in present study.

All 23 items in the learning strategy scale were adopted and reworded for the pre-class Internet-based learning environment. Since in-class collaborative activities did not allow students to personalize their learning space and time during class, the 3 items related to time and space management strategy were eliminated from the learning strategy scale for the in-class collaborative learning environment, which resulted in a 20-item scale. The modified learning strategy scales asked participants to rate their agreement to the statement about the level of truthfulness of using a certain learning strategy on a 7-point Likert scale that ranges from 1 (not true at all) to 7(very true) (Appendix D). A sample item adjusted for the pre-class Internet-based learning environment is “While I'm studying the pre-class online math materials, I go over the formulas or definitions in order to memorize them.” A sample item adjusted for the in-class collaborative learning environment is “When I'm studying in the recitation session, I go over the formulas or definitions in order to memorize them.”

**Learning outcomes**

Consented students’ grade data was retrieved from the instructors after the fall 2014 semester ended. The grade data included three midterm scores, online homework scores, take-home assignment scores, and final exam scores. As I described in the target course section, students in both Calculus I and II were required to first watch online lectures and complete online homework before going to face-to-face recitation sessions.
Therefore, the online homework score consisting of the lecture completeness score and online quiz score was considered as the indicator of students’ online learning outcome. As for the in-class learning outcome, the take-home quiz served as the indicator because students were asked to complete a take-home quiz after the recitation session to demonstrate their mastery of in-class learning.

**Coding Schema**

All the responses will be coded starting from 1 to the number of options in the question based on the order of the options. For example, for question gender, two options are ordered as male and female. Thus, male will be coded as 1, and female will be coded as 2. As for the question with seven options ordered as “not true at all to very true,” the “not true at all” will be coded as 1 and the “very true” option will be coded as 7.

**Data Analysis**

*Exploratory factor analysis*

Exploratory factor analysis (EFA) is used to explore number factors and the relations of observed variables with these factors (Lomax & Hahs-Vaughn, 2013). The EFA approach seeks to find a model to fit the data. It is commonly used when developing a new scale and serves to identify a set of latent constructs underlying a battery of measured variables (Fabrigar, Wegener, MacCallum, & Strahan, 1999). In the present study, ISE was adjusted to the specific context of this flipped math class based on ISS that has not been widely validated in other empirical studies. Therefore, ISE was considered as a newly established scale, and its validity needed to be reexamined by conducting EFA. The software AMOS 22 was employed to perform EFA (Arbuckle, 2013).
**Confirmatory factor analysis**

Confirmatory factor analysis (CFA) is used to confirm that a set of observed data defines certain factors (Lomax & Hahs-Vaughn, 2013). The CFA approach seeks to statistically test the significance of a hypothesized factor model that is whether the observed data confirms the model. The hypothesized model is often built upon theories or literatures. If the additional sample of data fits the model, the validity of the hypothesized model would be further confirmed (Byrne, 2013). In the present study, MSE, CLSE, and learning strategies scales are adjusted based on corresponding subscales in MSLQ. It is known that MSLQ is grounded in motivation and cognitive theory and has been repeatedly validated in a variety of research studies (Berger & Karabenick, 2011; Pintrich & De Groot, 1990; Pintrich, et al., 1993). Therefore, CFA was conducted to assess the validity of these three scales. The software AMOS 22 was employed to perform the CFA (Arbuckle, 2013).

**Structural Equation Modeling**

Structural Equation Modeling was the primary method used for data analysis. Specifically, it was employed to answer research questions 1 and 2. SEM analysis was conducted by using AMOS 22 (Arbuckle, 2013).

**Rational of Using SEM**

Lomax & Hahs-Vaughn (2012) defined SEM as the mixture of a confirmatory factor analysis (CFA) and path analysis (PA). It is known that CFA focuses on the construction of unobserved variables (factors) by observed variables, whereas PA focuses on assessing the relations among observed variables (Lomax & Hahs-Vaughn, 2013). SEM, taking advantages of these two approaches, is capable of measuring the relations of
both observed and unobserved variables with the consideration of measurement error. In this study, two research questions contained both observed (i.e. prior domain knowledge and learning achievement) and unobserved (self-efficacy and use of learning strategy) variables. Thus, the SEM approach was an appropriate method to answer these two questions.

In addition, SEM can measure both direct and indirect effects of exogenous (predictor) and endogenous (outcome) variables simultaneously (Ullman, 2007). Considering the goal of this study was to examine the direct and indirect effects of students’ prior domain knowledge, self-efficacy, and the use of learning strategies on their academic achievement, SEM was an appropriate method to reach this goal.

Missing Data

Among many possible approaches dealing with missing data in SEM, this study adopted Full Information Maximum Likelihood (FIML) estimation. The FIML estimation refers to the parameter estimation approach maximizing the likelihood of extracting data from the population by borrowing the information from the observed proportion of the data (Enders & Bandalos, 2001). It has been evidenced as a superior method for dealing with missing data compared to other methods. Enders & Bandalos (2001) did a Monte Carlo simulation study that compared FIML with the other three missing data methods. Results showed that FIML estimates were unbiased and more effective, and the FIML method yielded the lowest proportion of convergence failures and provided near-optimal Type I error rates across the simulation. Therefore, FIML was an outstanding method to deal with the missing data in SEM.
Steps of Conducting SEM

Kline (2005) recommended five basic steps of SEM: (1) model specification; (2) model identification; (3) data preparation and screening; (4) estimation of the model; and (5) model re-specification.

(1) Model Specification: This is the primary step, in which relations among interested variables are postulated based on theories or literatures. In this study, this step was completed after the review of literatures, and the initial structural models were postulated at the end of Chapter 2. As shown in Figure 4 and 5, the hypothesized models have been proposed based on self-regulation theory and relevant literatures. In Figure 4, the prior math level was the exogenous variable (predictor), and the rest were endogenous variables (outcome). In Figure 5, the online quiz was the exogenous variable (predictor), and the rest were endogenous variables (outcome).

(2) Model Identification: This step examined whether or not the models can be theoretically identified as a unique estimate of every model parameter. Without this step, further steps cannot proceed.

(3) Data preparation and screening: After data collection, a one-way analysis of variance (ANOVA) was conducted to examine the difference of all endogenous variables (e.g. math self-efficacy, use of learning strategy, online quiz, and homework). No significant difference of these endogenous variables allows for combining the data of two flipped courses: Calculus I and II. Also, missing data, normality, and outliers were further tested prior to further analysis. Detailed results of data preparation and screening appear in Chapter 4.
(4) Estimation of the model: a goodness-of-fit index indicates how well a model can reproduce the data (Markus, 2012). In this study, I reported two levels: overall model fit assessment and component fit assessment. For overall model fit assessment, this study reported the examined chi-square with degree of freedom ($df$), and the Root Mean Square Error of Approximation (RMSEA) with its 90% confidence interval. For the comparative fit assessment, this study reported the Comparative Fit Index (CFI) and TFL (Hu & Bentler, 1999). Table 2 summarizes these fit indices and their criteria (Lomax & Hahs-Vaughn, 2013).

(5) After overall model fit was satisfied, component fit would be examined. This study reported standardized regression weights, t-statistics, and p-value of the t-statistics. If the p-value of a parameter estimate is less than .05, this would indicate a significant parameter (Byne, 2013). If the overall model fit was not satisfied, model respecification would be conducted to rebuild another hypothesized model based on theories and literatures.

Table 2. Recommended Model Fit Indices and Criteria

<table>
<thead>
<tr>
<th>Model Fit Indices</th>
<th>Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-square/df</td>
<td>&lt;2</td>
</tr>
<tr>
<td>RMSEA</td>
<td>Equal to or less than .06</td>
</tr>
<tr>
<td>TFL</td>
<td>Equal to or greater than .90</td>
</tr>
<tr>
<td>CFI</td>
<td>Equal to or greater than .95</td>
</tr>
</tbody>
</table>
Chapter 4: RESULTS

The purpose of this study was to examine the relationships among prior domain knowledge, students’ perceived self-efficacy, the use of learning strategies, and their academic achievement in a large-size undergraduate flipped math course. Specifically, the aim of this study was twofold: (a) first, to conceptualize a self-regulated learning model to explain the relationships of prior domain knowledge, self-efficacy, and the use of learning strategies with academic achievement in the context of the flipped math class; and (b) second, to investigate the relationships among prior domain knowledge, self-efficacy, the use of learning strategies, and academic achievement in both the pre-class Internet-based and in-class collaborative learning environments of the flipped math class.

This study investigated the following two research questions based on the hypothesized structural models for the pre-class Internet-based and in-class collaborative learning environments of the flipped classroom (see Figure 4 and 5), which were the following:

Question 1: What are the relationships between prior math level, math self-efficacy, Internet self-efficacy, the use of learning strategies, and online achievement in the pre-class Internet-based learning environment?

Question 2: What are the relationships between online achievement, math self-efficacy, collaborative learning self-efficacy, the use of learning strategies, and in-class the achievement in in-class collaborative learning environment?
In this chapter, I first present the factor analyses including exploratory factor analysis conducted on Internet self-efficacy (ISE), and confirmatory factor analysis conducted on the rest scales including math self-efficacy (MSE), collaborative learning self-efficacy (CLSE), and use of learning strategy. Second, I describe the structural equation modeling (SEM) analysis process in terms of data preparation and screening and model fitting. Last, I interpret the results based on the SEM model fitting indexes.

**Exploratory Factor Analysis**

An exploratory factor analysis (EFA) was conducted to examine the number of factors of adjusted Internet self-efficacy (ISE) scale. In total, 142 responses were available for this analysis.

Initially, all 8 items were examined. Several well-recognized criteria were used as the guidance for this EFA (Williams, Brown, & Onsman, 2012). First, all correlations among 8 items were significant at alpha .05 level, and the correlation coefficients were all above .30 except item 4 and 7, suggesting reasonable factorability. Second, the Kaiser-Meyer-Olkin measure of sampling adequacy was .84, above the recommended value of .60, indicating the sample size is adequate for factor analysis. Bartlett’s test of sphericity was significant \( \chi^2 (28) = 643.65, p < .05 \), implying there are relationships between variables. The diagonals of the anti-image correlation matrix were all over .50, supporting the inclusion of each item in the factor analysis. Finally, the communalities were all above .60 (see Table 3), further confirming that each item shared great variance with other items. Given these overall indicators, factor analysis was conducted on all 8 items.
The Principal Component Analysis (PCA) extraction method was used because the primary purpose was to identify and compute composite coping scores for the factors underlying the ISE scale. Oblimin rotation method was used since if there were more than one variable of this scale, they would be correlated with each other to some extent. The initial run of PCA extracted two factors. The initial eigen values showed that the first factor explained 56.36% of the variance and the second factor explained 15.04% of the variance. The factor loading matrix of the oblimin solution was presented in Table 3. The table showed that all items had primary loadings at least .70. Although the cross-variable loading of all items were at least .29, their strong primary factor loadings suggest that we should keep all items in the scale.

Factor labels – Knowledge Differentiation and Knowledge Sharing – were proposed based on the Initial Kim and Glassman’s (2013) Internet self-efficacy scale on which this scale was based. Composite scores were created for these two factors. The mean, standard deviation, distribution indices, internal reliability (Cronbach’s alpha) were presented in Table 4.

Overall, this EFA analysis indicated that two distinct factors were underlying students’ responses to the Internet Self-efficacy scale. These factors have relatively high reliability, indicating the survey items were internally consistent. The skewness and kurtosis of these two factors were within the range of -3 to 3, providing an evidence for an approximate normal distribution. Therefore, the data were suited for the following structural equation modeling analysis.
Table 3. *Exploratory Factor Analysis Summary for the Adjusted Internet Self-efficacy Scale (N=142)*

<table>
<thead>
<tr>
<th>Survey Items</th>
<th>Component</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. I can improve my performance through information gained from Youtube or</td>
<td>Knowledge Differentiation: .86  Knowledge Sharing: .74</td>
</tr>
<tr>
<td>online videos.</td>
<td></td>
</tr>
<tr>
<td>2. I can use the Internet to answer my own questions about this class to</td>
<td>Knowledge Differentiation: .80  Knowledge Sharing: .63</td>
</tr>
<tr>
<td>achieve a correct answer.</td>
<td></td>
</tr>
<tr>
<td>3. I can use Youtube or online videos to find information that is</td>
<td>Knowledge Differentiation: .84  Knowledge Sharing: .70</td>
</tr>
<tr>
<td>important to this class.</td>
<td></td>
</tr>
<tr>
<td>5. I can use the Internet to answer questions posed by this class to get a</td>
<td>Knowledge Differentiation: .78  Knowledge Sharing: .62</td>
</tr>
<tr>
<td>correct answer.</td>
<td></td>
</tr>
<tr>
<td>6. I can use Youtube or online videos to find information that is</td>
<td>Knowledge Differentiation: .82  Knowledge Sharing: .67</td>
</tr>
<tr>
<td>important to me.</td>
<td></td>
</tr>
<tr>
<td>8. I can organize information find on the Internet so that it is coherent</td>
<td>Knowledge Differentiation: .79  Knowledge Sharing: .62</td>
</tr>
<tr>
<td>and answers specific questions.</td>
<td></td>
</tr>
<tr>
<td>7. I can improve others' performance in this class by sharing information</td>
<td>Knowledge Differentiation: .93  Knowledge Sharing: .87</td>
</tr>
<tr>
<td>on Piazza.</td>
<td></td>
</tr>
<tr>
<td>4. I can improve my own performance in this class by sharing information</td>
<td>Knowledge Differentiation: .92  Knowledge Sharing: .86</td>
</tr>
<tr>
<td>on Piazza.</td>
<td></td>
</tr>
</tbody>
</table>

*Extraction Method: Principal Component Analysis.*  
*Rotation Method: Oblimin with Kaiser Normalization.*
Table 4. Descriptive Statistics for the Two Internet Self-efficacy Factors (N=149)

<table>
<thead>
<tr>
<th>Factor Label</th>
<th># of items</th>
<th>M(SD)</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge Differentiation</td>
<td>6</td>
<td>5.50 (1.12)</td>
<td>-.97</td>
<td>1.65</td>
<td>.89</td>
</tr>
<tr>
<td>Knowledge Sharing</td>
<td>2</td>
<td>4.22 (1.55)</td>
<td>-.04</td>
<td>-.53</td>
<td>.84</td>
</tr>
</tbody>
</table>

**Confirmatory Factor Analysis**

Two confirmatory factor analyses (CFA) were conducted to analyze the pre-class and in-class measurement models. The analyses were based on these models’ covariance matrix and Full Information Maximum Likelihood (FIML) estimation was implemented in AMOS 22 (Arbuckle, 2013).

**The pre-class Internet-based measurement model**

CFA was first run on all 26 survey items. The initial measurement model yielded an adequate model fit to the data (see the model fit indices in Table 4-3). Also, four items whose factor loadings were below .60: RM_Q4_Pre (.50), Meta_Q9_Pre (.54), Cog_Q2_Pre (.56), and Cog_Q5_Pre (.57). According to the rule of thumb that a given sample size is around 150, items whose factor loadings below .60 are suggested to be eliminated from the scale. Therefore, these four items were deleted, and CFA was re-run on the remaining 22 items. The reduced measurement model provided a great model fit to the data (see Table 5), and all items’ factor loadings were above .60, indicating this reduced measurement model fits the data very well and is suitable for the following SEM analysis.

The factor loadings and measurement error variances of the reduced measurement model were presented in Appendix E. All path estimates of each observed variable
(survey item) to underlying latent variables (factors) were statistically significant at the .001 level, indicating all survey items are significant indicators of this reduced measurement model.

<table>
<thead>
<tr>
<th>Model</th>
<th># of items</th>
<th>$\chi^2$/df</th>
<th>CFI</th>
<th>TFL</th>
<th>RMSEA</th>
<th>90% CI of RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Model</td>
<td>26</td>
<td>1.632</td>
<td>.911</td>
<td>.885</td>
<td>.065</td>
<td>(.054; .076)</td>
</tr>
<tr>
<td>Reduced Model</td>
<td>22</td>
<td>1.385</td>
<td>.956</td>
<td>.942</td>
<td>.051</td>
<td>(.035; .065)</td>
</tr>
</tbody>
</table>

The In-class Collaborative Measurement Model

The same procedures were implemented on the in-class collaborative measurement model. CFA was first run on all 29 survey items. The initial measurement model yielded a great model fit to the data (see model fit indices in Table 6). However, two items whose factor loadings were below .60: Cog_Q2_In (.57) and RM_Q1_In (.58). According to the rule-of-thumb of factor loadings of CFA, these two items were eliminated from the scales. CFA was then rerun on the remaining 27 survey items. There was slightly improvement in the model fit indices of the reduced model (as shown in Table 6). Overall, the reduced measurement model provided a great model fit to the data, and all items’ factor loadings were above .60, indicating this reduced measurement model fits the data very well and is suitable for the following SEM analysis.

The factor loadings and measurement error variances of the reduced measurement model were presented in Appendix F. All path estimates of each observed variable.
(survey item) to underlying latent variables (factors) were statistically significant at the .001 level, indicating all survey items are significant indicators of this reduced measurement model.

Table 6. Model Fit Indices of the Initial and Reduced In-class Measurement Model (N=151)

<table>
<thead>
<tr>
<th>Model</th>
<th># of items</th>
<th>$\chi^2$/df</th>
<th>CFI</th>
<th>TFL</th>
<th>RMSEA</th>
<th>90% CI of RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Model</td>
<td>29</td>
<td>1.580</td>
<td>.925</td>
<td>.905</td>
<td>.062</td>
<td>(.054; .071)</td>
</tr>
<tr>
<td>Reduced Model</td>
<td>27</td>
<td>1.583</td>
<td>.930</td>
<td>.911</td>
<td>.062</td>
<td>(.053; .071)</td>
</tr>
</tbody>
</table>

Structural Equation Modeling

Data Preparation

The comparison between two math courses allowed for combining the data from Calculus I and the data from Calculus II. One-way analysis of variance (ANOVA) showed that there were no significant differences between these two courses regarding all the endogenous variables: math self-efficacy [$F(1, 149)=.896, p=.345$], collaborative learning self-efficacy [$F(1, 149)=.403, p=.527$], knowledge differentiation [$F(1, 147)=1.513, p=.221$], knowledge sharing [$F(1, 147)=.494, p=.483$], pre-class cognitive strategy [$F(1, 112)=.106, p=.746$], pre-class metacognitive strategy [$F(1, 12)=.000, p=.994$], pre-class help seeking strategy [$F(1, 111)=2.705, p=.103$], pre-class environmental control strategy [$F(1, 112)=.304, p=.583$], in-class cognitive strategy [$F(1, 112)=.295, p=.588$], in-class metacognitive strategy [$F(1, 110)=1.834, p=.178$], in-class group learning strategy [$F(1, 110)=2.410, p=.123$]. The detailed descriptive statistics of
these endogenous factors of two courses and the ANOVA results were summarized in Appendix G.

**Data Screening**

Data screening examined outliers, normality, multicollinearity, and reliability of measures. Table 7 shows the mean, standard deviation, distribution information, and Cronbach’s alpha of measures after combining two courses’ data.

First, outliers and normality of measures were examined. As shown in Table 7, all variables range within 3 standard deviations from the mean of the variable, supporting that no univariate outlier exists. With respect to normality, Kline (2005) suggested using absolute cut-off values of 3.0 for skewness and 8.0 for kurtosis. Table 7 shows that all measures were well within these ranges (ranging from -.970 to -.044 for skewness and from -.532 to 1.649 for kurtosis), indicating all measures largely follow the normal distribution.

Second, the multicollinearity was checked in two ways. First of all, zero-order correlation coefficients of predictor variables in structural models were examined by eyeballing (see Table 8). Kaplan (1994) proposed a general diagnostic rule for the multicollinearity in structural educational models: multicollinearity is extreme when the correlation coefficient is around 0.95; it could be substantial when the coefficient is between 0.6 and 0.8; and it could be negligible when the coefficient is between 0.4 and 0.5. Please note that only the correlation coefficients of predictor variables included in the same structural model were examined. For example, although the correlation coefficient was .90 between pre-class cognitive strategy and in-class cognitive strategy, these two predictor variables belonged to two different structural models. Therefore, the
high coefficient, 0.9, is negligible in this step’s examination. Second, if the correlation coefficient of predictor variables in the same structural model is above 0.6, a collinearity test was performed to statistically examine the multicollinearity based on the rules-of-thumb for Variance Inflation Factors (VIF) and tolerance. The VIF and tolerance are “both widely used measures of the degree of multicollinearity of the \( i \)th independent variable with other independent variables in a regression model” (O’Berien, 2007, p.673). The most common rule of thumb of VIF and tolerance is 10. Many practitioners believe that when VIF and tolerance reaches 10, the threshold value, there is a severe or serious multi-collinearity issue in the structural equation model.

In this study, the correlation table (Table 8) demonstrated two substantial correlation coefficients in pre-class structural model: 0.59 (coefficient between pre-class cognitive and pre-class metacognitive strategies) and 0.65 (coefficient between pre-class environmental control and pre-class metacognitive strategies). It also demonstrated one substantial correlation coefficient in in-class structural model: 0.67 (coefficient between in-class cognitive and in-class metacognitive strategies). By conducting collinearity test in SPSS 22.0 (IBM Corp, 2013), no statistically significant multicollinearity issue was detected among these predictor variables based on the rules of thumb of VIF and tolerance. The results of VIF and tolerance of predictor variables in both structural models are presented in Table 9.

Finally, the internal consistency or reliability of measures was examined by checking the Cronbach’s alpha. Cronbach (1951) suggested that the alpha value between .70 to .90 indicates good reliability and larger than .90 indicates excellent reliability. As
shown in the last column of Table 7, all measures’ alpha values were at least .75, indicating all measures are fairly reliable.

In sum, the data collected from 151 participants satisfied all three key examinations of SEM, thus, further analyses were conducted with this data.

Table 7. *Descriptive Statistics and Reliability Coefficients for Measured Variables*

<table>
<thead>
<tr>
<th>Measures</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Skewness (SE)</th>
<th>Kurtosis (SE)</th>
<th>Min</th>
<th>Max</th>
<th>alpha</th>
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<tbody>
<tr>
<td>Math self-efficacy</td>
<td>151</td>
<td>4.816</td>
<td>1.487</td>
<td>-.703 (.197)</td>
<td>-.089 (.392)</td>
<td>1</td>
<td>7</td>
<td>.93</td>
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<td>Collaborative Learning</td>
<td>151</td>
<td>4.578</td>
<td>1.483</td>
<td>-.439 (.197)</td>
<td>-.303 (.392)</td>
<td>1</td>
<td>7</td>
<td>.93</td>
</tr>
<tr>
<td>Self-efficacy</td>
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<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Knowledge Differentation</td>
<td>149</td>
<td>5.503</td>
<td>1.121</td>
<td>-.970 (.199)</td>
<td>1.649 (.395)</td>
<td>1</td>
<td>7</td>
<td>.89</td>
</tr>
<tr>
<td>Knowledge Sharing</td>
<td>149</td>
<td>4.225</td>
<td>1.553</td>
<td>-.044 (.199)</td>
<td>-.532 (.395)</td>
<td>1</td>
<td>7</td>
<td>.84</td>
</tr>
<tr>
<td>Cognition_Pre-Class</td>
<td>114</td>
<td>4.566</td>
<td>1.444</td>
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<td>-.370 (.449)</td>
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<td>.75</td>
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<td>Metacognition_Pre-Class</td>
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<td>4.721</td>
<td>1.193</td>
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<td>HelpSeeking_Pre Class</td>
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<td>EnvControl_Pre Class</td>
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<tr>
<td>Cognition_In Class</td>
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<td>Metacognition_In Class</td>
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<td>.93</td>
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<td>GroupLearning_In Class</td>
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<td>.326 (.453)</td>
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<td>7</td>
<td>.91</td>
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Table 8. Correlation Coefficients for All Variables in Both Pre-class and In-class Structural Models

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<th>2</th>
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<td>MSE</td>
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<td>Diff.</td>
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<td>Sharing</td>
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<td>.44**</td>
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<td>CLSE</td>
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<td>.40**</td>
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<tr>
<td>Cog_Pre</td>
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<td>.08</td>
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<td>.33**</td>
<td>-</td>
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<td>Meta_Pre</td>
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<td>-</td>
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<tr>
<td>HS_Pre</td>
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<td>-.18</td>
<td>.13</td>
<td>.20**</td>
<td>.37**</td>
<td>.43**</td>
<td>-</td>
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<tr>
<td>EC_Pre</td>
<td>.22*</td>
<td>.03</td>
<td>.13</td>
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<td>.47**</td>
<td>.65**</td>
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<td>Cog_In</td>
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<td>.34**</td>
<td>.51**</td>
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<td>.70**</td>
<td>.38**</td>
<td>.50**</td>
<td>-</td>
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<tr>
<td>Meta_In</td>
<td>.34**</td>
<td>.11</td>
<td>.29**</td>
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<td>.78**</td>
<td>.43**</td>
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<td>HS_In</td>
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<td>-.08</td>
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<td>.07</td>
<td>-.08</td>
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<td>-.03</td>
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<td>Quiz</td>
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<td>.11</td>
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<td>.21**</td>
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<td>.25**</td>
<td>.26**</td>
<td>.17</td>
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<td>.24*</td>
<td>.16</td>
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<td>Tkhome</td>
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<td>.08</td>
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<td>.07</td>
<td>.25**</td>
<td>.40**</td>
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<td>.15</td>
<td>.24**</td>
<td>.28**</td>
<td>.14</td>
<td>.49**</td>
<td>-</td>
</tr>
</tbody>
</table>

Note 1: *p < .01, **p < .001

Note 2: MSE= Math Self-efficacy; Diff= Knowledge Differentiation; Sharing= Knowledge Sharing; CLSE= Collaborative Learning Self-efficacy; Cog_Pre= Pre-class cognitive learning strategy; Meta_Pre= Pre-class metacognitive learning strategy; HS_Pre= Pre-class help seeking learning strategy; EC_Pre = Pre-class environmental control learning strategy; Cog_In= In-class cognitive learning strategy; Meta_In= In-class metacognitive learning strategy; HS_In= In-class help seeking learning strategy; Prior= Prior math level; Quiz= Online quiz score; Tkhome= Take home assignment score after recitation sessions.
Table 9. Collinearity Test for Selected Measured Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Cog_Pre</th>
<th>MetaCog_Pre</th>
<th>EC_Pre</th>
<th>Cog_In</th>
<th>MetaCog_In</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIF</td>
<td>1.564</td>
<td>2.130</td>
<td>1.772</td>
<td>1.853</td>
<td>1.987</td>
</tr>
<tr>
<td>Tolerance</td>
<td>.640</td>
<td>.470</td>
<td>.564</td>
<td>.540</td>
<td>.503</td>
</tr>
</tbody>
</table>

*Note:* Cog_Pre= Pre-class cognitive learning strategy; Meta_Pre= Pre-class metacognitive learning strategy; EC_Pre = Pre-class environmental control learning strategy; Cog_In= In-class cognitive learning strategy; Meta_In= In-class metacognitive learning strategy;

**Structural Equation Modeling Analysis**

*Pre-class Internet-based Structural Model*

The initial pre-class structural model resulted in a moderate to good fit, $\chi^2$/df=1.59 smaller than 2, CFI=.90 close to .95, RMSEA=.06 equal to .60. However, nonsignificant paths were observed between the prior math level and the two domains of Internet self-efficacy (Prior math level → Knowledge differentiation; Prior math level → Knowledge sharing), between the prior math level and the four domains of learning strategies (Prior math level → Cognitive strategy; Prior math level → Metacognitive strategy; Prior math level → Help seeking strategy; Prior math level → Environmental control strategy), as well as between the prior math level and online achievement (Prior math level → Online quiz score). The prior math level in this dissertation was measured by participants’ self-reported highest math level before taking the flipped math class. Such a measure is considered as a weak predictor of prior math knowledge according to the prior domain knowledge literature, and is expected to have weak relations to Internet self-efficacy, the use of learning strategies, and online learning outcome. Therefore, these relations could be removed from the initial model.
By removing these 7 nonsignificant paths, a reduced model was constructed and tested. The reduced model slightly improved the model fit indices, providing a moderate to good model fit to the observed data. According to the chi-square difference test, the reduced model did not differ significantly from the initial structural model, \( \Delta \chi^2 = 4.548 < \chi^2 = 14.067 \) (the critical chi-square value at .05 alpha level), \( p > .05 \). Following the parsimony principle (Kline, 2005), the reduced model was therefore used as the final pre-class Internet-based structural model. Table 10 summarizes the model fit indices of the pre-class Internet-based initial and reduced models. The reduced model with standardized path coefficients is presented in Figure 15.

As shown in Figure 15, the prior math level had a positive direct effect on students’ math self-efficacy (\( \beta = .24 \)), which is consistent with the prior domain knowledge literature.

In terms of self-efficacy constructs, as expected, math self-efficacy or domain-knowledge self-efficacy showed a positive direct influence on students’ use of metacognitive (\( \beta = .30 \)) and environmental control strategies (\( \beta = .25 \)), as well as their online learning outcome (\( \beta = .31 \)). That is, the more confident students are of their capabilities to learn math, the more metacognitive and environmental control strategies they would use and the higher online quiz score they would obtain. The knowledge sharing domain of Internet self-efficacy showed a positive direct effect on the use of both cognitive (\( \beta = .49 \)) and help seeking strategies (\( \beta = .34 \)), whereas the knowledge differentiation domain of Internet self-efficacy showed no significant effect on any variables in this model. Also, both domains of Internet self-efficacy had no significant influence on students’ online learning outcome. This implies that the more confident
students are of sharing knowledge in online community, the more cognitive and help seeking strategies they would enact.

In terms of learning strategy constructs, only help seeking strategy showed a positive direct impact on online learning outcome ($\beta=.25$). The remaining strategies had no significant influence on online achievement.

Table 10: *Model Fit Indices of the Pre-class Internet-based Initial and Reduced Models (N=151)*

<table>
<thead>
<tr>
<th>Model</th>
<th>$x^2$</th>
<th>df</th>
<th>$x^2$/df</th>
<th>CFI</th>
<th>TLI</th>
<th>RMSEA</th>
<th>90% CI of RMSEA</th>
<th>$\Delta$df</th>
<th>$\Delta x^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Model</td>
<td>669.087</td>
<td>421</td>
<td>1.589</td>
<td>.901</td>
<td>.876</td>
<td>.063</td>
<td>(.054; .071)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reduced Model</td>
<td>673.635</td>
<td>428</td>
<td>1.574</td>
<td>.902</td>
<td>.879</td>
<td>.062</td>
<td>(.053; .071)</td>
<td>7</td>
<td>4.548</td>
</tr>
</tbody>
</table>

*Note:* CFI= Comparative fit index; TLI= Tucker-Lewis index; RMSEA= Root-Mean-Square-Error of approximation.
In-class Collaborative Structural Model

The initial in-class structural model yielded an adequate model fit, $x^2/df=1.55$ smaller than 2, CFI=.93 close to .95, RMSEA=.06 equal to .60. Although nonsignificant paths were observed between math self-efficacy and three domains of the use of learning strategies, no strong evidence in literature suggests that these paths can be removed. Therefore, the initial in-class collaborative structural model was used as the final structural model. Table 11 summarizes the model fit indices of the in-class collaborative initial and final models. The model with standardized path coefficients is presented in Figure 16.

As shown in Figure 16, the online quiz score, the indicator of prior domain knowledge for learning in class, had a positive direct effect on students’ math self-
efficacy ($β=.36$), the use of cognitive learning strategy ($β=.22$), and in-class achievement – take home score ($β=.44$). These results are consistent with prior domain knowledge literatures.

In terms of self-efficacy constructs, math self-efficacy or academic self-efficacy had a positive direct effect on in-class achievement ($β=.21$), however, it had no direct significant influence on any domains of the use of learning strategies. In contrast, collaborative self-efficacy had a positive direct effect on all three domains of the use of learning strategies: cognitive strategy ($β=.57$), metacognitive strategy ($β=.43$), and help seeking strategy ($β=.46$), whereas it had no significant direct effect on in-class achievement. That is, the more confident students believe in their math learning abilities, the higher achievement they would obtain for in-class learning. Also, the more confident students believe in learning in groups, the more self-regulation strategies they would enact during in-class learning.

In terms of learning strategy constructs, group learning strategy had a positive direct effect on in-class achievement ($β=.33$), whereas cognitive strategy had a negative direct effect on in-class achievement ($β=-.44$). The finding regarding cognitive strategy use is theoretically unexpected because cognitive strategy use is commonly positively related to academic achievement in the learning strategy literature (e.g. Crede & Philips, 2011). Thus, further examination was conducted to investigate the validity of this finding.

Based on the correlation table (see Table 8), the cognitive strategy use in in-class learning had a significant positive zero-order correlation with in-class math achievement. However, it had negative betas with in-class math achievement in the structural equation modeling analysis when metacognitive and help seeking strategies were included in the
model. This phenomenon suggests a suppressor effect. Therefore, multi-level regression analysis was conducted to detect suppressor variables by examining the partial betas and zero-order correlations between cognitive, metacognitive, and help seeking strategies (Conger, 1974; Tzelogy & Stern, 1978). The results are presented in Table 12.

The analysis suggests that cognitive strategy could be classified as a negative suppressor variable. Cognitive strategy use was significantly and highly correlated with metacognitive strategy ($r = .67$), and metacognitive strategy was a better predictor of achievement when both variables were included in the multilevel regression model (model 2: $\beta = -.02$, $p = .88$ for cognitive strategy and $\beta = .26$, $p = .04$ for metacognitive strategy). When the metacognitive strategy accounted for a certain variance in achievement, the remaining variance correlated with the cognitive strategy revealed a negative relation. In other words, the analysis suggests that there are a significant number of students who reported that they often used cognitive strategy also reported infrequent use of metacognitive strategies during in-class learning. Examination of the actual number of students who showed this pattern revealed that 10 students (9% of the sample) could be classified as being in the top half on cognitive strategy use and the bottom half on metacognitive strategy use.
Table 11. Model Fit Indices of the In-class Collaborative Initial and Reduced Models (N=151)

<table>
<thead>
<tr>
<th>Model</th>
<th>$x^2$</th>
<th>df</th>
<th>$x^2$/df</th>
<th>CFI</th>
<th>TLI</th>
<th>RMSEA</th>
<th>90% CI of RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Model</td>
<td>725.855</td>
<td>468</td>
<td>1.551</td>
<td>.927</td>
<td>.907</td>
<td>.061</td>
<td>(.052; .069)</td>
</tr>
</tbody>
</table>

*Note:* CFI= Comparative fit index; TLI= Tucker-Lewis index; RMSEA= Root-Mean-Square-Error of approximation.

Figure 16. Parameter estimates for the in-class collaborative reduced structural model

*Note:* The significant paths are marked in red, the non-significant paths are marked in gray. Also, the positive paths are marked in solid line, the negative paths are marked in dotted line.
Table 12: *Multi-level Regression Analysis Results (N=112)*

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>t</th>
<th>Sig.</th>
<th>R Square</th>
<th>Model Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>SE</td>
<td>Beta</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Constant</td>
<td>1.934</td>
<td>.192</td>
<td>10.098</td>
<td>.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Cog_In</td>
<td>.066</td>
<td>.040</td>
<td>.154</td>
<td>1.632</td>
<td>.106 .024</td>
</tr>
<tr>
<td>2</td>
<td>Constant</td>
<td>1.823</td>
<td>.196</td>
<td>9.278</td>
<td>.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Cog_In</td>
<td>-.008</td>
<td>.054</td>
<td>-.020</td>
<td>-.155</td>
<td>.877</td>
</tr>
<tr>
<td></td>
<td>MetaCog_In</td>
<td>.101</td>
<td>.049</td>
<td>.257</td>
<td>2.050</td>
<td>.043 .043</td>
</tr>
</tbody>
</table>

*Note:* Cog_In= In-class cognitive learning strategy; Meta_In= In-class metacognitive learning strategy
Chapter 5: DISCUSSION

The purpose of this study was to investigate whether self-regulatory factors affect students’ achievement in a flipped math class. Specifically, one goal of this study was to examine whether three key self-regulatory factors, including prior math knowledge, self-efficacy, and the use of learning strategies directly affected students’ math achievement in both the pre-class Internet-based and in-class collaborative learning environments of a flipped math course. The other goal was to investigate whether there were relationships among these three factors, which could also affect math achievement in both learning environments.

To achieve these research goals, I proposed two hypothesized structural models to examine the relationships between prior math knowledge, self-efficacy, the use of learning strategies, and math achievement in both the pre-class Internet-based and in-class collaborative learning environments of a flipped math class. The models assumed that prior math knowledge had a direct effect on math achievement and also an indirect effect on the achievement mediating through self-efficacy and the use of learning strategies. Further, the models also assumed that both self-efficacy and the use of learning strategies had direct effects on math achievement.

Three major findings emerged, as follows:

- First, with respect to the prior domain knowledge construct, the study found that the pre-class prior math knowledge (i.e. highest math level in high school) had a positive direct effect on math self-efficacy but no significant effect on pre-class
math achievement. The in-class prior math knowledge (i.e. pre-class math achievement) had positive direct effects on both math self-efficacy and in-class math achievement.

- Second, with respect to the self-efficacy construct, the study found that math self-efficacy had a positive direct effect on both pre-class and in-class math achievement. Internet self-efficacy had a positive indirect effect on pre-class math achievement, and collaborative learning self-efficacy had a positive indirect effect on in-class math achievement.

- Third, with respect to the learning strategies construct, the study found that the help seeking strategy had a positive direct effect on both pre-class and in-class math achievement. The cognitive strategy had a negative direct effect on in-class math achievement due to the suppressing effect.

The following discussion of the results is presented in three parts. First, the findings are discussed in detail, based on the research questions. Second, the implications of self-regulated learning theory and flipped classroom instructional design are discussed. Finally, the discussion concludes with limitations of the study and suggestions for future research.

**Discussion of Research Findings**

**Research Question 1: What are the relationships between prior math level, math self-efficacy, Internet self-efficacy, the use of learning strategies, and online achievement in the pre-class online learning environment?**

Pre-class Internet-based learning is one essential part of the flipped math class. Students in this study were required to complete online lectures and associated online
quizzes to be prepared for the corresponding in-class collaborative learning. Such online learning environment requires students to manage a high degree of self-regulation in order to effectively finish online tasks (Azevedo & Comely, 2004). A hypothesized structural model (see Figure 4) was proposed to examine the students’ self-regulation process in this learning environment, and findings are discussed as follows.

**Prior math knowledge:** The results from structural equation modeling indicated that there was a positive direct relationship between the prior math level and math self-efficacy. That is, the higher level of math course that students report to have taken in high school, the more confident they felt in accomplishing or performing a math task in the flipped class. This result is consistent with previous research that has examined the relationship between prior domain knowledge and self-efficacy (Ferla, Valcke, & Cai, 2009; Rimal, 2001; Song, 2010). For example, Ferla et al. (2009) concluded that students’ self-concept of previous academic knowledge strongly influenced their academic self-efficacy beliefs. This suggests that students judge their confidence for performing tasks based on their perceived level of domain knowledge. Students with limited prior domain knowledge have little to guide their decisions about subsequent activities, which makes them feel less confident to pursue the task; while students with higher level prior domain knowledge have a more developed understanding of the conceptual structure of the domain, which helps them feel more confident (Moos & Azevedo, 2009)

Furthermore, the results showed that the prior math level influenced pre-class achievement indirectly through the mediating effect of math self-efficacy. This indicates that students who took a higher level math course in high school tended to feel more
confident in learning math, and such confidence assisted their achievement. This finding provides empirical support for Bandura’s (1986) hypothesis that self-efficacy beliefs mediate the effect of prior academic experience on subsequent performance. That is, when prior domain knowledge is controlled, self-efficacy judgments are better predictors of academic performance.

However, the current analyses found no direct relationship between the prior math level and the use of learning strategies, which implies that the use of learning strategies during online learning is independent of students’ prior math level. The result is not consistent with the findings in relevant literatures (Moos & Azevedo, 2005, 2008; Murphy & Alexander, 2002; Song, 2011). For example, Murphy and Alexander (2002) found that students with higher domain knowledge tended to use more diverse and deep-process strategies, while students with lower domain knowledge tended to use less varied strategies during learning. In addition, a series of research studies conducted by Azevedo and his colleagues also showed that the activation of prior knowledge was a key component in the use of self-regulated learning strategy (Azevedo & Cromley, 2004; Azevedo, Greene, & Moos, 2007). This non-significant finding might be explained by the way of measuring the prior math knowledge for the pre-class learning environment. In general, prior domain knowledge is measured by a pre-test, which is designed for measuring students’ understanding of a specific knowledge domain. In this dissertation, due to limitations of the authentic research design, prior math knowledge was not measured through a calculus pre-test; instead, it was measured by students’ self-reported highest math level course that they had taken in high school. Although this is a generic measure of prior math knowledge that is commonly used as a predictor of students’
performance in an introductory math course (Pajares & Miller, 1994), it might not be accurate enough to indicate students’ authentic prior knowledge for such an introductory course. Therefore, this generic measure of prior math knowledge might lead to the nonsignificant relationship between the prior math level and the use of learning strategies in the pre-class learning environment.

**Math Self-efficacy (MSE):** Besides its mediating effect mentioned above, the results also showed that students’ perceived math self-efficacy had positive direct effects on pre-class math achievement (i.e. online homework score) as well as the use of metacognitive and environmental control strategies. As for the relationship between math self-efficacy and pre-class achievement, the results showed a positive relationship between math self-efficacy and the online homework score, indicating the more self-efficacious students feel in learning math, the higher the score they would obtain during pre-class learning of the flipped math class. This finding is consistent with previous self-efficacy research which suggests a predictive influence of academic self-efficacy on academic achievement (e.g. Pajares, 2008; Pintrich & Zusho, 2007; Pintrich & De Groot, 1990; Schunk & Pajares, 2005; Zimmerman, Bandura, & Martinez-Pons, 1992). The result also provides empirical support for the self-regulated learning theory (Winne & Hadwin, 1998, 2008), which suggests that students’ learning outcomes can be predicted by their motivational belief (e.g. self-efficacy). That is, students who are more efficacious in learning math tend to be more self-regulated to make efforts and persevere in the face of challenge when learning in pre-class. The self-regulation then helps them achieve a higher grade on the homework assignment.
As for the relationship between math self-efficacy and the use of learning strategies, the results showed a positive relationship between math self-efficacy and the use of metacognitive and environmental control strategies. These results indicate that students with a higher confidence level of solving math problems are more likely to enact metacognitive (e.g. planning, monitoring strategy) and environmental control (e.g. making schedule strategy) strategies in the pre-class Internet-based learning environment. This finding is consistent with previous research that highlights the importance of the monitoring process while learning in a computer-based learning environment (e.g. Crede & Philips, 2011; Diseth, 2011; Moss & Azevedo, 2009). For example, Moos and Azevedo (2009) found that students who were more efficacious tended to use more monitoring strategies related to monitoring understanding (i.e. examining the relevancy of the content to with respect to the conceptual knowledge) and monitoring environment (i.e. examining the relevancy of the content with respect to the overall learning goal). The monitoring process is a certain “cognitive cost” that requires students to observe discrepancies between desired outcomes and their actions and modify their learning process to better meet learning goals (Winne, 2001; Winne & Hadwin, 1998). Engaging in the monitoring process takes effort and consumes a large portion of working memory. Therefore, students may decide to enact metacognitive and environmental control strategies related to the monitoring process only if they feel efficacious to do so (Moos & Azevedo, 2009).

**Internet Self-efficacy (ISE):** The results of structural equation modeling showed that the knowledge sharing factor of ISE had a positive direct effect on the use of cognitive and help seeking strategies. However, the knowledge differentiation factor of
ISE had a negative effect on the use of the help seeking strategy. Moreover, neither factor had a significant direct effect on pre-class math achievement. These results mainly reflect that the knowledge sharing and knowledge differentiation factors had a counter-effect on the use of the help seeking strategy. Students who are more confident in sharing knowledge through an online discussion community (i.e. Piazza) would be more likely to ask for help from instructors, peers, or tutors, while students who are more confident in differentiating useful and non-useful online information on their own are less likely to seek help from others.

Additionally, the study found that the knowledge sharing factor of ISE positively influenced pre-class math achievement through the mediating effect of the help seeking strategy. This suggests that students who are more confident in sharing useful knowledge and their understanding of course content in an online discussion community are more likely to seek help from others, which then facilitates their achievement in online learning. In contrast, the results showed that the knowledge differentiation factor of ISE had a negative indirect effect on pre-class math achievement through the mediating effect of the help seeking strategy. These results imply that the knowledge sharing self-efficacy is essential to math achievement in the pre-class Internet-based learning environment.

There has been limited empirical research that examines the relationship between the Internet self-efficacy scale and academic achievement based on Kim and Glassman’s (2013) Internet Self-efficacy scale. This study fills this literature gap by providing preliminary results for the examination of such a relationship. The current results suggest that online learning achievement could be improved by encouraging students to share their understanding of knowledge in a class-based discussion community.
Learning Strategies: The results showed that the help seeking strategy had a significantly positive effect on pre-class math achievement. This suggests that the more often students seek help from others to continue the learning process while encountering obstacles or difficulty in learning materials, the higher the score they would obtain for pre-class online learning. The result is consistent with some research findings, especially the research that was conducted in the computer-based learning environment. For example, Aleven et al. (2003) concluded that the use of the help seeking strategy has substantially improved the learning process and outcome based on their review of help seeking literatures in computer-supported Interactive Learning Environments (ILEs). Taplin et al. (2001) also found that the effective help seeking was a critical strategy that affected the success of distance learners. Many researchers believe that the use of the help seeking strategy is a reflection of students’ own metacognitive thinking and domain-specific knowledge (Aleven et al., 2003; Newwan, 1994, 1998). Oftentimes students who seek help from others are those who are interested in learning and are willing to make efforts to learn. These students often have clear achievement goals and hold positive epistemological beliefs, rather than those who are unclear of learning goals and solely dependent on others’ help (Ryan & Pintrich, 1997). Therefore, the help seeking strategy is a critical strategy that is conducive for the development of independent skill, rather than a behavior that signals the dependence of the learners (Newman, 1994). The result in this study provides additional support for the existing findings regarding the help seeking strategy.

However, the pre-class structural model did not show enough evidence to support the relationship between pre-class math achievement and other strategies including
cognitive, metacognitive, and environmental control strategies. The findings regarding the relationship between academic achievement and the use of learning strategies have been inconsistent in the learning strategy literature. On one side, extensive research has demonstrated the significant influence of the cognitive and metacognitive strategies on academic achievement in a traditional face-to-face learning environment (Crede & Philips, 2011; Duncan & McKeachie, 2005). On the other side, Azevedo and his colleagues (Azevedo & Cromley, 2004; Azevedo, Greene, & Moos, 2007; Azevedo, Guthrie, & Seibert, 2004) did not find such a significant relationship in the studies they conducted in a hypermedia learning environment.

The results in this study are consistent with the later findings in the literature. One possible reason for the nonsignificant relationship might be due to the learning environment. The Internet-based learning environment of the flipped class creates a student-centered learning culture, which has already placed high cognitive demands on students, such as watching online lectures and completing online homework on their own. Enacting the cognitive and metacognitive strategies is considered as an extra “cognitive cost” for students. Due to the limited time of pre-class learning, students may undertake a “cost-benefit” analysis when enacting these strategies. If the cost of using effortful self-regulation strategies such as the cognitive and metacognitive strategies outweighed by the benefit of using these strategies, students may decide not to use them.

In summary, in the pre-class Internet-based learning environment of the flipped math courses, students’ confidence in successfully accomplishing math tasks and their help seeking behaviors directly influenced their pre-class math achievement. In addition, students’ prior math level and their confidence in sharing their understanding of online learning
materials also indirectly influenced pre-class math achievement. Therefore, students who are more likely to succeed in the pre-class learning environment of the flipped courses are those who hold strong confidence in solving math problems and are skilled in seeking help from others when they encounter problems. The characteristics of taking higher level math courses in high school and perceiving a high level of confidence in sharing knowledge in an online community also contribute to the success of the pre-class flipped learning.

**Research Question 2: What are the relationships between online achievement, math self-efficacy, collaborative learning self-efficacy, the use of learning strategies, and in-class achievement in the in-class collaborative learning environment?**

In-class collaborative learning is another essential part of the flipped math class. Students in this study are required to work in groups to collaboratively solve a few practice problems associated with pre-class online materials. Such a collaborative learning environment also requires students to manage a high degree of self-regulation in order to successfully learn in groups (Johnson & Johnson, 1999). A hypothesized structural model (see Figure 5) was proposed to examine students’ self-regulation process in this learning environment, and the findings are discussed below.

**Prior domain knowledge:** The study found that students’ prior math knowledge, measured by online homework scores, had a significant positive effect on students’ math self-efficacy. The result indicates that the higher the grade that students obtain in pre-class learning, the more confident they felt in solving math tasks. Furthermore, the study also found that online homework scores positively influenced in-class achievement through the mediating effect of math self-efficacy, suggesting that the higher the grade
students obtain during pre-class learning, the more confident they are to solve math tasks. Such strong confidence, in turn, assists their in-class learning. These two findings are consistent with the findings of pre-class prior math knowledge and also are consistent with the research that examined the associations among prior domain knowledge, domain-specific self-efficacy, and academic achievement (Ferla, Valcke, & Cai, 2009; Rimal, 2001; Song, 2011). The discussion of the prior math knowledge findings in the in-class learning environment is similar to the discussion regarding the pre-class learning environment.

Besides the above two findings that were consistent with the findings of pre-class prior math knowledge (i.e. highest math level in high school), the results also demonstrate two new findings of the in-class prior math knowledge (i.e. online homework score). One is that the online homework score had a positive direct impact on math achievement for in-class learning (i.e. take-home assignment), implying that the higher the grade they obtain for online learning, the higher the grade they would achieve for in-class learning. This is consistent with research that examines the direct relationship between prior domain knowledge and academic achievement (Best et al., 2005; Thomson & Zamboanga, 2004; Song, 2011). For example, Thomson and Zamboanga (2004) found students’ domain-specific prior knowledge was positively related to course achievement in a psychology course. In the context of the flipped classroom, students’ pre-class learning achievement serves as the prior math knowledge for their in-class learning and assists their in-class collaborative activities. Students who obtain higher achievement in pre-class learning are more likely to take control of their learning process, learn from collaborative activities during class, and perform better in take-home assignments.
The other new finding of the in-class prior math knowledge is that it was directly related to the use of cognitive strategies, suggesting that students who obtain a higher grade in online learning are more likely to use the cognitive strategies such as summarizing and outlining strategies during in-class learning. This finding is somewhat surprising, because according to Winne and Hadwin’s self-regulation theory, when students encounter a task in which they have limited domain knowledge, students may only be able to use shallow-processing and less varied self-regulation strategies, such as cognitive summarizing and outlining. This is because the majority of their working memory (i.e. hypothetical location where information becomes a topic of information processing) may be used for processing information (Moos & Azevedo, 2008; Winne & Hadwin, 2008).

One possible reason to explain this unexpected finding might be the collaborative nature of in-class activities in the flipped math courses. As part of the flipping design in the target courses, each recitation class is structured as a 5-10 minute’ warm-up question-answer session and a 30-35 minute’ group work session. In the group work session, students were required to collaborate with 3 to 5 peers to solve practice problems associated with previous online materials. During the collaboration, students who achieved higher in pre-class learning tend to have more knowledge to solve the problems. Therefore, they often play a leading role during the collaboration and try to explain their solutions to the group. To effectively obtain the answer and describe the solution to peers, these students oftentimes have to retrieve knowledge from working memory, organize knowledge obtained from online lectures, make connections with the practices problems, and outline relevant formulas. Therefore, due to the collaborative nature of the in-class
learning environment, students with higher level prior math knowledge are more likely to enact various cognitive strategies.

**Math Self-efficacy:** Besides its mediating effect mentioned above, the result also showed that students’ math self-efficacy had a positive direct effect on students’ take-home assignment, indicating the more confident students feel in their capabilities to solve math tasks, the higher the grade they would obtain for in-class learning. This result is consistent with the research that examines the relationship between academic self-efficacy and its corresponding achievement (e.g. Pajares, 2008; Pintrich & Zusho, 2007; Pintrich & De Groot, 1990; Schunk & Pajares, 2005; Zimmerman, Bandura, & Martinez-Pons, 1992). The discussion of this finding is similar to the discussion in the math self-efficacy section of Research Question 1.

Interestingly, the results showed no significant relationships between math self-efficacy and the use of any in-class self-regulatory strategies including cognitive, metacognitive, and help seeking strategies. This suggests that students’ use of self-regulatory strategies is independent from their confidence in their capabilities to learn math during in-class learning. This result is consistent with some research that showed no direct relationship between self-efficacy and the use of learning strategies (e.g. Bonyadi, Nikou, & Shahbaz, 2012). For instance, Bonyadi et al. (2012) found no significant relationship between self-efficacy and the use of learning strategies on language learning among 130 first year university students. However, they found that gender and years of English study contributed to the significant difference of language learning strategies. The same analogy can be applied to the nonsignificant finding here. That is, although math self-efficacy had no significant influence on the use of learning strategies, other
factors can contribute to the difference of using strategies. Due to the collaborative nature of the in-class learning environment of the flipped courses, it could be more likely that the factors related to collaboration or working in groups have more impact on the choices of learning strategies than academic self-efficacy. The results did provide evidence for this hypothesis, and the detailed discussion is presented in the following section:

collaborative learning self-efficacy.

**Collaborative Learning Self-efficacy**: The structural equation modeling results showed that collaborative learning self-efficacy had a positive effect on the use of all self-regulatory strategies including, cognitive, metacognitive, and help seeking strategies during in-class learning. This suggests that students who are confident in their capabilities to successfully learn through collaborative activities tend to use diverse learning strategies, including cognitively summarizing and outlining, metacognitively planning and monitoring, as well as seeking help from others.

These results are consistent with the proposed hypothesis in the math self-efficacy section. A collaborative characteristic of in-class learning is that it creates a unique learning environment in which students mainly learn through working with others in a group instead of learning on their own (FL Network, 2014). Therefore, the factors related to collaboration have more influence on students’ enactment of learning strategies during in-class learning. In this study, collaborative learning self-efficacy reflects students’ confidence of learning in groups. Students with a high level of confidence are more likely to use varied learning strategies during group learning in class than those with a low level of confidence.
**Learning Strategies**: This study found that the in-class help seeking strategy was significantly associated with take-home assignments, suggesting that the more often students seek help from others when they met problems or difficulties during learning in class, the higher the grade they would obtain for in-class learning. This result is consistent with the finding in pre-class Internet-based learning setting and also with some research that examines the relationship between the help seeking strategy and academic achievement (Aleven et al., 2003, 2006). The discussion for this finding is similar to the discussion in the help seeking strategy section of Research Question 1. The result found in the in-class learning environment serves as additional evidence for proving the importance of the help seeking strategy in the flipped classroom learning environment.

In addition, although the structural equation modeling results showed that in-class cognitive strategies had a negative effect on take-home assignments, the multilevel regression analysis further examined this result. It suggested that this negative relationship was a suppressor effect due to the high and significant correlation between cognitive and metacognitive strategy variables. This means that when both in-class cognitive and metacognitive strategies entered as predictors of academic achievement, in-class metacognitive strategy was a better predictor. These findings parallel the work of Pintrich and De Groot (1990), who also found the suppressing effect of cognitive strategy due to the high correlation between cognitive and metacognitive strategies. In the context of in-class collaborative learning, these results suggest that the use of cognitive strategies is not conducive for students’ in-class math achievement without the joint use of metacognitive learning strategy. This interpretation echoes the research about the metacognition and self-regulation suggesting that to succeed, students need to not only be
aware of what cognitive strategies are, but more importantly, they should also be aware of when and how to use these strategies appropriately.

In summary, in the in-class collaborative learning environment of the flipped math courses, students’ prior online learning achievement, the confidence of successfully solving math problems, and help seeking behaviors directly influence their in-class learning math achievement. In addition, the use of cognitive strategies is not conducive for in-class math learning unless it accompanies the metacognitive strategy. Therefore, students who are more likely to succeed in the in-class environment of the flipped course are those who successfully accomplish online lessons, have strong confidence in solving math problems, tend to seek help more often in the face of obstacles, and know when and how to appropriately use cognitive strategies.

**Implications**

**Implication to Theory**

With flipped classroom practices receiving considerable empirical attention (Baepler, Walker, & Driessen, 2014; Chen, Wang, & Kinshuk, & Chen, 2014; Findlay-Thompson & Mombourquette, 2014; Lage, Platt, & Treglia, 2000; Strayer, 2012, 2013), examining how students learn in the flipped learning environment should be the focus area of future flipped classroom study. Research in this area is important because though flipped classroom is seen as a promising teaching approach, theoretical understanding of how students learn within this environment is still developing. In order to advance the theoretical understanding of the learning process involved in the flipped classroom learning environment, research is needed that empirically examines factors traditionally related to academic learning, such as prior domain knowledge (e.g. Song, 2011) and self-
regulatory factors including self-efficacy (e.g. Pajares, 2008) and the use of learning strategies (Crede & Philips, 2011).

The results of this study demonstrated two self-regulatory processes that could help students succeed in the flipped classroom, especially in the flipped math classroom. One process is the direct effect of the cognitive condition (i.e. prior domain knowledge and academic self-efficacy) on learning products. The other process is the indirect effect of the cognitive condition (i.e. task condition-related self-efficacy) on learning products through the mediating effect of the operation (i.e. the use of learning strategies). Students demonstrated these two self-regulatory processes in both the pre-class and in-class learning environments of the flipped math class.

With respect to the former process, the understanding of a learner’s own cognitive condition is an essential step to help the learner appropriately define a learning task. A learner could define whether a learning task is easy or not based on his or her prior domain knowledge and the confidence of his or her ability to learn the knowledge. The definition of the task would then directly influence the achievement of the task. In this study, in terms of the pre-class Internet-based learning setting, students are required to learn the lower cognitive level knowledge through online lectures. Those who are confident in their abilities of learning math (i.e. math self-efficacy) tend to effectively produce an appropriate definition of an online learning task (e.g. video watching, embedded quiz), which helps them obtain high achievement in the online homework. In terms of the in-class collaborative learning setting, students are asked to solve problems collaboratively in groups. Although the task is designed to let students apply higher cognitive level knowledge that is different from the pre-class task, the same self-
regulatory process is observed from the results. The students who have high levels of confidence in learning math are more likely to generate an appropriate understanding of an in-class task, which helps them perform better in the take-home assignment. Additionally, the achievement in the online homework also directly influences the take-home assignment, indicating the knowledge preparation in pre-class can guide the practice of higher cognitive level knowledge in the in-class collaborative work.

With respect to the later process, the understanding of the task condition (e.g. learning environment) is also a key step for the task definition. However, such an understanding is not enough to have a significant impact on the learning product. It needs to accompany the use of learning strategies to demonstrate the significant impact on the achievement. In this study, in terms of the pre-class learning, all learning tasks are designed for the Internet-based learning environment. Students who are aware of such a task condition and have confidence in their abilities to learn in this condition (e.g. sharing knowledge in the class discussion forum) tend to seek help from others while meeting obstacles. The use of the help seeking strategy then helps them perform better on the online homework. A similar process is observed in the in-class collaborative learning environment. The students who are aware of the collaborative condition while learning in class and are confident in their abilities to work with others tend to seek help more often and achieve higher in the take-home assignment.

Overall, this dissertation study supports Winne and Hadwin’s (1998, 2001) self-regulation theory and extends the theory into the flipped classroom learning environment. By examining the effects of prior domain knowledge and self-regulatory factors on
academic achievement, the study provides empirical evidence to demonstrate two self-regulation processes that could help students succeed in the flipped classroom learning.

**Implication to Instructional Design**

There are three major implications for the instructional design in the flipped math classroom, which include implications to prior math knowledge, math self-efficacy, and the use of self-regulatory strategies. Below are the detailed discussions.

**Prior math knowledge**

The analysis showed that the pre-class online homework (i.e. indicator of the prior math knowledge for in-class learning) had a positive impact on the in-class take-home assignment, suggesting that *pre-class learning matters*. Students who fully completed online lectures and obtained higher grades in online homework were more likely to succeed during in-class learning. Since students’ in-class learning is significantly dependent on their preparation in pre-class, instructor’s support to help students go through the online lecture and complete online homework is essential. A few instructional methods have been documented in the flipped classroom literature that are conducive for engaging students in pre-class online learning, including incentives (e.g. grades) for completing pre-class work (Brame, 2013), a mechanism to assess students’ understanding of pre-class materials (Schell, 2013), and interpolated memory tests embedded in online lecture videos (Szpunar, Khan, & Schacter, 2013). Overall, there is a strong link between pre-class and in-class learning. Students who performed better in pre-class learning tend to also have higher achievements in in-class learning. Therefore, a variety of formative assessment tools are recommended to instructors for helping students
regulate themselves to finish the review of online lectures and complete associated homework.

**Math Self-efficacy**

The results have shown that math self-efficacy is consistently and positively associated with learning achievement in both the pre-class and in-class learning environments of the flipped math courses. This indicates that the enhancement of students’ confidence in their capabilities to successfully accomplish math tasks can lead to the improvement of academic achievement in the flipped math class. Based on the social cognitive theory (Bandura, 1987, 1997), mastery experience (i.e. learning through successful experiences) and emotional arousal are the two major sources for developing people’s self-efficacy beliefs. In the context of the flipped math learning, instructional designers and instructors could utilize a few methods to help students build these learning experiences.

With respect to the mastery experience, it refers to one’s interpretation of his or her own previous attainments and is considered to be the most powerful and effective way to instill a strong sense of self-efficacy (Bandura, 1997). The successful experience of completing a task raises people’s confidence to accomplish similar or related tasks, which, in turn, motivates them to repeat the behaviors and efforts that lead them to another success in the future. In the flipped math class, the online quiz embedded in the online lecture could be considered as an effective way to build students’ successful learning experiences (Lee, 2008). The embedded quiz in the studied courses consists of two parts: a correct answer and a metacognitive feedback that was pre-written by the instructor. It is designed to measure students’ understanding of a portion of the online
lecture. Theoretically, if students complete the review of the lecture, it should not be difficult for them to solve the quiz problem. If they fail, the metacognitive feedback would be promoted to provide a hint for students to solve the problem. The successful experiences of answering these quiz questions during online learning may help students develop the belief that as long as they make efforts to learn the content, they could be successful of learning in this class.

With respect to emotional arousal or social persuasion, the persuaders such as teachers, parents, and peers, play an important role in the development of people’s self-efficacy beliefs (Bandura, 1997). Positive persuasion may empower people’s self-confidence, which leads them to exert greater efforts and have more chances to succeed; while negative persuasion might discourage and defeat one’s self-efficacy beliefs. Pajares (2008) argued that it was easier to weaken one’s self-efficacy through negative comments than to encourage the self-efficacy through positive appraisals. In the flipped math courses, instructors could verbally increase students’ confidence by complimenting their growth, attributing the poor performance to the lack of effort, and encouraging them to try harder (Siegle & McCoach, 2007).

In summary, students with high levels of math self-efficacy are more likely to succeed in the flipped math courses. However, students’ confidence in their abilities to learn math varies. To improve such confidence, instructors could use both an instructional assessment tool (e.g. embedded online quiz) and verbally positive comments to encourage students to believe in their abilities and make more efforts while meeting obstacles in both the pre-class online and in-class collaborative learning environments.
Self-Regulatory Learning Strategies

The current study has found that the use of the help seeking strategy not only directly improved learning achievement but also mediated the improvement in both the pre-class and in-class learning environments of the flipped courses. This indicates that seeking help from others (i.e. peers, tutors, instructors) when encountering problems during online and collaborative learning is helpful for students to obtain high achievement in the flipped math courses. Additionally, the use of both cognitive and metacognitive strategies directly impacted learning achievement in the in-class learning environment. This reveals that during collaborative learning in class, students need not only be able to utilize cognitive strategies, but more importantly, they should also be aware of when and how to use these strategies appropriately to achieve high performance for in-class learning. Overall, these findings suggest that supporting and guiding the use of appropriate self-regulatory strategies are necessary for students to effectively learn and succeed in the flipped classroom.

Therefore, instructional designers and instructors should first provide instructions on how to use the aforementioned self-regulatory strategies and create time and space to facilitate students’ use of these strategies in the flipped classroom. For example, to support students’ use of the help seeking strategy in the pre-class online environment, instructors could create an online course discussion forum to enable and encourage students to ask and answer each other’s questions regarding online lectures by giving extra grades. As for the support in the in-class collaborative environment, instructors could pay more attention to those who are not engaged in the group activity, provide
individualized instructions on the content, and encourage them to work together with group members (Kim, Kim, Khera, & Getman, 2014; Xie & Huang, 2014).

In terms of supporting the use of both cognitive and metacognitive strategies during in-class collaborative learning, instructors could first introduce various cognitive strategies such as summarizing, outlining, and organizing information and encourage students to use them while working in groups. At the same time, instructors should also ask students to reflect on when and how to use a certain strategy that could help them effectively solve problems during group learning. For example, after a group presents their work to the entire class in the in-class setting, the instructor could ask follow-up questions such as “How did you get the answer, by outlining the formulas, or by making charts?” Such an instructional method could help students not only practice the problem, but also may let them understand the outcome of using a certain strategy.

In summary, the results have shown that the appropriate use of certain self-regulatory strategies are conducive for learning in both the pre-class online and in-class collaborative learning environments. However, not every student is skilled to use these strategies. Therefore, to assist more students to succeed in the flipped classroom, instructors should provide support and facilitation to help students first understand how to use a certain self-regulatory strategy and then reflect on the outcome of using this strategy.

Limitations of Study

The current study has several limitations that need to be considered before generalizing the findings. First, the findings in this study may only hold true for college students. The participants of this study were undergraduate students enrolled in the
introductory to calculus courses in a large public university in the midwestern United States. The results of this study are limited to the population with similar characteristics.

Second, the findings of this study may only apply to the mathematics discipline. Since pre-class online materials and in-class collaborative activates might significantly differ across disciplines, and instructor’s involvement in a flipped classroom might also vary across disciplines. Caution should be used in generalizing the findings to other disciplines.

Third, the findings may only be valid on the specific flipped class design in the studied courses. The flipped design in this study is not a classic flipped class design. It had distinct design features, including a flexible component in the course that allowed for more flexible ways of taking recitation or in-class sessions such as participating online, the recitation sessions being taught by teaching assistants instead of course instructors, and the teaching assistants varying in terms of age, gender, ethnicity, and teaching experiences. Therefore, the flipped design in this study can be considered as a unique version of the classic flipped design. Caution should be used in applying the findings to other flipped math courses.

Last, as is a common challenge in all structural equation modeling studies, caution is advised in the interpretation of the results, because the factors in the hypothesized structural models might not correspond to a real concept (Kline, 2005). For example, in this study, the students’ prior math knowledge in the pre-class online learning environment was measured by students’ self-reported highest level math course taken in high school, which is a generic measure and is commonly used in teaching practice. However, such a measure can only represent part of students’ prior math knowledge.
There are other ways to define prior math knowledge, such as a content domain test. Therefore, care should be taken in the interpretation of factors in this model.

**Future Directions**

While this study contributes to our understanding of how prior math knowledge, self-efficacy, and the use of learning strategies impact math achievement in both the pre-class Internet-based and in-class collaborative learning environments of two flipped undergraduate math courses, future research could extend this research agenda in the following three directions:

First, replicating the findings of the current study might be useful if the suggested instructional design components are incorporated in the flipped math class. Future research could design an experimental-control study to examine the effectiveness of specific instructional interventions (e.g. promoting an online community) that was suggested in the current study.

Second, the help seeking strategy could be further explored in future research. Nelson-LeGall (1981) proposed a five-step helping-seeking model, which consists of the following steps: 1) become aware of the need for help; 2) decide to seek help; 3) identify potential helpers; 4) use strategies to elicit help; and 5) evaluate the help-seeking episode. Given the importance of the help seeking strategy found in this study, it is worth investigating what the help seeking process is for students learning in the pre-class and in-class environments of the flipped classroom, determining whether the process is consistent with Nelson-LeGall’s model, and asking whether differences exist in the help seeking process between the pre-class and in-class learning environments.
Third, there is a definite need for developing new instruments to measure students’ use of cognitive and metacognitive strategies in both the Internet-based and collaborative learning environments. The results in this study have shown that neither of these two strategies had individual direct effects on the pre-class and in-class achievement. One possible reason for explaining these non-significant results is that the current instrument for measuring these two learning strategies does not reflect the actual strategies students are using in the online and collaborative learning environments. Therefore, it is necessary to update the instrument in order to capture the use of cognitive and metacognitive learning strategies in these two learning environments.

**Conclusion**

The current study examines Winne and Hadwin’s (1998) self-regulation theory in the flipped classroom environment and proposes two structural models to explain students’ self-regulation processes during their pre-class Internet-based and in-class collaborative learning. Specifically, the results demonstrated two self-regulation processes that facilitate students’ learning in the flipped math class. One is that prior math knowledge directly influences students’ math self-efficacy, which then has a direct impact on students’ academic achievement. The other is that task-related self-efficacy (i.e. knowledge sharing domain of Internet self-efficacy and collaborative learning self-efficacy) directly influences students’ use of the help seeking strategy, which then has a direct impact on their academic achievement.

Moreover, this study provides an empirical and theoretical understanding of students’ self-regulation process in the flipped classroom, which is helpful for flipped classroom instructional designers and instructors to identify students’ difficulties during
self-regulated learning and to create strategies to overcome the difficulties. For example, the current study promotes the need for the support of using the help seeking strategy in both the pre-class and in-class learning environments and the discouragement of using cognitive strategies without the joint use of the metacognitive strategy in the in-class learning environment.

Last but not least, the examination of students’ self-regulation process in the flipped classroom furthers the flipped classroom research in the direction of studying how students learn in a flipped class. Also, dividing the flipped classroom environment into the pre-class online and in-class collaborative learning environments provides a comprehensive understanding of students’ learning process in a flipped class.
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Appendix A: Informed consent form

This is an online consent form for research participation. It contains important information about this study and what to expect if you decide to participate. Please consider the information carefully. Feel free to ask questions before making your decision whether or not to participate.

**Study Title:** Effects of self-efficacy and learning strategies on students’ learning in the flipped class

**Researchers:** Kui Xie, Assistant Professor; Zhiru Sun, Doctoral Candidate

**Purpose of the study:** The purpose of this research is to study the effects of self-efficacy and learning strategies on students’ learning in the flipped class. You are being asked to participate in this research study because you are a student enrolled in the flipped and flexible section of Math 1151 at Ohio State University.

**Study tasks or procedures:** to participate in this research, you will be asked to complete two online surveys. This is the first online survey. By granting consent below, you indicate your agreement to have your responses to the survey questionnaire included in the process of data analysis. All students have the opportunity to complete the survey. The survey will take you approximately 5 to 10 minutes to complete. Students who are under 18 and who do not agree to participate will not be included in the aggregate data analysis. If you agree to take part in the research, your survey response will be aggregated with your course grades and Carmen usage data based on osu email.
**Your Rights:** This activity involves research. Your participation is voluntary, and you may choose to withdraw at any time without penalty or impact on your grade. You can refuse to participate without penalty or impact on your grade. For questions about your rights as a participant in this study or to discuss other study-related concerns or complaints with someone who is not part of the research team, you may contact Ms. Sandra Meadows in the Office of Responsible Research Practices at 1-800-678-6251.

**Risks & Benefits:** Minimal to none risks are anticipated in this research. Benefits include the opportunity to contribute to the understanding of what type of achievement goal, self-efficacy and learning strategies are effective for students’ success in the flipped class.

**Incentives:** Students who participated in the survey would have at least 1% chance to win a 16GB Apple iPad mini.

**Confidentiality:** Your survey response, course grades, and Carmen usage data will be kept confidential. The course grades data and Carmen usage data will be merged with survey response data by OSU ID. All identifiers will be stripped from the data before they are analyzed. Comparisons will be kept confidential, and no individual grades or responses will be shared – data will be reported as a class aggregate only. We will work to make sure that no one sees your online responses without approval. But, because we are using the Internet, there is a chance that someone could access your online responses without permission. In some cases, this information could be used to identify you. If you have any questions about the research study or if you feel you were harmed as a result of study participation, please contact the co-investigator, Zhiru Sun, via email sun.272@osu.edu.

INFORMED ELECTRONIC CONSENT
Please select your choice below.

Check “Agree” to indicate that:

- you have read the above information (or someone has read it to you)
- you voluntarily agree to participate in the research study
- you have had the opportunity to ask questions and have had them answered to your satisfaction
- you are at least 18 years of age.

☐ Agree

Check “Disagree” if you do not wish to participate in the research study.

☐ Disagree
Appendix B: Demographic and prior math level survey items (1st survey)

Please select the option that best describes you

1. Gender:  □  Male  □  Female

2. What is your ethnicity?
   □  African American / Black  □  American Indian or Alaska Native
   □  Asian  □  Native Hawaiian or Pacific Islander
   □  Hispanic/Latino  □  White
   □  Other

3. What is your major? ______________________

4. Year in School:
   □  Freshman  □  Sophomore  □  Junior  □  Senior
   □  Graduate Student

5. What was the highest level of mathematics you took prior to college?
   □  Below Pre-Calculus  □  Pre-Calculus
   □  Non AP-Calculus  □  Calculus AP (AB)
   □  Calculus AP (BC)  □  Beyond Calculus AP (BC)
Appendix C: Math self-efficacy and Internet self-efficacy scales (1st survey)

The following items concern your math learning experience. Please answer all items. For each item, please indicate how true the statement is for you, using the following scale as a guide:

1  2  3  4  5  6  7
not at all  somewhat  very
true  true  true

1. I believe I will receive an excellent grade in math.
2. I’m certain I can understand the most difficult material in math.
3. I’m confident I can understand the basic concepts taught in math.
4. I expect to do well in math.
5. I’m confident I can do an excellent job on the assignments and tests in math.

The following items concern your Internet using experience. Please answer all items. For each item, please indicate how true the statement is for you, using the following scale as a guide:

1  2  3  4  5  6  7
not at all  somewhat  very
true  true  true
1. I can use Internet to answer questions posed by this class to get a correct answer.

2. I can use Internet to answer my own questions about this class to achieve a correct answer.

3. I can organize information found on the Internet so that it is coherent and answers specific questions.

4. I can improve my performance through information gained from Youtube or online videos.

5. I can use Youtube or online videos to find information that is important to this class.

6. I can use Youtube or online videos to find information that is important to me.

7. I can improve my own performance in this class by sharing information that I find on Internet in Piazza.

8. I can improve others’ performance in this class by sharing information that I find on Internet in Piazza.
Appendix D: Collaborative learning self-efficacy and the use of learning strategy scales for the pre-class and in-class learning environments (2nd survey)

The following items concern your in-class collaborative learning experience. Please answer all items. For each item, please indicate how true the statement is for you, using the following scale as a guide:

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>not at all</td>
<td>somewhat</td>
<td>very</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>true</td>
<td>true</td>
<td>true</td>
<td></td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

1. I believe the in-class group learning can help me receive an excellent grade in the course.

2. I’m certain the in-class group learning can help me understand the most difficult material in the course.

3. I’m confident the in-class group learning can help me understand the basic concepts taught in the course.

4. I expect I can do well in the in-class group learning.

5. I’m confident I can do an excellent job on the assignments and tests for the in-class group learning.
The following items concern your pre-class math learning experience. Please answer all items. For each item, please indicate how true the statement is for you, using the following scale as a guide:

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>not at all</td>
<td>somewhat</td>
<td>very</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>true</td>
<td>true</td>
<td>true</td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

1. While I study math through pre-class online materials, I go over the formulas or definitions in order to memorize them.

2. While I study math through pre-class online materials, I do the practice problems over and over again to memorize them.

3. While I study math through pre-class online materials, I make a list of the formulas or definitions to organize what I need to know.

4. While I study math through pre-class online materials, I make charts, diagrams, or tables to organize what I need to learn.

5. While I study math through pre-class online materials, I connect what I learn in math to what I am learning in other non-math classes.

6. While I study math through pre-class online materials, I try to connect new material to what I already know.

7. While I study math through pre-class online materials, I make connections between how I solve one math problem with the way I could solve others.

8. Before I begin studying math through pre-class online materials, I think about what and how I am going to learn.

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9. Before I begin studying math through pre-class online materials, I plan how much time I will need to learn a topic.

10. Before I begin studying math through pre-class online materials, I set goals for myself to help me learn.

11. While I’m studying math through pre-class online materials, I ask myself questions to make sure I know what I have been learning.

12. While I’m studying math through pre-class online materials, I try to determine how well I have learned what I need to know.

13. While I’m studying math through pre-class online materials, I test myself to see whether I know the material.

14. If I get confused with something while I’m studying math through pre-class online materials, I go back to lecture videos and other relevant resources and try to figure it out.

15. If the math I am studying through pre-class online materials is difficult to learn, I slow down and take my time.

16. If I’m having trouble solving online math quizzes, I try other ways to solve them.

17. While I’m studying math through pre-class online materials, if I don’t understand something in math I ask my teacher or tutor for help.

18. While I’m studying math through pre-class online materials, if I don’t understand something in math I ask other students for help.

19. While I’m studying math through pre-class online materials, if I don’t understand something in math I ask for help to better understand general ideas and principles.
20. While I’m studying math through pre-class online materials, if I don’t understand something in math I ask others for the answers I need to complete my work.

21. I study pre-class math materials (i.e. lecture videos, online quizzes etc.) in a place where I can concentrate.

22. I use a study schedule for learning the pre-class math materials.

23. I make sure I have as few distractions as possible when I study pre-class math materials.

The following items concern your in-class math learning experience. Please answer all items. For each item, please indicate how true the statement is for you, using the following scale as a guide:

1  2  3  4  5  6  7
not at all  somewhat  very
true  true  true

1. While I study math in class, I go over the formulas or definitions in order to memorize them.

2. While I study math in class, I do the practice problems over and over again to memorize them.

3. While I study math in class, I make a list of the formulas or definitions to organize what I need to know.

4. While I study math in class, I make charts, diagrams, or tables to organize what I need to learn.

5. While I study math in class, I connect what I learn in math to what I am learning in some other classes.
6. While I study math in class, I try to connect new material to what I already know.

7. While I study math in class, I make connections between how I solve one math problem with the way I could solve others.

8. Before I study math in class, I think about what and how I am going to learn.

9. Before I study math in class, I plan how much time I will need to learn a topic.

10. Before I study math in class, I set goals for myself to help me learn.

11. While I’m studying math in class, I ask myself questions to make sure I know what I have been learning.

12. While I’m studying math in class, I try to determine how well I have learned what I need to know.

13. While I’m studying math in class, I test myself to see whether I know the material.

14. If I get confused with something while I’m studying math in class, I go back to lecture notes or personal notes and try to figure it out.

15. If the math I am studying in class is difficult to learn, I slow down and take my time.

16. If I’m having trouble solving math problems in class, I try other ways to solve them.

17. While I’m studying math in class, if I don’t understand something in math I ask my teacher or tutor for help.

18. While I’m studying math in class, if I don’t understand something in math I ask other students for help.

19. While I’m studying math in class, if I don’t understand something in math I ask for help to better understand general ideas and principles.

20. While I’m studying math in class, if I don’t understand something in math I ask others for the answers I need to complete my work.
## Appendix E: Factor loadings and measurement error variance of reduced pre-class measurement model

<table>
<thead>
<tr>
<th>Factor</th>
<th>Survey Item</th>
<th>Path Estimate</th>
<th>Standardized Error</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cognition Strategy</strong></td>
<td>Cog_Q1_Pre</td>
<td>.82***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Cog_Q3_Pre</td>
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<td>.14</td>
</tr>
<tr>
<td></td>
<td>Cog_Q4_Pre</td>
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<td>.17</td>
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<tr>
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<td>.21</td>
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<tr>
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<td>Meta_Q2_Pre</td>
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<td>.97***</td>
<td>.13</td>
</tr>
<tr>
<td><strong>Environmental Control Strategy</strong></td>
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<tr>
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<td>.82***</td>
<td>.12</td>
</tr>
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</table>

Note: *** $p<.001$
Appendix F: Factor loadings and measurement error variance of reduced in-class measurement model

<table>
<thead>
<tr>
<th>Factor</th>
<th>Survey Item</th>
<th>Path Estimate</th>
<th>Standardized Error</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cognition Strategy</strong></td>
<td>Cog_Q1_In</td>
<td>.79***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Cog_Q3_In</td>
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<td>Cog_Q4_In</td>
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</tr>
<tr>
<td></td>
<td>Cog_Q6_In</td>
<td>.72***</td>
<td>.10</td>
</tr>
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<td>.10</td>
</tr>
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<td></td>
</tr>
<tr>
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<td>Meta_Q2_In</td>
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Appendix G: Descriptive statistics and ANOVA results between Calculus I and II courses

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