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The role of self-regulated learning in students' success in flipped undergraduate math courses

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ABSTRACT

Based upon the self-regulated learning theory, this study examined the relationships between academic achievement and three key self-regulatory constructs - prior domain knowledge, self-efficacy, and the use of learning strategies - in two flipped undergraduate math courses. Structural equation modeling was employed as the primary method to analyze the relationships in both the pre-class and in-class learning environments of the flipped courses. The results of the study showed that students' self-efficacy in learning math and the use of help seeking strategies were all significantly positively related with academic achievement in both pre- and in-class learning environments. In addition, students' self-efficacy in collaborative learning had a positive impact on their use of help seeking strategies during in-class learning. The theoretical and instructional implications are discussed.

1. Introduction

The flipped classroom model of instruction has received a great deal of recent attention (Bergmann & Sams, 2012). Although some have argued that the concept of a flipped classroom has been practiced in education for decades (e.g., Tucker, 2012), the development of the Internet infrastructure and multimedia production, and increased accessibility to personal technologies have brought this instructional model to the forefront. In a typical flipped class, students learn content material prior to class through online instructional videos and text readings at their own pace and schedule. Then, they work in-person with the course instructor to apply their newly acquired knowledge through problem-based and group-based learning activities (Yarbro, Arfstrom, McKnight, & McKnight, 2014). In essence, the flipped classroom model consists of two major components: pre-class Internet-based individual learning and in-class interactive group learning (Bishop & Verleger, 2013). This model aims to maximize the face-to-face in-class time for instructors to interact with students and provide personalized feedback on students' learning (Bergmann & Sams, 2012; Herreid & Schiller, 2013). It also allows students to engage with each other in group learning activities, to potentially achieve at a level that they would under an individual tutoring condition (Guskey, 2007).

With growing interests in the flipped classroom model, a number of empirical studies have examined its effectiveness compared to traditional face-to-face instructions. These studies have yielded mixed findings. On one hand, some studies supported the effectiveness of the flipped classroom model. For example, Mason, Shuman, and Cook (2013) found that students in a flipped classroom demonstrated equal or better academic performance and showed greater satisfaction with the learning model than did those in traditional classes. Similarly, Schullery, Reck, and Schullery (2011) suggested that the flipped classroom design successfully engaged more students in active learning and improved the connections both among students and between students and the college (Baepler, Walker, & Driessen, 2014; Fulton, 2012). In contrast, some studies did not found the flipped classroom model more effective than the traditional classroom model. For example, Davies, Dean, and Ball (2013) found no significant differences between flipped and traditional classes in students' evaluation of instruction, perceived learning, or their final achievement. Strayer (2012) found that students in a flipped class were actually less satisfied with how the classroom structure oriented them to learning tasks. This dissatisfaction was based on students' feeling less settled in the flipped class because of the variety of learning activities in the class.

These mixed findings may be due to several reasons. There is a considerable variability in the design and implementation of flipped classrooms, although researchers use this common terminology – “flipped classroom”. First, the design of flipped classroom often is guided by various conceptual frameworks, such as Bloom's Taxonomy

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(e.g., Bergmann & Sams, 2012) and the Four Pillars of FLIP framework (e.g., Muir & Geiger, 2016), reflecting different assumptions about student learning and, therefore, effective instruction. Secondly, there is a wide range of content areas and larger programmatic contexts within which flipped classes operate. Third, students in flipped classrooms are not homogeneous. Some students may be successful in the flipped classroom, with more engagement and higher achievement, while others may not. In order to meaningfully interpret the results of previous studies, the conceptual frameworks, the theoretical and pedagogical underpinnings of the design, the contexts of study, and importantly students' characteristics need to be considered. Therefore, research needs to move beyond the comparison between flipped and traditional classes, and specifically examine how students learn in the context of flipped classrooms, in order to uncover the nature of flipped classrooms and describe students' learning in these contexts. The present study particularly focuses on individual characteristic variables that may explain differences in student success in flipped classrooms.

2. Theoretical framework

2.1. Self-regulated learning theory

The flipped classroom model offers opportunities to students to take control of their learning pace and be responsible for their learning process (Fulton, 2012); at the same time, however, it demands more from students (Flipped Learning Network, 2014). In a flipped class, students are expected to be self-directed and complete pre-class tasks in order to be well-prepared for in-class activities (Talbert, 2014). To actively engage in in-class activities, students need to set personal learning goals, deploy appropriate learning strategies, and be capable of monitoring their behaviors (Estes, Ingram, & Liu, 2014). In this situation, knowing how to regulate time, resources, and strategies to achieve learning goals is important (Connor, Newman, & Deyoe, 2014). Research shows that students with higher levels of self-regulation tend to learn effectively and achieve better in a flipped classroom than those with lower levels of self-regulation (Lai & Hwang, 2016). In the present study, we used self-regulated learning theory as the underlying theoretical framework in guiding the investigation of students' learning processes in the flipped classroom model.

Self-regulated learning is an integrated learning process guided by a set of motivational beliefs, behaviors, and metacognitive activities that are planned and adapted to support the pursuit of personal goals (Schunk & Zimmerman, 2012). We adopt the framework developed by Winne and Hadwin (1998, 2008) because their model specifically addresses self-regulated learning in technology-enhanced contexts (Azevedo et al., 2011; Azevedo, Moos, Greene, Winters, & Cromley, 2008), which are aligned well with the characteristics of flipped classes. Winne and Hadwin's self-regulated learning model consists of four stages: *task definition, goal setting and planning, enactment, and adaption*, with each stage occurring within a micro-cognitive system that includes fives processes: *conditions, operations, products, evaluation, and standards*. The self-regulated learning process is such that, when a student is given a task, he would first define the task (e.g., as an easy or a hard task) based on both task and his individual cognitive factors (*conditions*), and then create a profile of standards for satisfactory task performance (*standards*). After setting the standards, he would enact learning strategies (*operations*) to produce learning outcomes (*products*), and then compare those outcomes with the standards to obtain internal feedback regarding his behaviors and performances (*evaluations*). At the same time, he may also be provided with external feedback (*evaluations*) from peers and teachers.

Winne and Hadwin's self-regulated learning model emphasizes the *conditions* and *operations* processes. The *conditions* play a foundational role in self-regulated learning and have a direct impact on the processes that follow (Greene & Azevedo, 2007), and *operations* connect *standards* and *products*, during which learners manipulate information obtained in previous processes, enact certain learning strategies, and produce learning outcomes to match with set standards (Winne, 2001). In the *conditions* process, how to define a task is highly dependent on students' prior task-domain knowledge and self-efficacy (Winne & Hadwin, 2008); while the selection of appropriate strategies and putting them to work are essential in the *operations* process (Winne, 2001). Consistent with the emphasis of Winne and Hadwin's work, researchers have identified the significant impact of these key constructs – *prior domain knowledge, self-efficacy*, and *the use of learning strategies* on students' self-regulated learning (e.g. Diseth, 2011; Murphy & Alexander, 2002; Pintrich, Smith, García, & McKeachie, 1993).

Prior domain knowledge – a construct in the *conditions* process – refers to "… the knowledge, skills or ability that students bring to the learning process" (Jonassen & Grabowski, 2012, p.417). Research has revealed a significant relationship between prior knowledge and self-efficacy (Ferla, Valcke, & Cai, 2009), the use of learning strategies (Murphy & Alexander, 2002; Taub, Azevedo, Bouchet, & Khosravifar, 2014), and academic achievement (Song, 2010; Thompson & Zamboanga, 2004). Pajares and Miller (1994) reported that students' prior math experience had direct effects on math performance and math self-efficacy, and they emphasized that prior knowledge affected performance largely through its influence on math self-efficacy. Murphy and Alexander (2002) found that students with limited domain knowledge tended to use more surface text-processing strategies, such as rereading or omitting unfamiliar words, for the initial understanding of a written text, while those with more developed domain knowledge tended to use more deep and advanced text-processing strategies, such as relating the text to prior knowledge or building a mental image.

Self-efficacy – another construct in the *conditions* process – 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). Extensive research has demonstrated its association with academic achievement (Caprara, Vecchione, Alessandri, Gerbino, & Barbaranelli, 2011; Phan, 2012; Pintrich & Zusho, 2007), as well as students' use of learning strategies (Diseth, 2011; Liem, Lau, & Nie, 2008). Bandura (1986) argued that people are more influenced by how they interpret their experience rather than by their actual attainment per se. For this reason, self-efficacy usually predicts future behavior and achievement better than other psychological and study skill factors. This hypothesis has been supported in multiple empirical studies, as demonstrated in the meta-analysis conducted by Robbins et al. (2004). Self-efficacy is also positively related to the use of cognitive and metacognitive learning strategies. Students who believe in their capabilities are more likely to self-regulate their behaviors by using cognitive strategies and reflecting on their performance during learning (Pintrich & De Groot, 1990). To increase the accuracy of the measurement of self-efficacy, Pajares (1996) has emphasized the importance of defining efficacy at the domain-specific level, for instance, math self-efficacy—students' perceived confidence in their abilities to learn math and complete math tasks (Pajares & Miller, 1995), Internet self-efficacy—students' perceived ability of using the Internet as a problem solving tool (Kim, Glassman, Bartholomew, & Hur, 2013), and collaborative learning self-efficacy—students' perceived confidence in their abilities to work with peers and as a group in collaborative learning activities (Johnson & Johnson, 1999).

Learning strategies – a construct in the *operations* process – denote "behaviors and thoughts in which a learner engages and which are intended to influence the learner's encoding process" (Weinstein & Mayer, 1983, p.3). The effective use of learning strategies is believed to be the hallmark of sophisticated self-regulated learning (Winne, 2001). Three main areas of learning strategies include cognitive strategies, metacognitive strategies, and resource management strategies (Pintrich et al., 1993). Specifically, cognitive strategies involve students' use of basic strategies to process information from texts and lectures such as repeating words, paraphrasing, summarizing, outlining, and critical thinking. Metacognitive strategies concern students' use of strategies to control and regulate their cognitive behaviors such as setting goals, monitoring comprehension, and regulating learning behaviors. Finally, resource management strategies refer to learners' regulatory strategies for controlling other resources besides their own cognition, such as effectively using time and seeking help from peers or instructors when needed (Pintrich et al., 1993). The use of these learning strategies, in general, is significantly associated with students' academic achievement (Duncan & McKeachie, 2005; Pintrich & De Groot, 1990), however, the importance of any given learning strategy varies with the learning environment. For instance, Credé and Phillips (2011) concluded from their meta-analysis that the use of help-seeking strategies is weakly related with grades in the traditional classroom model, whereas Aleven, Stahl, Schworm, Fischer, and Wallace (2003) found that the effective use of help-seeking strategies could substantially improve students' achievement in a computer-supported learning environment.

Based upon our review of these three key self-regulatory constructs (i.e. prior domain knowledge, self-efficacy, learning strategies), we propose a general theoretical model that describes the relationships among these three constructs and academic achievement. As shown in Fig. 1, we hypothesize that prior domain knowledge directly influences self-efficacy, learning strategies, and achievement; self-efficacy influences students' choice of learning strategies and their academic achievement; and the use of learning strategies influences academic achievement. This model has been validated to some extent in several earlier studies. For example, Zimmerman and Martinez-Pons (1992) studied the role of prior achievements and self-efficacy beliefs on final achievement with academic goals included in the path model. Pintrich and De Groot (1990) established associations between self-efficacy, learning strategies and academic achievement in a correlational study. Similarly, Greene, Miller, Crowson, Duke, and Akey (2004) tested the impact of self-efficacy and the use of learning strategies on academic achievement, while controlling for students' perceptions of the instrumentality of class work and achievement goals. Although these studies examined the relationships among the three key constructs in different combinations, the general findings support a theoretical framework that describes the relationships among prior knowledge, self-efficacy, learning strategies, and academic achievement as shown in Fig. 1. To understand students' self-regulated learning in the flipped classroom context, we situate this model in the context of flipped math classes. We hope to identify malleable self-regulatory factors that influence students' success in flipped math classes and provide design suggestions associated with those constructs.

2.2. Situating self-regulated learning theory in a flipped math classroom context

The context of this study was two introductory undergraduate-level math courses, calculus I and II, which were delivered as flipped classes. We selected these two courses as our study contexts for the following

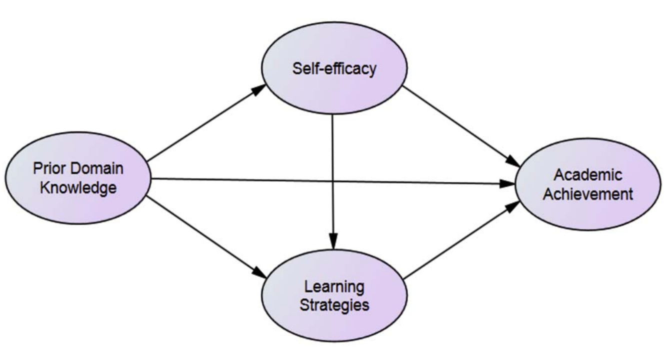

Fig. 1. Conceptual model for the essence of the self-regulated learning process.

reasons. First, calculus is historically a challenging discipline due to a number of students' epistemological discontinuities. These discontinuities can remain epistemological obstacles on the road toward the construction of other important math concepts such as discrete/continuum, finite/infinite, determinate/indeterminate and so on (Ferrara, Pratt, & Robutta, 2006). Second, although several studies have examined the effects of technology-based pedagogical approaches on students' learning of calculus (e.g. Doerr & Zangor, 1999; Ubuz & Kirkpinar, 2000), the impact of the flipped classroom approach has rarely been explored in this domain. Third, these two calculus courses have a large enrollment each semester (approximately 300 students in each course) offering an opportunity for research on students' learning. Prior to the implementation of the flipped classroom model, the courses had been always taught only as traditional face-to-face classes. This large lecture course format raises concerns including incompatibility with different learner characteristics, little or no individualized attention and instruction to students, limited interactions among peers and with instructors (Schullery et al., 2011), and an achievement gap between students with different knowledge and social backgrounds (Haak, HilleRisLambers, Pitre, & Freeman, 2011). The flipped classroom model was implemented in hopes of addressing these issues.

These two calculus courses were both designed based upon the Bloom's Revised Taxonomy (Krathwohl, 2002), with the pre-class learning activities targeting lower level cognitive skills including remembering, understanding, and sometimes applying, and the in-class learning activities targeting higher level cognitive skills including applying, analyzing, evaluating, and creating. In general, students went through online lectures and completed associated online homework prior to recitation sessions, and then attended the recitation sessions to apply learned knowledge through collaborative activities. Specifically, the pre-class learning was designed to introduce foundational math terminologies, principles, and models to prepare students for the following in-class group activities. Although the pre-class activities were largely structured by the teacher, students were the ones who took control of the learning process, such as deciding how much time to spend on the lecture, how much content to cover, and how many times to attempt assignments in order to get the highest possible grade. In contrast, in the in-class setting, both the teacher and students shared the responsibilities for regulating the learning process. For example, while students worked in groups, the teacher might talk with an individual student, provide personal feedback if needed, and encourage those who were not actively involved.

Due to the different characteristics of the pre- and in-class learning environments, students may enact different self-regulated learning strategies in these two contexts. Therefore, it is valuable to examine the effects of the three key self-regulatory constructs – *prior domain knowledge, self-efficacy*, and *the use of learning strategies* – on students' academic achievement in both learning environments separately, rather than treating the flipped classroom as one unified learning environment. Based upon this idea, we expanded our proposed conceptual model (Fig. 1) to two situated structural models in order to describe the self-regulated learning process in the pre- and in-class learning environments. The key self-regulatory constructs in the model are represented by different measures, correspondingly.

In the pre-class Internet-based learning environment, the main activity for students was to learn content materials on their own. Students' prior math knowledge is believed to play a critical role in navigating through various learning sources (e.g. lecture video, lecture slide, and embedded quiz) and understanding foundational math concept and formulas (Chen, Fan, & Macredie, 2006; Moos & Azevedo, 2008). We hypothesized that the more advanced math courses students had taken prior to the flipped course, the more confident they would be in their abilities to complete the pre-class task, and the more advanced learning strategies they may enact during pre-class learning. Besides prior math knowledge, students' perceived confidence in learning math (i.e., math self-efficacy) has been consistently shown to have direct effects on the use of learning strategies and math achievement (Caprara et al., 2011; Pintrich & Zusho, 2007). Also, since all online lectures were delivered through the Internet, students' perceived confidence in knowing how to learn effectively on the Internet was assumed to be highly related with academic achievement (Tsai, Chuang, Liang, & Tsai, 2011; Wang, Shannon, & Ross, 2013). In particular, students' perceptions of successfully using the Internet as a problem solving tool, such as differentiating relevant information (i.e., signal) from irrelevant information (i.e., noise), referred as Internet self-efficacy, has been shown to influence academic performance in a blog-centered class (Kim et al., 2013). Therefore, we hypothesized that both Internet self-efficacy and math self-efficacy would have direct effects on the use of learning strategies and pre-class achievement. Additionally, research on learning strategies suggests that the use of cognitive, metacognitive, and resource management strategies directly influences students' pre-class achievement (Credé & Phillips, 2011; Pintrich et al., 1993). In the Internet-based learning environment, the use of resource management strategies, including environmental control and help seeking strategies, was expected to be especially significant in impacting achievement, because students learning in the Internet-based learning environment oftentimes find it difficult to sustain their concentration and easily feel desperate while meeting obstacles (Winter, Cotton, Gavin, & Yorke, 2010).

In the in-class collaborative learning environment, students were mainly involved in group activities to practice the knowledge learned in the pre-class sessions. Since the in-class activities were normally designed to be associated with the pre-class learning materials, students' pre-class achievement was considered prior math knowledge for students' in-class learning and was expected to directly impact their in-class achievement. Additionally, pre-class achievement could also influence in-class achievement through the mediating effect of self-efficacy (Bandura, 1986) and the use of learning strategies (Murphy & Alexander, 2002). We hypothesized that the higher the grade students obtained in the pre-class homework, the more confidence they would feel in their abilities to work in groups and complete group work; the more advanced strategies they would enact to work with peers on solving problems; and the better their performance would be on the in-class assignments. In contrast to the pre-class learning environment, students were not using the Internet to learn content materials, instead, they were guided by the teacher to work collaboratively with peers. Thus, students' perceived confidence in their abilities to work in groups (i.e., collaborative learning self-efficacy), instead of Internet self-efficacy, may impact what strategies they use to work in groups and their performance on the in-class assignments (Johnson & Johnson, 1999). Therefore, both collaborative learning self-efficacy and math self-efficacy were hypothesized to have direct effects on students' use of learning strategies and in-class achievement. As for the use of learning strategies, as with the pre-class learning environment, we still hypothesized that the use of cognitive, metacognitive, and resource management strategies would have direct effects on students' in-class achievement. However, in terms of the resource management strategies, we assumed the environmental control strategy would not be salient in the in-class learning environment, because the in-class activities were highly organized by the teacher and students rarely had opportunities to manipulate or control their surroundings (e.g., learning time, location, and peers) to achieve personal learning goals. Therefore, to simplify the structural model, environmental control strategies were not included in the in-class structural model.

3. Research purpose and questions

The goals of this study were twofold: (1) to identify the self-regulatory factors affecting achievements in the two learning environments of flipped undergraduate math courses: pre-class Internet-based learning environment and in-class collaborative learning environment, and (2) to provide suggestions for designing an effective flipped math course, based on the understanding of students' self-regulated learning process in these two learning environments. Specifically, built upon the Winne and Hadwin's theoretical framework of self-regulated learning, we aimed to examine the relationships between three self-regulatory constructs: *prior domain knowledge, self-efficacy*, and *the use of learning strategies* and academic achievement in both the pre-class and in-class learning environments of flipped math courses. The following two research questions guided the design of this research.

> Research Question 1: What are the relationships among prior math level, math self-efficacy, Internet self-efficacy, the use of learning strategies, and students' achievement in the pre-class Internet-based learning environment?
> Research Question 2: What are the relationships among online achievement, math self-efficacy, collaborative learning self-efficacy, the use of learning strategies, and students' math achievement in the in-class collaborative learning environment?

4. Research methods

A quantitative study was conducted to answer above two research questions. Two online surveys were sent to consenting students during the 3rd and 10th weeks of the semester. In addition, the first author also observed 16 in-person recitation sessions of the Calculus I and II courses to experience and verify the enactment of the flipped classroom model.

4.1. Participants and context

Participants consisted of 151 undergraduate students from 16 flipped sections of Calculus I and II courses in a large Midwestern university. Among the participants, gender was roughly evenly distributed (i.e., male 47.9% and female 52.1%). In terms of 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 class standing, both courses were dominated by freshman and sophomore students (approximately 85%) 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 engineering majors (10.6%). The other majors included agriculture, communication/liberal arts, computer science, mathematics and undecided.

Both target courses, calculus I and II, were designed by the same instructors in the same design format, following the same design principles, and with the similar learning activities. Both were 14-week long courses that consisted of three online lessons and two recitation sessions per week, for a total 33 online lessons and 28 recitation sessions for the entire semester. The instructors created a course site in the *Desire2Learn* learning management system where they uploaded course materials and created links to the homework system and online discussion forums. During the semester, students engaged in two major activities: (1) watching online lectures and finishing associated homework prior to the recitation session, and (2) participating in the recitation session and completing associated homework.

Every Tuesday and Thursday, students attended in-class recitation sessions. The in-class recitation sessions lasted 55 min and typically included approximately 30 students per section. In each session, the instructor first spent approximately 10 min going through one or two warm-up examples related to the previous online lecture with the entire class and then divided the class into groups. Each group had 3–4 students and they worked together to solve practice problems. After each 5–10 min of group discussion, either the instructor or a randomly selected group presented solutions to the entire class. After each recitation session, students were required to complete a corresponding take-home assignment or quiz individually and submit the solution to the teacher at beginning of the next recitation session. The total take-home

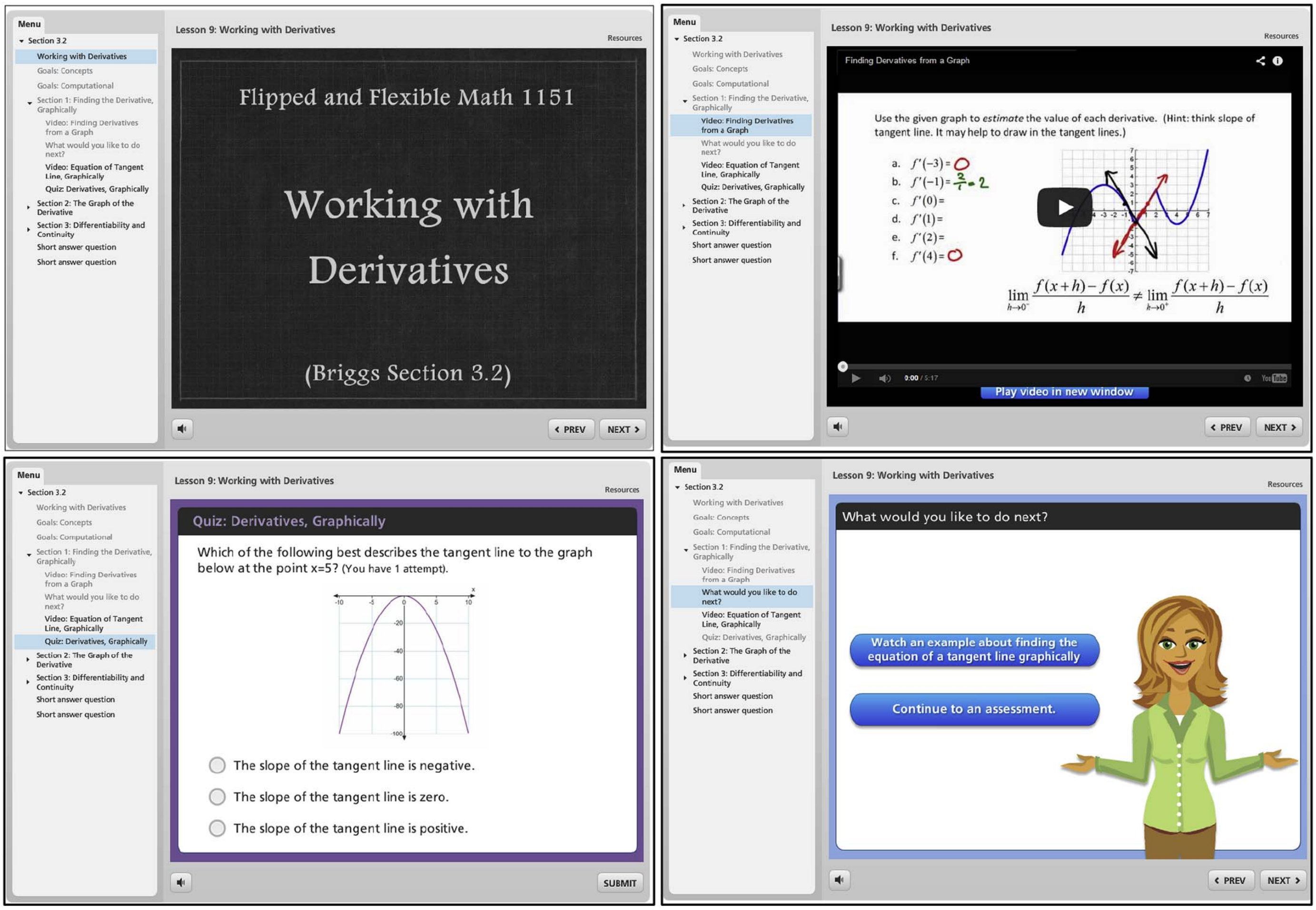

Fig. 2. Screenshots of online lectures: Top left is a screenshot of the first page of an online lecture, top right is a screenshot of an online lecture slide with an embedded video clip, bottom left is a screenshot of an online lecture slide with an embedded quiz question, and bottom right is an online lecture slide with an interactive question.

assignment grade accounted for 10% of final grade.

To be prepared for the in-class activities, students were required to complete the associated online lectures. The suggested schedule for finishing the online lectures was every Monday, Wednesday, and Friday, before the corresponding recitation session. The online lectures were designed by the course instructors based upon the Bloom's Revised Taxonomy (Krathwohl, 2002) and commonly consisted of short instructional slides and videos, graphical representations, embedded quizzes, and associated homework. Fig. 2 provides four screenshots from a sample online lecture, for illustration. The course instructors uploaded online lectures to the course site in the learning management system all in once, before the start of the semester. This provided students with an overview of the topics that would be covered during the semester and also allowed them to proceed through the course at their own pace. During pre-class learning, students went through these online lectures whenever and wherever they preferred and also had options to stop and rewind the lecture until they understood the topic. They could also communicate with peers in the course online discussion forum. After every online lecture, students were required to complete a corresponding online homework assignment. The total pre-class homework score accounted for 11% of final grade.

4.2. Measures

All the survey items were measured on a seven-point Likert-type scale, ranging from 1 (*not at all true of me*) to 7 (*very true of me*).

4.2.1. Prior domain knowledge

Students' self-report of the highest-level math class completed in high school was selected as an indicator of their prior math knowledge for the pre-class learning setting. Because this flipped course was the first college math course for the majority of participants, students' math level achieved in high school was expected to influence their learning process in the pre-class setting (Chen et al., 2006). The information regarding the math level was obtained by asking students the question "What was the highest level of mathematics you took prior to college?" Six options were provided ranging from 1 (*below pre-calculus*) to 6 (*beyond calculus AP (BC)*). For the in-class learning setting, pre-class homework grades were selected as the indicator of prior math knowledge, because of the high association between the in-class activities and pre-class learning materials. These grades were continuous numbers with the total score as 11 points and they were retrieved from instructors.

4.2.2. Self-efficacy

Self-efficacy is most effectively measured at the domain-, or even task-specific, level (Pajares, 1996). Therefore, in the current study, three domains of self-efficacy construct were measured: Math Self-efficacy (MSE), Collaborative Learning Self-efficacy (CLSE), and Internet Self-efficacy (ISE). Both the MSE and CLSE scales were adapted from the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1993). Artino (2005) has provided evidence that the MSLQ is a widely used measure in the areas of motivation and self-regulated learning. Extensive research has also documented the high reliability and validity of the MSLQ scales (Duncan & McKeachie, 2005; Pintrich

Table 1
Descriptive statistics and reliability coefficients for variables in both pre-class and in-class structural models.

	Pre-class structural model			In-class structural model		
	Variable	Mean (*SD*)	*α*	Variable	Mean (*SD*)	*α*
Prior domain knowledge	High school math level	3.28 (*1.13*)		Pre-class achievement	9 (*1.56*)	
Self-efficacy	Math self-efficacy	4.82 (*1.49*)	0.93	Math self-efficacy	4.82 (*1.49*)	0.93
	Internet self-efficacy	4.22 (*1.55*)	0.84	Collaborative learning self-efficacy	4.58 (*1.48*)	0.93
Learning strategies	Cognitive strategy	4.57 (*1.44*)	0.75	Cognitive strategy	4.59 (*1.19*)	0.88
	Metacognitive strategy	4.72 (*1.19*)	0.89	Metacognitive strategy	4.49 (*1.31*)	0.93
	Help seeking strategy	4.45 (*1.63*)	0.82	Help seeking strategy	4.97 (*1.39*)	0.91
	Environmental control strategy	5.08 (*1.19*)	0.75			
Academic achievement	Pre-class achievement	9 (*1.56*)		In-class achievement	7.8 (*1.39*)	

Note: 1. The prior domain knowledge for pre-class structural model was measured by the survey question, "What is your highest-level math course taken in high school?" 1. Below pre-calculus, 2. Pre-calculus, 3. Non AP-calculus, 4. Calculus AP (AB), 5. Calculus AP (BC), 6. Beyond calculus AP (BC).
2. The self-efficacy and learning strategies variables were all measured on seven-point Likert scales.
3. The academic achievement was all standardized on a 100-point scale.

et al., 1993). Thus, self-efficacy subscale from the MSLQ was adapted to refer to confidence in math and in collaborative learning, respectively. For example, the original item "I expect to do well in this class" was changed to "I expect to do well in math" for the MSE scale, and "I expect to do well in the in-class group learning" for the CLSE scale. Confirmatory factor analysis was conducted on the adapted full self-efficacy scale, five items whose factor loadings were above 0.60 were selected for this study. Appendix A presents the five items and their descriptive statistics.

ISE was measured using an adapted version of the 4-item knowledge differentiation scale from Kim et al.'s (2013) Internet self-efficacy scale. For example, the original item "I can use hyperlinks to find information that is important to me" was changed to "I can find information that is important to me through the lecture videos". Internal consistency coefficients of the three self-efficacy measures are presented in Table 1.

4.2.3. Learning strategies

Twenty-three items from the learning strategies subscales from the MSLQ (Pintrich et al., 1993) were adapted to assess learning strategies used in both the pre-class and in-class settings of the flipped math courses. The rehearsal, elaboration, organization, and critical thinking scales served as measures of learners' use of the cognitive strategies. The metacognitive self-regulation scale served as the measure of using metacognitive strategies. The time and study environment scale was adapted to measure the use of environmental control and help seeking strategies. All items were worded to fit into the specific learning settings. For example, the original item "When I study for this class, I go over the formulas or definitions in order to memorize them" was changed to "When I study math through pre-class online materials …" to fit into the pre-class learning setting and "When I learn math through in-class group activities …" to fit into the in-class learning setting. Confirmatory factor analysis was conducted on the adapted full learning strategies scale, seven items of cognitive strategy scale, nine items of metacognitive strategy scale, and seven items of item and study environment scale were selected whose items' factor loadings were above 0.60. The selected items and their descriptive statistics are shown in Appendix A. Internal consistency coefficients of the learning strategy measures are shown in Table 1.

4.2.4. Learning outcomes

At end of each online and in-class session, students were required to complete an associated homework. For the online session, the homework is an online multiple-choice quiz and automatically graded after students' attempt. As for the in-class session, homework is a take-home problem-based assignment, which is graded by the instructor. The online homework grades and take-home assignment grades were selected as the indicators of learning outcomes for pre-class and in-class learning, respectively. The scores were continuous points on a 100-point scale.

4.3. Data analysis

Structural equation modeling (SEM) was the primary method used to answer research questions, since it is capable of measuring the relations of both observed and unobserved variables with the consideration of measurement error. The analytical procedure was guided by the three steps of SEM (Lomax & Hahs-Vaughn, 2013), which include data preparation, data screening, and estimation of the model. Specifically, a one-way analysis of variance (ANOVA) was first conducted to examine the difference of all endogenous variables (e.g. math self-efficacy, use of the learning strategies). Normality, outliers, multicollinarity, and reliability of measures were then tested for model estimation. As for the estimation of the model, two levels of goodness-to-fit index were reported to indicate how well a model can reproduce the data (Markus, 2012), including overall model fit assessment and component fit assessment. For overall model fit assessment, the examined chi-square with degree of freedom (x^2/df) and the Root Mean Square Error of Approximation (RMSEA) were reported. Goodness-of-fit (GFI) and the Adjusted Goodness-of-fit (AGFI) indices were reported as the component fit assessment. The recommended cut-off points for these assessments are: x^2/df < 2, RMSEA ≤ 0.06, GFI ≤ 0.90, and AGFI ≤ 0.90 (Lomax & Hahs-Vaughn, 2013)

5. Results

5.1. Data preparation

The target two calculus courses, Calculus I and II, were designed and implemented in the same format, design principles, learning activities as described earlier, providing justifications for merging the datasets from the two courses. To assure the feasibility of merging the datasets, one-way analysis of variance (ANOVA) was conducted. The results showed that there were no significant differences between these two courses regarding all the endogenous variables: math self-efficacy [F(1, 149) = 0.896, p = 0.345], collaborative learning self-efficacy [F(1, 149) = 0.403, p = 0.527], knowledge differentiation [F(1, 147 = 1.513), p = 0.221], pre-class cognitive strategy [F(1, 112) = 0.106, p = 746], pre-class metacognitive strategy [F(1, 12) = 0.000, p = 0.994], pre-class help seeking strategy [F(1, 111) = 2.705, p = 0.103], pre-class environmental control strategy [F(1, 112) = 0.304, p = 0.583], in-class cognitive strategy [F(1, 112) = 0.295, p = 0.588], in-class metacognitive strategy [F(1, 110) = 1.834, p = 0.178], and in-class group learning strategy [F(1, 110) = 2.410, p = 0.123]. Therefore, the combined dataset was used for the subsequent analyses.

Table 2
Correlation coefficients for all variables in both pre-class and in-class structural models.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. MSE	–												
2. ISE	0.36**	–											
3. CLSE	0.59**	0.34**	–										
4. Cog_Pre	0.06	0.08	0.33**	–									
5. Meta_Pre	0.32**	0.16	0.34**	0.59**	–								
6. HS_Pre	0.07	− 0.18	0.20**	0.37**	0.43**	–							
7. EC_Pre	0.22*	0.03	0.29**	0.47**	0.65**	0.39**	–						
8. Cog_In	0.31**	0.11	0.51**	0.90**	0.70**	0.38**	0.50**	–					
9. Meta_In	0.34**	0.11	0.49**	0.56**	0.78**	0.43**	0.58**	0.67**	–				
10. HS_In	0.11	− 0.08	0.34**	0.27**	0.38**	0.58**	0.36**	0.38**	0.45**	–			
11. Priormath	0.23**	0.05	0.07	− 0.08	0.05	0.06	0.10	− 0.04	− 0.03	0.05	–		
12. Preclass	0.37**	0.11	0.21**	0.16	0.25**	0.26**	0.17	0.27**	0.24*	0.16	0.12	–	
13. Inclass	0.33**	0.02	0.15	0.07	0.25**	0.40**	0.21*	0.15	0.24**	0.28**	0.14	0.49**	–

Note: 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; Priormath = Highest level math course taken in high school; Preclass = Pre-class achievement; Inclass = In-class achievement.

* $p < 0.01$.

** $p < 0.001$.

5.2. Data screening

Data screening examined outliers, normality, multicollinearity, and reliability of measures. It also revealed correlations of measured variables. Table 1 shows the mean, standard deviation, and Cronbach's alpha for all measures after combining two courses' data. Table 2 displays the zero-order correlation coefficients among all measured variables.

First, outliers and normality of the measures were examined. All variables ranged within 3 standard deviations from the mean of the variable, thus no outliers were evident. With respect to normality, Kline (2005) suggested using absolute cut-off values of 3.0 for skewness and 8.0 for kurtosis. All measures were well within these ranges (ranging from − 0.970 to − 0.044 for skewness and from − 0.532 to 1.649 for kurtosis), indicating that all measures largely followed the normal distribution.

Second, multicollinearity was checked in two ways. First of all, zero-order correlation coefficients of predictor variables in the structural models were examined (see Table 2). Kaplan (1994) proposed a general diagnostic rule for multicollinearity in structural educational models: multicollinearity is considered extreme when the correlation coefficient is around 0.95; substantial when the coefficient is between 0.6 and 0.8; and negligible when the coefficient is between 0.4 and 0.5. This general rule only applies for the predictor variables in the same structural model (e.g., correlation between the pre-class cognitive strategies variable and the pre-class metacognitive strategies variable). If two predictor variables were in different structural models (e.g., correlation between the pre-class cognitive strategies variable and the in-class cognitive strategies variable), the rule would not apply. Thus, although the correlation coefficient between pre-class cognitive strategy use and in-class cognitive strategy use was $r = 0.90$ (shown in Table 2), these two predictor variables belonged to two different structural models and, therefore, their correlation was not cause for concern. Second, if the correlation coefficient of predictor variables in the same structural model was above $r = 0.60$, 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 independent variable with other independent variables in a regression model" (O'Brien, 2007, p.673). The most common threshold value of VIF and tolerance is 10, with many practitioners suggesting that when VIF and tolerance reach this value, there is a severe or serious multicollinearity concern in the structural equation model (Menard, 1995).

In this study, three substantial zero-order correlation coefficients were observed indicating potential multicollinearity concerns. These included 0.59 (the coefficient between the pre-class cognitive and pre-class metacognitive strategies), 0.65 (the coefficient between the pre-class environmental control and pre-class metacognitive strategies), and 0.67 (the coefficient between the in-class cognitive and in-class metacognitive strategies). However, the collinearity test in SPSS 22.0 (IBM Corp, 2013) found no statistically significant multicollinearity among these predictor variables based on the accepted thresholds for VIF and tolerance (see Table 3). Therefore, it was concluded that there were no serious concerns with multicollinearity among the predictor variables in both the pre-class and in-class structural models.

Finally, the internal consistency of measures was examined by computing Cronbach's alpha. Cronbach (1951) suggested that an alpha value between 0.70 and 0.90 indicates good reliability and larger than 0.90 indicates excellent reliability. As shown in Table 1, all measures' alpha values were at least 0.75, indicating all measures had good reliability.

In sum, the data collected from 151 participants satisfied all three key requirements for SEM, thus, further analyses were conducted with this combined dataset.

The zero-order correlations revealed some expected patterns of results at the bivariate level (see Table 2). For example, math self-efficacy was positively related to the use of metacognitive and environmental control strategies during pre-class learning, the use of cognitive and metacognitive strategies during in-class learning, as well as the pre-class and in-class math achievements. The use of metacognitive and help seeking strategies all had significant positive correlations with pre-class and in-class math achievements. Also, in-class math achievement was positively related to the pre-class math achievement.

Table 3
Collinearity test for selected measured variables.

Variable	Cog_Pre	MetaCog_Pre	EC_Pre	Cog_In	MetaCog_In
VIF	1.564	2.130	1.772	1.853	1.987
Tolerance	0.640	0.470	0.564	0.540	0.503

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.

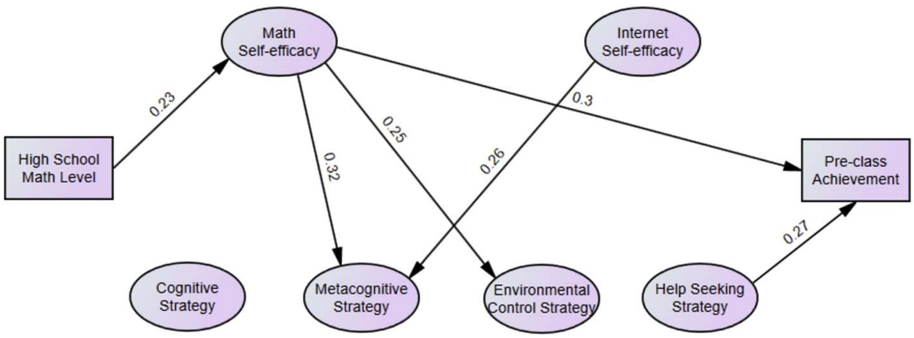

Fig. 3. Model estimation for pre-class Internet-based learning structural model.

5.3. Structural equation modeling analysis

To answer the two research questions in the study, SEM analysis was conducted using AMOS 22 (Arbuckle, 2013). Full Information Maximum Likelihood (FIML) estimation method was adopted to estimate the fit of the two hypothesized structural models, since it has been evidenced as a superior method for dealing with missing data (Enders & Bandalos, 2001). Significant paths of the fully estimated structural models are shown in Figs. 3 and 4. Standardized beta coefficients (β) are reported, so that the path coefficients illustrate the strength of each explanatory variable controlling for all the other explanatory variables in the model (Lomax & Hahs-Vaughn, 2013).

5.3.1. 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

Examination of the pre-class Internet-based structural model resulted in a moderate to good fit, x^2/df = 1.48 smaller than 2, RMSEA = 0.05, GFI = 0.99, and AGFI = 0.95. As shown in Fig. 3, the level of math class previously completed had a direct positive effect on students' math self-efficacy (β = 0.23), which then had a positive direct effect on online homework achievement (β = 0.30). This indicates that the higher level of students' prior math knowledge, the more confident they felt in accomplishing the online learning tasks. This confidence, then, was associated with higher grades in the online homework. Math self-efficacy was also found to have positive relations with the use of metacognitive (β = 0.32) and environmental control (β = 0.25) strategies. These results suggest that the more confident students feel in their abilities for learning math, the more often they would take actions to control when and where to learn the online materials, monitor their own understandings of learned knowledge, and reflect on their use of learning strategies and the completion of set learning goals. Additionally, Internet self-efficacy had a positive effect on the use of metacognitive strategies (β = 0.26), implying that students who were confident in differentiating relevant and irrelevant information on the Internet tended to self-monitor and self-evaluate their own learning process. In terms of strategy use, only help-seeking strategies showed a positive direct effect on online learning achievement (β = 0.27), suggesting that the more often students sought help from others while encountering problems during online learning, the higher the grade they obtained in the online homework.

5.3.2. Relationships between prior math level, math self-efficacy, internet self-efficacy, the use of learning strategies, and online achievement in the in-class collaborative learning environment

Examination of the in-class collaborative structural model yielded an adequate model fit, x^2/df = 1.55 smaller than 2, RMSEA = 0.06, GFI = 0.98, AGFI = 0.91. As shown in Fig. 4, the online homework score had a positive direct effect on both students' math self-efficacy (β = 0.36) and their achievement on take-home assignments (β = 0.44), indicating that the higher the grade students obtained in the online learning, the more confident they felt in their ability to complete in-class learning tasks, and the higher grade they obtained for in-class learning. No direct relations were found between math self-efficacy and the use of learning strategies in this context. Instead, collaborative learning self-efficacy had positively direct relations with the use of all measured learning strategies, including cognitive strategies (β = 0.57), metacognitive strategies (β = 0.43), and help seeking strategies (β = 0.46). These results imply that students who are more confident in their ability to learn in groups are more likely to use a variety of learning strategies to complete tasks. As with the pre-class structural model, only the help-seeking strategy was found to have a positive direct effect on achievement (β = 0.33), suggesting that the more often students sought help from others, the higher the grade they obtained. Interestingly, in this model, cognitive strategy use was significantly negatively related with in-class achievement ($\beta = -0.44$). This finding was unexpected since cognitive strategy use is commonly positively related to academic achievement in the literature (e.g. Credé & Phillips, 2011). Thus, further examination was conducted to investigate the validity of this finding.

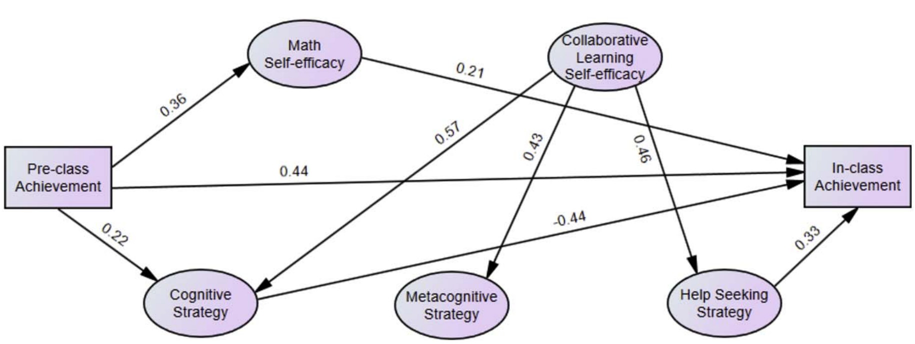

Fig. 4. Model estimation for in-class group-based learning structural model.

Table 4
Multi-level regression analysis results (N = 112).

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.	R square	Model sig.
		B	SE	Beta				
1	Constant	1.934	0.192		10.098	0.000		
	Cog_In	0.066	0.040	0.154	1.632	0.106	0.024	0.106
2	Constant	1.823	0.196		9.278	0.000		
	Cog_In	−0.008	0.054	−0.020	−0.155	0.877		
	MetaCog_In	0.101	0.049	0.257	2.050	0.043	0.043	0.035

Note: Cog_In = In-class cognitive learning strategy; Meta_In = In-class metacognitive learning strategy.

Students' use of cognitive strategies during in-class learning had a significant positive zero-order correlation with in-class math achievement. However, this association became negative in the SEM analysis when metacognitive and help-seeking strategies were included in the model. This pattern of coefficients 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). These results are presented in Table 4.

The results suggest that cognitive strategy could be classified as a negative suppressor variable. Cognitive strategy use was significantly and quite highly correlated with metacognitive strategy use (r = 0.67), and metacognitive strategy was a better predictor of achievement when both variables were included in the multilevel regression model (model 2: $\beta = -0.02$, p = 0.88 for cognitive strategy and $\beta = 0.26$, p = 0.04 for metacognitive strategy). When the metacognitive strategy measure 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 a significant number of students who reported that they often used cognitive strategies 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.

6. Discussion

The goals of this study were to identify self-regulatory factors affecting achievements in both the pre-class Internet-based and in-class collaborative learning environments of two flipped math courses and provide suggestions for designing effective pre-class and in-class activities of a flipped math course. Results of the present study show that math self-efficacy and the use of help seeking strategies significantly impact students' math learning achievements in flipped math classes. Previous research has highlighted the important roles of math self-efficacy and help seeking strategies in both traditional face-to-face and online learning environments, results of this study specifically link the positive impact of these two factors to academic achievements in the context of flipped math classroom. Suggestions of enhancing students' math self-efficacy and the use of help seeking strategies in flipped math classroom are discussed as follows.

6.1. Math self-efficacy and its implications for course design

The results showed that students who were more self-efficacious in learning math were more likely to achieve at higher levels in both the pre-class and in-class environments. These findings are consistent with previous research in regular classroom settings, showing the robust effects of domain-specific self-efficacy on academic achievement (Pajares, 2008; Pintrich & Zusho, 2007). It also supports Winne and Hadwin's self-regulated learning model. Students' strong belief in their ability to learn math can assist them in generating appropriate goals for completing online lectures and engaging in group-based math learning activities, guide their learning behaviors, and eventually lead them to higher achievement on in assignments (Winne & Hadwin, 1998, 2008). Consistent with prior research (e.g., Song, 2010), we found that students' perceived efficacy for learning math was positively related with their prior math knowledge. For example, students who took higher-level math courses in high school (e.g. Calculus AP) reported higher efficacy for learning from math lectures in the pre-class online environment. Similarly, students who achieved higher in the pre-class assignments tended to be more confident engaging in in-class activities. Such the finding also supports Winne and Hadwin's self-regulated learning model. Students' level of math knowledge directly predicted their confidence in completing relevant math learning activities.

Based on these findings, we suggest that teachers should help students build their confidence of learning math and help them believe they are able to succeed in learning math. Bandura (1997) argued that experiencing success was one of the key sources of self-efficacy. For pre-class activities, teachers should select and structure the online lectures, learning tasks, and assignments in ways that are suitable for the development of students' mathematics reasoning so they experience small successes early in the course to help develop their confidence to learn advanced topics later in the course. Furthermore, since teachers are not physically with students while they are participating in lectures online prior to the class, they should show their virtual presence in ways such as providing immediate feedback to student's questions, sending reminders with guiding instructions, and creating mechanisms to assist students' understanding (Kim, Kim, Khera, & Getman, 2014). In particular, teachers should pay extra attention to students who report low levels of achievement in previous math classes, because such students may not be well prepared for learning online math lectures on their own. For these students, teachers should first identify learning needs based on their pre-class quiz performance, and then offer calibrated support for individual students to help them progress to higher math skill levels (Marshman & Brown, 2014).

In addition to prior success, Bandura (1997) asserted that observing success in others and verbal persuasion are two essential factors influencing student's perceived confidence to complete a task. Two possible teaching strategies can be enacted to enhance students' confidence of completing in-class activities. One strategy is to design learning tasks in the group-based format so students could observe how peers solve math problems. If students see their peers successfully solve a problem, they may be more likely to feel confident in their own abilities and be more willing to engage in problem-solving activities (Johnson & Johnson, 1999). Another strategy is to provide positive feedback on students' progress in solving in-class math problems. Teachers should pay particular attention to students who demonstrate low math confidence, such as individuals who do not engage in group discussions or class tasks. To improve their confidence of learning math, teachers could compliment their growth, attribute poor performance to a lack of effort or appropriate strategies, and encourage them to try harder (Siegle & McCoach, 2007).

6.2. Help-seeking strategies and their implications for course design

The results showed that the use of help-seeking strategies had a positive effect on students' pre-class and in-class achievement, indicating that students' appropriate approaches to seeking help from peers and the teacher, when it is needed, increase the likelihood that they will perform well on assignments. This finding is consistent with previous research on help-seeking in both the computer-supported and traditional face-to-face learning environments. For example, Aleven et al. (2003) emphasized that the use of help-seeking strategies is especially important in computer-supported interactive learning environments, and have shown its substantial influence on the improvement of learning outcomes. They agree with previous researchers that help-seeking reflects students' metacognitive and domain-specific skills and knowledge (Newman, 1998) and particularly manifests students' self-regulatory behaviors (Winne, 2001). Meanwhile, Ryan, Patrick, and Shim (2005) have shown that help-seeking behaviors are critical for learning and achievement in the traditional face-to-face classroom. In addition, we found that students who were more self-efficacious in collaborating with others during in-class group-based learning were more likely to ask for help when needed, indicating that social factors, such as social competence (e.g., mature social skills in interacting with others) and social relationships with peers and teachers (e.g. warm, supportive relationships with teachers) promote help-seeking behaviors in the face-to-face learning environment (Ryan et al., 2005; Ryan & Pintrich, 1997).

Building upon the above findings, we provide two suggestions for designing effective flipped math classes. First, while learning math in the Internet-based environment, students often encounter various obstacles due to the intrinsic complexity of subject (e.g., abstract concepts and symbols) and the lack of on-site support from the teacher. These obstacles often lead to incompletion of the online lectures. To help students overcome these obstacles and successfully complete the online lectures, teachers should provide opportunities for students to ask help, create virtual space to answer students' questions, and encourage them to seek help if necessary. For example, teachers could set up a math-friendly discussion forum, where students can ask and answer questions easily using math symbols or equations instead of text only. Students are encouraged to help each other and answer questions in the forum. Teachers should also act as an active member in the forum, constantly checking to provide feedback on unsolved questions and solve any conflicts that emerge (Xie, Miller, & Allison, 2013).

Second, in the in-class group-based learning, teachers should support students in seeking help from peers and the teacher, when needed. Research has shown various benefits of students' enactment of help-seeking strategies in the face-to-face classroom. For example, seeking help from teachers can promote students' motivation, learning, and achievement (Marchand & Skinner, 2007). Additionally, seeking help from peers can help students engage in metacognitive learning processes and make learning more enjoyable (Newman, 1998). Although teachers may well convey the usefulness of help seeking strategies to students, not every student is skilled in enacting such strategies on their own. As discussed earlier, a number of social interpersonal reasons have been identified to explain students' unwillingness to seek help, even when they know it is needed, including efficacy beliefs about their math learning abilities and perceived relationships with teachers and peers (e.g., Ryan et al., 2005; Ryan & Pintrich, 1997). In order to facilitate students' use of help-seeking strategies, a few tactics could be enacted. For example, teachers could promote a classroom environment that emphasizes competence development, personal progress, and the intrinsic value of learning (referred to as a mastery goal structure); students in mastery goal-focused classrooms have shown higher tendencies to demonstrate desirable learning behaviors including higher persistence, greater effort, and lower disruptive behavior and cheating (Meece, Anderman, & Anderman, 2006). Also, teachers can promote mutual respect and support among students and not allow students to make fun of each other, since being cared and valued by peers have been noted as important elements for improving students' achievement (Shim, Kiefer, & Wang, 2013), especially in group learning formats. Furthermore, teachers can encourage help-seeking strategies that are conducive to learning such as requesting clarification, explanation, or hints about the correct process or solution, and discourage strategies that are detrimental to achievement such as asking for ready-made answers without explanation (Karabenick & Newman, 2006).

7. Limitations and conclusion

This study has several limitations that must be acknowledged. First, the participants of this study were undergraduate students enrolled in introductory calculus courses in a large public Midwest university. Even though the participants represented a good mix of demographic characteristics, caution should be used in generalizing the results to other populations and disciplines. Future studies should examine the extent to which the current findings would hold true for other flipped designed courses and disciplines. Secondly, apart from students' grades, all the other variables were self-reported at a single time-point. For example, prior domain knowledge in the pre-class learning setting was operationalized as the highest math class completed in high school. However, there is so much variability in this variable (e.g. instructor, learning setting, learning process, course material). Future studies would be benefit from using multiple data sources, such as, pre-knowledge-test on mathematics, think-aloud protocols, interviews, or behavioral engagement data (e.g., learning analytics). Finally, the sample size in the present study was not sufficiently large for SEM analysis, so it should be cautious to generalize the findings. Nevertheless, the current study adds to the literature in identifying specific aspects of students' self-regulation associated with success in the two phases of flipped courses.

In conclusion, this study moves away from the question of whether flipped classrooms are effective and focuses on how to make flipped classrooms effective for more students. The results demonstrate the importance of students' self-regulated learning processes in both the pre-class Internet-based and in-class collaborative learning environments, particularly in terms of students' prior math knowledge, math self-efficacy, and the use of help-seeking strategies for students' academic success in those two learning environments. To effectively design the pre-class and in-class activities in the context of flipped math classrooms, instructors must consider the relations of the identified maladaptive factors with achievement, enact appropriate strategies to support students' self-regulated learning and, ultimately, guide them to succeed.

Appendix A. Descriptive statistics of items of each factor

Factor	Item	Mean	Std. Deviation
Math self-efficacy	I believe I will receive an excellent grade in math.	4.35	1.72
	I'm confident I can do an excellent job on the assignments and tests in math.	4.46	1.72
	I'm certain I can understand the most difficult materials in math.	4.40	1.74
	I'm confident I can understand the basic concepts taught in math.	5.70	1.52
	I expect to do well in math.	5.17	1.67
Collaborative-learning self-efficacy	I'm confident that I can do an excellent job on the tasks and tests assigned to the group in the recitation.	4.72	1.61
	I'm certain the group learning in the recitation can help me understand the basic concepts taught in the course.	4.81	1.69
	I'm certain the group learning in the recitation can help me understand the most difficult material in the course.	4.19	1.79
	I believe the group learning in recitation can help me receive an excellent grade in the course.	4.21	1.74
	I believe I can do well in the in-class group learning.	4.96	1.52
Internet self-efficacy	I can improve my performance through information gained from Youtube or online videos.	5.48	1.34
	I can use Youtube or online videos to find information that is important to this class.	5.51	1.42
	I can use Youtube or online videos to find information that is important to me.	5.70	1.21
	I can organize information find on the Internet so that it is coherent and answers specific questions.	5.42	1.45
Cognitive strategy_pre-class setting	While I'm studying the pre-class online math materials, I go over the formulas or definitions in order to memorize them.	5.07	1.70
	While I'm studying the pre-class online math materials, I do the example problems over and over again to memorize them.	3.36	1.88
	While I'm studying the pre-class online math materials, I make a list of the formulas or definitions to organize what I need to know.	5.02	1.72
	While I'm studying the pre-class online math materials, I make charts, diagrams, or tables to organize what I need to learn.	3.61	1.88
	While I'm studying the pre-class online math materials, I connect what I learn in this class to what I am learning in other non-math classes.	3.60	1.78
	While I'm studying the pre-class online math materials, I try to connect the new online materials to what I already know.	5.19	1.48
	While I'm studying the pre-class online math materials, I make connections between how I solve one math problem with the way I could solve others.	5.07	1.57
Metacognitive strategy_pre-class setting	Before I begin study the pre-class online math materials, I think about what and how I'm going to learn.	4.34	1.68
	Before I begin study the pre-class online math materials, I plan how much time I will need to learn a topic.	4.56	1.72
	Before I begin study the pre-class online math materials, I set goals for myself to help me learn.	4.36	1.73
	While I'm studying the pre-class online math materials, I ask myself questions to make sure that I know what I have been learning.	4.45	1.55
	While I'm studying the pre-class online math materials, I try to determine how well I have learned what I need to know.	4.99	1.39
	While I'm studying the pre-class online math materials, I test myself to see whether I know the material.	4.66	1.66
	While I'm studying the pre-class online math materials, If I get confused with something while I'm studying through the online materials, I go back to the lecture videos and other relevant resources and try to figure it out.	5.22	1.49
	While I'm studying the pre-class online math materials, If the online materials are difficult to learn, I slow down and take my time.	5.18	1.40
	While I'm studying the pre-class online math materials, If I'm having troubles solving the problem in the online quiz, I continue to work until I solve the problem.	5.25	1.49
Help-seeking strategy_pre-class setting	If I don't understand something during the pre-class online learning, I ask my teacher or tutor for help.	4.13	1.99
	If I don't understand something during the pre-class online learning, I ask other students for help.	4.53	1.85
	If I don't understand something during the pre-class online learning, I ask for help to better understand general ideas and principles.	4.68	1.87
	If I don't understand something during the pre-class online learning, I ask others for the answers I need to complete the work.	3.17	1.97

Environmental control strategy_ pre-class setting	When I'm studying the pre-class online materials, I pick a place where I can concentrate.	5.71	1.25
	When I'm studying the pre-class online materials, I use a study schedule for learning.	4.32	1.86
	When I'm studying the pre-class online materials, I make sure I have as few distractions as possible	5.24	1.40
Cognitive strategy_in-class setting	When I'm studying in the recitation session, I go over the formulas or definitions in order to memorize them.	4.51	1.76
	When I'm studying in the recitation session, I do the practice problems over and over again to memorize them.	3.64	1.84
	When I'm studying in the recitation session, I make a list of the formulas or definitions to organize what I need to know.	4.25	1.87
	When I'm studying in the recitation session, I make charts, diagrams, or tables to organize what I need to learn.	3.49	1.85
	When I'm studying in the recitation session, I connect what I learn in the recitation to what I am learning in other non-math classes.	3.87	1.91
	When I'm studying in the recitation session, I try to connect what I'm learning in the recitation with what I learned in the previous online lectures.	5.26	1.51
	When I'm studying in the recitation session, I make connections between how I solve one math problem with the way I could solve others.	4.88	1.52
Metacognitive strategy_in-class setting	Before I go to the recitation session, I think about what and how I'm going to learn.	4.01	1.72
	Before I go to the recitation session, I plan how much time I will need to solve a problem.	3.42	1.83
	Before I go to the recitation session, I set goals for myself to help me learn.	3.89	1.77
	When I'm studying in the recitation session, I ask myself questions to make sure I know what I have been learning.	4.38	1.65
	When I'm studying in the recitation session, I try to determine how well I have learned what I need to know.	4.83	1.66
	When I'm studying in the recitation session, I test myself to see whether I understand the solution.	4.68	1.62
	When I'm studying in the recitation session, If I get confused with something while I'm solving the practice problem, I go back to relevant resources and try to figure it out.	5.14	1.55
	When I'm studying in the recitation session, If the practice problems are difficult to solve, I slow down and take my time.	4.97	1.56
	When I'm studying in the recitation session, If I'm having troubles solving the practice problem, I try various ways to solve them.	4.98	1.43
Help-seeking strategy_in-class setting	If I don't understand something in the recitation session, I ask my teacher for help.	5.09	1.79
	If I don't understand something in the recitation session, I ask other students for help.	5.20	1.72
	If I don't understand something in the recitation session, I ask for help to better understand general ideas and principles.	5.26	1.63
	If I don't understand something in the recitation session, I ask others for the answers I need to complete the work.	3.66	2.05

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