The Role of a Peer-Led Academic Intervention in College Students' Development of Self-Regulated Learning: A Person-Centered Approach

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THE ROLE OF A PEER-LED ACADEMIC INTERVENTION IN COLLEGE

STUDENTS' DEVELOPMENT OF SELF-REGULATED LEARNING:

A PERSON-CENTERED APPROACH

by

Soojeong Jeong

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ABSTRACT

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This study focuses on the role of the SI program in college students' development of SRL from a person-centered perspective. First, this study examines the heterogeneous effects of the SI intervention on students' development of SRL by combining latent profile modeling and propensity score matching. Second, it explores the changes in

student SRL profiles over the intervention period and determines factors affecting the prediction of such changes using latent transition modeling.

Results identify three distinct student profiles: competent regulator, self-confident regulator, and goal-oriented regulator. Within the *competent regulator* profile, both SI and non-SI attendees' overall SRL scores significantly decreased over time, though non-SI attendees showed a greater downturn. For the *self-confident regulator* profile, only SI attendees' overall SRL scores increased. Both SI and non-SI attendees in the *goal-oriented regulator* profile had small decreases in scores, which were not statistically significant.

Regarding students' longitudinal transitions between SRL profiles, students in the most desirable profile (*competent regulator*) remained most stable over time. Students' SRL in the *goal-oriented regulator* profile was most malleable in a positive way; approximately 40% of these students moved into the *competent regulator* profile. In addition, students whose decision to attend the SI sessions was more mastery-oriented tended to fall into more positive transition groups. Furthermore, students whose levels of self-confidence in learning, critical thinking skills, and group work skills increased as a result of their participation in SI sessions were more likely to become members of more positive transition groups.

The findings of this study extend previous work by longitudinally examining individual differences in college students' SRL development. They also provide significant implications for the future design of more targeted interventions.

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CHAPTER I

INTRODUCTION

Self-regulated learning (SRL) refers to "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment" (Pintrich, 2000, p. 453). Students' ability to effectively self-regulate their learning is essential to their academic success at every level of education, but it is especially important during college, as college students are expected to deal with a potentially overwhelming amount of materials in a more autonomous learning environment (Bjork & Yan, 2014; Cohen, 2012). Further, learning does not end when students exit degree programs; rapid societal and technological advances offer more opportunities and demands to continue learning outside of formal educational settings (Dunlap & Lowenthal, 2011). Thus, students' SRL ability is a necessary "survival tool" for their lives even after college (Bjork, Dunlosky, & Kornell, 2013, p. 418).

Extensive research has demonstrated that higher SRL abilities improve academic performance and the likelihood of retention among college students (e.g., Richardson, Abraham, & Bond, 2012; Robbins, Lauver, Davis, Langley, & Carlstrom, 2012). Unfortunately, many college students appear to have insufficient skills and strategies to regulate their learning independently (Hartwig & Dunlosky, 2012). For instance, they often struggle to manage their study time (van der Meer, Jansen, & Torenbeek, 2010) and make inaccurate predictions about their test preparation and performance (Peverly,

Brobst, Graham, & Shaw, 2003). Therefore, students need specific support and guidance to promote and develop their SRL skills and strategies.

Social cognitive theory assumes that students' SRL does not develop as a natural consequence of human development (Schunk, 2001). Rather, it must be intentionally learned and improved, especially through interaction with social environments (Bandura, 1986, 1989; Pintrich, 1995; Schunk, 2001; Zimmerman, 2000). Schunk and Zimmerman (2003) have argued that becoming a self-regulated learner is a *social-to-self transformation process*, through which students internalize necessary study strategies and motivational beliefs. Learners are taught these skills through diverse social sources (e.g., teachers, peers, schools, and events).

Previous studies that have applied this perspective implement specific interventions designed to facilitate college students' SRL development. They have found that such interventions are effective (Bol, Campbell, Perez, & Yen, 2016; Fitch, Marshall, & McCarthy, 2012). However, these studies often estimate intervention effects by aggregating the participants into monolithic treatment and control groups, failing to discern how individual students differ in terms of their responses to the intervention. More research is needed to determine if differential effects of SRL interventions exist to provide students with more personalized, targeted support and administer "the right program to the right individuals" (Lanza & Brittany, 2013, p. 157).

Further, to better understand students' SRL development, it is also imperative to know how students' SRL skills and strategies change longitudinally during a specific period of time. This avenue of investigation has been understudied in SRL research in

general and particularly in college samples (Fryer, 2017; Hoyle & Dent, 2018). Findings from more recent studies taking a longitudinal perspective have agreed that college students' self-regulation strategies tend to remain stable across time (e.g., several months or years; De Clercq, Galand, & Frenay, 2013). However, most of these studies employ a variable-centered framework (in contrast to person-centered), focusing on the longitudinal associations between SRL-relevant variables. As such, their findings are limited in terms of identifying or explaining discrepancies in individual students' development patterns within larger treatment groups or cohorts. Although some studies have examined such discrepancies using exploratory methods to show the presence of differential growth in self-regulation among college students, these studies typically focus on unitary outcomes (e.g., Coertjens, Donche, De Maeyer, van Daal, & Van Petegem, 2017), failing to take into account the multidimensional aspects of SRL.

Recently, growing interest in person-centered approaches to the analysis of students' SRL has resulted in the identification of distinct, meaningful subpopulations among college students based upon the students' configuration of a range of different SRL strategies (Barnard-Brak, Lan, & Paton, 2010; Broadbent & Fuller-Tyszkiewicz, 2018; Vanslambrouck, Pynoo, Lombaerts, Tondeur, & Scherer, 2019). While these person-centered approaches extend the current knowledge in individual variations in SRL, surprisingly few attempts have been made to explore how student SRL profile membership changes over time. In one recent study, Fryer and Vermunt (2018) applied this approach longitudinally, revealing that students belonging to a group with average-level strategy use showed the most stable pattern in their self-regulation strategy growth,

while members of the least adaptive student group were most mobile and flexible. Although these person-centered longitudinal findings hold significant implications for better identifying who need more support and when, the causes or influences of such variance remain unknown. Thus, these results are limited in their ability to give suggestions of how instruction and interventions for developing SRL are specifically tailored to different subgroups.

Supplemental Instruction as an Intervention for SRL Development

Supplemental instruction (SI) is a peer-led academic support program that shows promise in helping students to become more independent and proactive learners who are highly self-regulated in their learning (Malm, Bryngfors, & Mörner, 2015). SI is a non-remedial, voluntary, regularly scheduled, course-specific intervention. It embeds diverse pedagogical practices that social cognitive theorists and SRL researchers recognize as important components of SRL, such as modeling, collaborative learning, and peer interactions (Ning & Downing, 2010).

A core element in the SI model is the use of senior peers, called SI leaders, who lead and facilitate each study session (Hurley & Gilbert, 2008). SI leaders are often former students who successfully completed the targeted course with higher grades. These leaders are also qualified by means of a training workshop and are evaluated by SI supervisors while working as leaders. In the SI model, peers are intentionally used as SI leaders since peers are assumed to be more approachable and psychologically comfortable to learn with, thereby maximizing the effects of SI sessions (Martin &

Arendale, 1992). In each study session, the SI leaders are expected to function as role models for students, using diverse techniques, such as coaching, rewording, providing feedback, and accepting, to help students internalize the skills and knowledge they must learn and eventually function independently.

Research on SI has documented a great deal of evidence of the educational benefits associated with participation in such programs (for a review, see Dawson, van der Meer, Skalicky, & Cowley, 2014). Among these benefits are improved academic performance (Hensen, & Shelley, 2003; Paloyo, Rogan, & Siminski, 2016), better retention rates (Ogden, Thompson, Russell, & Simons, 2003), greater academic skill acquisition (Ning & Downing, 2010; van der Meer & Scott, 2009), and enhanced social interactions (Court & Molesworth, 2008; Dobbie & Joyce, 2008).

The majority of these studies, however, have examined academic performance such as final course grades, overall semester GPAs, and coursework assessments (e.g., unit quizzes), as indicators of the effects of SI. For instance, Hensen and Shelley (2003) report that SI attendees’ final course grades in entry-level biology, chemistry, and mathematics courses were higher than those of their non-SI counterparts. This was also the case after adjusting for variations in pre-entry academic aptitude scores among the two groups. Such favorable impacts of SI on academic achievement have been observed even beyond the courses supported by SI; significant differences have been found in mean semester GPAs (Hodges & White, 2001) as well as in the mean cumulative GPAs of a couple of academic years after the initial SI participation (Ogden et al., 2003). Researchers speculate that such benefits might be attributed to the learning strategies and

skills (i.e., SRL) learned through SI sessions which seem to be transferred or generalized in other courses.

Although most of these studies agree that the primary goal of SI intervention is to help students develop effective learning skills and study habits, surprisingly limited empirical evidence has been established in order to claim such aspects of SI benefits (Dawson et al., 2014). Recently, several studies have explicitly addressed aspects related to SRL as a product of SI participation (e.g., Malm et al., 2015; Ning & Downing, 2010). For instance, Ning and Downing (2010) examine the impact of SI programs on SRL-related skills and strategies using the Learning and Study Strategies Inventory (LASSI) instrument. They found that first year college business students participating in SI sessions showed greater gains in information processing skills and motivation scores compared to their peers who were not participating in SI. Their findings also indicate that students' skill development function as a moderator on the relationship between SI attendance and academic performance. More studies should be undertaken in order to achieve a better understanding of the roles of SI in students' development of SRL abilities.

The Present Study

This dissertation aims to fill the gap in the existing literature on the development of SRL and the effectiveness of SI by applying a person-centered approach. Rather than focusing on relations between variables across individuals (i.e., variable-centered approach), a person-centered approach concerns particular configurations of variables

that operate within an individual (Laursen & Hoff, 2006). This approach is appropriate to examine group or individual differences on a set of variables and in patterns of developmental change (Laursen & Hoff, 2006).

This study pursues two objectives. First, it examines the differential effects of SI intervention on college students' development of SRL. Specifically, this study seeks (1) to identify unique, unobserved subgroups among college students with respect to their self-reported use of a range of SRL skills and strategies and (2) to determine the extent to which students differ in their responses to the intervention across subgroups. Second, the current study also aims to longitudinally investigate the heterogeneity of the patterns of SRL development among college students, particularly within the intervention context. It intends (1) to explore the extent to which student membership in different SRL subgroups changes during participation in the SI intervention, and (2) to examine various individual and intervention-related determinants that many influence such changes.

CHAPTER II

LITERATURE REVIEW

The current study examines college students' self-regulated learning (SRL) development within the context of a peer-led academic support program, Supplement Instruction (SI), addressing two sets of objectives. The first objective examines the heterogeneous effects of students' participation and non-participation in the SI intervention on their SRL development. The second investigates individual differences in the patterns of SRL development among students participating in the SI program.

This chapter begins with an overview of theoretical perspectives that frame the study, predominantly social cognitive theory (Bandura, 1986; Pintrich, 2000; Schunk, 2001; Zimmerman, 2000). It also reviews the literature that informed the research design and analyses of this dissertation.

Definitions and Assumptions of SRL

Over the past several decades, many different conceptual models have been advanced to explain how self-regulated learning (SRL) occurs and develops in academic settings (Boekaerts, 1992; Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 1989, 2000; for reviews, see Panadero, 2017; Puustinen, & Pulkkinen, 2001). Although these models vary in their emphasis on specific targets and processes, they share common key assumptions: SRL is (1) a multidimensional phenomenon that involves cognitive, metacognitive, motivational, and behavioral facets of engagement in learning (Schunk & Mullen, 2013); (2) a cyclical process as the motivational beliefs and strategies used for

current tasks affect those for future tasks (Panadero, 2017); (3) a series of goal-directed activities as goal setting initiates task-relevant actions (Sitzmann & Ely, 2011); and (4) a set of skills and abilities that can be acquired and developed (Hoyle & Dent, 2018).

Two major theoretical perspectives guide the predominant SRL models: information processing theory and social cognitive theory. The models grounded in information processing perspectives (e.g., Borkowski, Chan, & Muthukrishna, 2000; Efklides, 2011; Winne, & Hadwin, 1998; Winne, 2001) tend to focus on cognitive and metacognitive aspects of learning. For instance, Winne (1996) views SRL as "metacognitively governed behavior wherein learners adaptively regulate their use of cognitive tactics and strategies in tasks" (p. 327). According to this view, SRL skills are acquired and developed through practice while interacting with learning materials (Hoyle & Dent, 2018).

In contrast, a social cognitive model of SRL (Pintrich, 2000; Schunk, 2001; Zimmerman, 2002) emphasizes the situated and constructive nature of learning. Schunk and Zimmerman (2003), for example, describe SRL as "learning that results from students' self-generated thoughts and behaviors that are systematically oriented toward the attainment of their learning goals" (p. 59). Similarly, Pintrich (2000) defines it as "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment" (p. 453). From this perspective, interaction with the social environment is the vital influence in the development of SRL.

The Social Cognitive Model of SRL

The theoretical origins for the social cognitive model of SRL can be traced back to the work of Bandura (1986, 1991, 2001) and his notion of triadic reciprocal causation. According to Bandura, human motivation and behavior are the consequences of mutual interactions among intrapersonal (e.g., cognitive, affective and biological), behavioral, and environmental determinants. In academic settings, students' self- regulatory experiences and actions are determined by different internal and external influences. In this model of reciprocal causality, the environmental/external circumstances are often imposed, but they can also be chosen and even constructed (Bandura, 1986, 1997). For instance, students are usually placed in the same imposed settings in school. However, they differ in how they respond to that imposed environment; they may voluntarily participate in certain learning activities, events, and social groups or use particular institutional systems and resources. They also may generate their learning environments on their own in many different ways. These actions may considerably influence the reciprocal interactions among personal, behavioral and environmental factors.

Bandura (1986, 1991, 2001) suggests three cognitive subfunctions through which self-regulatory systems operate: self-observations, self-judgments and self-reactions. In order to make changes in their own motivation and actions, people first need to deliberately monitor their ongoing thoughts and behaviors. *Self-observations* provide information required to formulate realistic personal goals and to assess one's progress toward those goals. Various factors, such as pre-existing cognitive ability, self-beliefs, and emotional states, influence the self-observation process. Judging one's actions and

performance is another necessary step for self-directed change. *Self-judgments* occur by comparing the current level of one's own performance and one's personal standards to the performance levels attained by others (e.g., peers, teachers, parents, society). Finally, *self-reactions* provide the mechanism through which the performance judgments produce self-regulatory control. When people make self-satisfaction or self-rewards contingent upon attaining their own goals, their efforts continue, and they thereby succeed in regulating their actions and motivation.

In Bandura's social cognitive theory, the most influential determinant of successful self-regulation is *self-efficacy*, which refers to "beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (Bandura, 1997, p. 3). Bandura stresses that people's own beliefs in their efficacy contribute immensely to the various subprocesses in self-regulation, including goal-setting, self-monitoring, and interpretation of the causal attributions for success and failure. For instance, efficacious students tend to set challenging goals, monitor their learning progress actively, and sustain their efforts by attributing their failures to a lack of appropriate effort rather than their inability (Bandura, 1991).

Expanding Bandura's work, Zimmerman (2000, 2002, 2013) proposed a three-phase SRL model that elucidates cyclical self-regulatory processes that occur before, during, and after learning. The *forethought* phase takes place before engaging in learning tasks. During this phase, students analyze the given tasks by setting goals and making plans to achieve those goals. Goals that are specific, proximal, and difficult yet attainable result in greater self-efficacy and SRL compared to general, distant, and easy goals.

However, planned actions and strategies cannot be executed well without sufficient self-efficacy. Thus, self-efficacy beliefs play a pivotal role in this initial phase of SRL. Other motivational beliefs, such as intrinsic interest, task value, outcome expectations, and goal orientations (i.e., purposes of engaging in the learning tasks), are also crucial components during this phase.

The *performance* phase involves diverse activities and techniques necessary to perform learning tasks. Students monitor their ongoing learning process and predict their future performance. Based on the output of these self-observation activities, they also control their learning by employing different techniques, including time management skills, self-testing, imagery (i.e. connecting the current tasks to prior knowledge and experiences), help-seeking, task strategies, and environmental structuring (i.e. arranging the optimal physical setting for learning).

The *self-reflection* phase typically occurs after performing the learning tasks. During this phase, students evaluate their behaviors and performance according to their chosen goals and decide what possible factors caused their success or failure. These self-judgements lead to students' self-reactions. They are either satisfied or dissatisfied with their performance, and they create rewards or punishments contingent upon whether they have attained their goals. Their response affects their attitudes toward and approaches to later learning tasks. Self-reflection eventually returns students to the forethought phase because it informs their motivational beliefs in the particular domain relevant to the learning tasks.

The Social Cognitive View on SRL Development

A social cognitive perspective assumes that a student's self-regulated competence does not develop automatically (Schunk, 2001); rather, it is learned and acquired, especially by interactions with social environments (Bandura, 1986, 1989; Schunk, 2001; Zimmerman, 2000). Schunk and Zimmerman (2003) suggest a four-level model of the process of becoming a self-regulated learner. The model postulates that the acquisition and development of SRL is a *social-to-self transformation process* through which students internalize skills and abilities learned from social sources and eventually use them independently (Schunk, 1999).

At the first level, *observation*, students begin to acquire basic knowledge, strategies, and techniques from social sources and environments (e.g., teachers, peers, events). The focus during this phase is to observe closely the modeled performance and deliberately practice what they have learned from their models. Modeling not only provides information about the underlying rules and sequences of behavior that lead to desirable outcomes, but also increases observers' self-efficacy by letting them believe they will get the same outcomes if they mimic the models. Schunk (2003) also stresses the importance of the perceived similarities of the observers to the models that could be attributed to age, race, gender, and ability levels. He stated, "The more alike observers are to models, the greater is the probability that similar actions by observers are socially appropriate and will produce comparable results" (Schunk, 2003, p. 163). Further, since students at this level are unlikely to perform like their models and consequently may often feel frustrated or confused, external encouragement are especially important.

During the next level, *emulation*, students are able to imitate the general pattern or forms of their models' behaviors and performances although their skills are still not transferable to other contexts or situations. They continue observing the models and engaging in deliberate context-specific practice. Appropriate feedback and motivational support are required according to the progress in skill development.

While students depend heavily upon external (social) factors in developing their SRL competence during the first two levels, they focus more on internal (self) factors during the last two levels. At the third level of SRL acquisition, *self-control*, students use knowledge and strategies independently, although their skills and abilities are not yet automated. At the last level, *self-regulation*, students have finally automated and internalized relevant skills and strategies and employ them independently. It is important to note, however, that although students' reliance on social influence decreases as their SRL abilities increase, it is not eliminated; self-regulated learners still depend on and take advantage of external assistance and feedback.

Acquisition and Development of SRL through College-Based Interventions

Numerous studies show that intervention and teaching strategies foster college students' SRL behaviors effectively (Bol et al., 2016; Dörrenbächer & Perels, 2016a, b; Dignath-van Ewijk, Fabriz, & Büttner, 2015; Fitch et al., 2012; Gebbia, DeJesus, & Eckardt, 2019; Malan, Ndlovu, & Engelbrecht, 2014; Núñez et al., 2011). Some of these studies assess an intervention program that trains students in a wide range of SRL

strategies and found positive impacts of this intervention on students' SRL development (Dörrenbächer & Perels, 2016a; Núñez et al., 2011).

Other studies reveal the positive effects of individual instructional techniques, such as using a diary (Dignath-van Ewijk et al., 2015), group work with goal setting (Fitch et al., 2012), and problem-based instruction (Malan et al., 2014). For instance, Fitch et al. (2012) investigate the effects of a solution-focused group intervention on undergraduate students' academic skills related to SRL. Students who participated in group meetings with goal setting worksheets improved their self-efficacy, intrinsic value, cognitive strategy use, and overall SRL in comparison to those without intervention. However, the authors could not determine if goal-setting activities alone led to the observed changes or if group work was the underlying mechanism.

Malan et al. (2014) report that introducing college students to a problem-based learning (PBL) approach promoted students' use of self-regulating activities, including planning and reflecting on their own solutions. Similarly, Paris and Paris (2001) suggest that PBL is a specific task-based method that teachers can integrate into their instruction in an effort to promote their students' development of SRL. They explain, "If PBL activities are designed carefully with teachers who provide appropriate modeling and scaffolding, they promote and necessitate SRL. PBL affords opportunities for self-directed learning by giving students choice and control about what to work on, how to work, and what products to generate." (p. 94).

Although these studies of interventions have shed light on how to help college students become better self-regulators, there are some clear limitations. For example,

only very few attempts have been made to investigate the treatment effects on individual students' SRL development within the specific context of peer-learning (e.g., Fitch et al., 2012). In addition, most of these studies have examined the sample as a whole, neglecting the fact that students may vary in their response to treatment.

In fact, several studies show that students respond differently to interventions or interaction approaches as a function of their initial level of SRL abilities. For instance, Ertmer, Newby, and MacDougall (1996) report that veterinary students who were highly self-regulated in their learning made more gains in their SRL strategies, such as goal orientation, self-awareness, and self-evaluation, through problem-based instruction compared to their peers with low self-regulation. More recently, Dörrenbächer and Perels (2016b) classified a sample of college students into four subgroups with respect to students' SRL skills before implementing their SRL training program. Their findings reveal differential training effects across subgroup; students in the *moderate SRL* and *conflicting SRL with high motivation* groups had improvement in overall SRL scores after the training program, those in the *low SRL with moderate motivation* and *high SRL* groups did not. In the light of their findings, Dörrenbächer and Perels conclude that "an SRL basis is necessary for development in training" (p. 238). The results of these two studies suggest that more research is needed to better understand how individual students' differences in initial levels of SRL impact how interventions develop students' SRL. Such group-based analyses can "provide important information about how [treatment] programs may be targeted for or tailored to different population subgroups that are expected to show the strongest response" (p. 167).

Developmental Trajectories of SRL

In addition to the roles of different interventions and instruction methods, it is also important to know how students' SRL skills and strategies change over time. However, the developmental course of SRL receives less attention in the literature (Hoyle & Dent, 2017; Panadero, 2017). Previous studies taking a longitudinal approach to examining SRL or relevant constructs occur mostly at the elementary and secondary education levels. As a result, there are a limited number of longitudinal studies available that examine college student samples on this issue (Coertjens et al., 2017; De Clercq et al., 2013; Fryer, Ginns, & Walker, 2016; Severiens, Ten Dam, & Wolters, 2001).

In their three-year study, De Clercq and colleagues (2013) found that college students' self-regulation strategies, such information-seeking, supervising, and monitoring, tend to remain stable over time. Their findings also indicate that students' mastery goal orientation can have a positive impact on their subsequent deep processing strategies which in turn increase subsequent self-regulation. Coertjens et al. (2017) found that students' self-regulation remained constant during their first-year in college but it increased from the end of the first year to the beginning of the second year. Their results suggest that students vary in their SRL development, but this growth is not related to initial levels of self-regulation. However, these studies are limited in their ability to inform understanding of individual change because they use variable-centered analyses (e.g., regression, structural equation modeling) that focus on the relationships among variables across individuals (e.g., De Clercq et al., 2013; Fryer et al., 2016). Thus, their

findings fail to discern individual differences in the patterns of such development trajectories of SRL.

These limitations can be overcome by using person-centered analyses, suggesting that more research applying a person-centered longitudinal approach (e. g, latent profile modeling, latent transition modeling) is needed. Recently, Fryer and Vermunt (2018) applied latent profile transition analysis to investigate how students change the use of cognitive processing and regulation strategies change during their first year of undergraduate study. They identified four distinct subgroups of students, comprised of low-quality (i.e., a lack of deep approaches and self-regulation), low-quantity (i.e., a lack of strategy use), average (i.e., a moderate level of strategy use), and high-quantity (i.e., intense use of all strategies). Examining how these class memberships changed over time, they determined that the average group was the most stable, while the low-quantity group was most likely to change. However, this study did not examine potential predictors (e.g., intervention effects, demographic information der, or motivational constructs) that could affect these transitions, limiting the ability to understand potential causes of such longitudinal change.

SI Factors Affecting Development of SRL

Supplemental instruction (SI) is a well-recognized academic support intervention that has been implemented across countries, and research on the effectiveness of SI on students' outcomes has a long history (see Dawson et al. [2014] for a review). Numerous

studies on SI have focused on identifying variables that could contribute to students' decisions to attend SI and their outcomes as a result of attending SI.

Students' socio-demographic attributes have been also found to be effective variables to predict students' attendance to SI and their success as a result of SI participation. Overall, previous studies have yielded conflicting results on the differential effects of SI depending on gender (Fayowsk, & MacMillan, 2008; Malm, Bryngfors, & Fredriksson, 2018). However, female students were more likely to attend SI study sessions (Guarcello et al., 2017; Stock et al., 2013). Underrepresented minorities (URMs) were more likely to attend SI (Peterfreund, Rath, Xenos, & Bayliss, 2008) and they appeared to benefit from using SI study sessions (Rath, Peterfreund, Xenos, Bayliss, & Carnal, 2007; Summers, Acee, & Ryser, 2015). For example, Summers et al. (2015) found that Hispanic students had significantly lower course grades than their White counterparts, but this achievement gap decreased as their frequency of SI attendance increased. However, these traditionally disadvantaged students' (e.g., URMs, first-generation students) experiences with SI are understudied, limiting current understanding of its effective mechanisms.

Prior academic achievement (e.g., high school grade point averages (GPAs), college entrance exam scores, and past relevant course grades) are associated with students' participation in SI and their outcomes. Students with lower scores in college entrance exams are more likely to attend SI than their peers with higher scores in these exams (Rath et al., 2007; Stock et al., 2013; Summers et al., 2015). However, students' academic performance (i.e., course grades) after SI was positively influenced by their

previous achievement (Summers et al., 2015). In addition, Toby et al. (2016) have reported that students with higher grades in a past calculus course attended SI sessions more frequently in a physical chemistry course. Previous findings on the relationship between high school GPAs and SI attendance were rather mixed (Guarcello et al., 2017; Price, Lumpkin, Seemann, & Bell, 2012).

The number of SI sessions attended are consistently identified as a critical determinant of SI effectiveness in the literature. For example, Malm, Bryngfors, and Mörner (2012) classified first-year engineering students into four different categories according to their SI attendance frequency during an academic year: none (0), low (1-5), average (6-10), and high (≥ 11). Their findings indicated that student groups with average and high attendance yielded significantly better credit production than the group not attending SI, and all three attendance groups showed a better retention than the group not attending. However, the aggregation of SI attendance date limits the extent to which its effects can be understood.

While these studies provide useful information about the possible contributing factors to SI's effects on students' SRL development, very little known is about what specific features of SI programs are associated with positive outcomes for students. Malm and his colleagues (2015) surveyed students' perceptions of benefits of SI attendance. Approximately half of the participants reported that SI helped them develop their study skills, increased their ability to critically review course materials, improved their problem-solving and group work skills, and increased their confidence in their studies. Although the authors assumed that these factors were most likely to lead

students to academic success, they did not statistically examine casual relationships between these factors and student outcomes.

Research Questions

This dissertation aims to fill the gap in the existing literature, focusing on the development of SRL and the effectiveness of SI from a person-centered perspective. The following two sets of research questions and related hypotheses guided this dissertation. The first set focuses on the differential effects of the supplemental instruction (SI) program on students' development of self-regulated learning (SRL) across student baseline SRL profiles. Specifically:

1. What latent profiles of SRL emerge in undergraduate students enrolled in SI-supported courses?

Based on previous studies taking a person-centered approach, it is hypothesized that there will be at least three latent profiles emerging with respect to their patterns of use of different SRL strategies.

2. Matched against comparable SI non-attendees, do SI attendees benefit more from SI participation in terms of their development of SRL within each profile?

It is hypothesized that there will a significant improvement in overall SRL scores during the semester of SI participation for SI attendees only. SI attendees in more desirable profiles will have a smaller improvement than those in less desirable profiles.

The second set focuses on changes in SRL profiles of SI attendees across time. Specifically:

3. How does latent profile membership change following SI participation?

It is hypothesized that SRL profiles of SI attendees will change during the semester of SI participation. Students in more desirable profiles will be more stable. Further, there will be distinct, unique subgroups emerging based on the patterns in SI attendees' profile transitions.

4. How do features of SI participation predict latent profile transition patterns?

It is hypothesized that students with higher attendance, whose decision to attend the SI sessions was more mastery-oriented, and who perceived more benefits of SI will belong to more positive profiles and transition groups.

5. How do SRL profile transition patterns predict academic achievement during the semester of SI participation?

It is hypothesized that there will a significant difference in academic performance among students in different transition groups. Students in more positive profiles and transition groups will outperform those in less positive profiles and transition groups.

CHAPTER III

METHOD

The overall aim of this dissertation is to investigate the development of college students' self-regulated learning (SRL) strategies through Supplemental Instruction (SI), a peer-led academic support program, from a person-oriented perspective. Specifically, the first part of the study examines the heterogeneous effects of the program on students' SRL development. The primary analytic approach to achieve this goal combines latent profile analysis (LPA) with propensity score matching (PSM). The second part of the study discerns individual differences in longitudinal stability and change in students' SRL using latent profile transition analysis (LPTA). This chapter describes the rationale, design, and procedures of the research methods used in this study.

Research Design

Due to the self-selected nature of SI attendance, the first part of this dissertation utilizes a quasi-experimental design. Potential biases due to non-randomized sampling were controlled using PSM. The second part of the study uses a longitudinal observational design in which surveys were administered to the same participants at two time points. Data were analyzed using mixture modeling techniques (e.g., latent profile analysis).

Context

The Academic Success Center (ASC) at Utah State University (USU) runs a peer-led Supplemental Instruction (SI) program. The program is for selected entry-level college courses that are traditionally difficult for students (i.e., SI-attached courses). The mission of SI is to assist students in better understanding the course materials, which results in increased student achievement and persistence. Ultimately, however, SI aims to help students develop academic motivation and a range of cognitive and metacognitive strategies, thereby leading to become independent, self-regulated learners. For each SI-attached course, SI provides after-class study sessions scheduled twice a week, with 50 minutes for each session. A senior student, who is called an SI leader and has completed the given course with excellent results, facilitates each study session which includes a group of 15 students on average. The SI leaders are certified by means of an intensive training program before leading study sessions, and they are supervised by faculty members while serving as SI leaders.

Participants

Participants in this study were recruited from approximately six thousand undergraduate students (N = 5518) who were registered for any of the SI-attached courses in the fall semester of 2018. Six hundred and twenty-six students (response rate of 11.3%) participated in this study. Of these students, 352 students (SI attendees; 54.2% of the total) attended at least one SI-study session during the semester. These SI attendees were distributed across 34 SI-attached courses, with 20 science-related (58.8%), 8 social

science-related (23.5%), 4 engineering-related (11.8%), and 2 others (5.9%). Table 1 presents the demographic information of the participants. All participants completed an informed consent process under USU Institutional Review Board (IRB) protocol [irb-9531] (see Appendix A) that included permission to collect data both directly from participants and from their academic records maintained by the ASC and the USU registrar's office.

Table 1

Demographic distribution of participants

	Frequencies (%)				
	Whole sample (N=626)	SI attendees (N=352)		Whole sample (N=626)	SI attendees (N=352)
Gender			Year in school		
Female	386 (61.7)	218 (61.9)	Freshman	290 (46.3)	182 (51.7)
Male	210 (33.5)	113 (32.1)	Sophomore	183 (29.2)	89 (25.3)
Unknown	30 (4.8)	21 (6.0)	Junior	95 (15.2)	50 (14.2)
			Senior	26 (4.2)	8 (2.3)
Race			Unknown	32 (5.1)	23 (6.5)
Hispanic	10 (1.6)	8 (2.3)			
Asian	9 (1.4)	3 (0.9)	Major		
White	558 (89.1)	309 (87.8)	Art & Humanities	32 (5.1)	17 (4.8)
Other	16 (2.6)	8 (2.3)	Social science	198 (31.6)	100 (28.4)
Unknown	33 (5.3)	24 (6.8)	Engineering	81 (12.9)	46 (13.1)
			Science	276 (44.1)	166 (47.2)
International student status			Exploratory	66 (10.5)	38 (10.8)
International	3 (0.5)	2 (0.6)	Unknown	5 (0.8)	2 (0.6)
Domestic	590 (94.2)	327 (92.9)			
Unknown	33 (5.3)	23 (6.5)	SI-supported course		
			Social science-related		52 (8.3)
First-generation student status			Engineering-related		19 (3.0)
First-gen	133 (21.2)	64 (18.2)	Science-related		271 (43.3)
Non-First-gen	459 (73.3)	264 (75.0)	Other		10 (1.6)
Unknown	34 (5.4)	24 (6.8)			

Measures

Socio-Demographic Characteristics

Participants' self-reported socio-demographic information included gender, age, race/ethnicity (i.e., Latino/Hispanic (not white), Asian/Asian-American, White, and other, year in school (i.e., freshman, sophomore, junior, and senior), major, international student status, and first-generation student status (i.e., neither parent holds a bachelor's degree).

Previous Academic Performance

As a means of assessing participants' pre-college academic performance, the university registrar's office provided participants' high school grade point averages (GPAs) and American College Testing (ACT) composite scores.

Self-Regulated Learning Strategies

Participants' levels of perceptions regarding their use of SRL strategies were assessed at the beginning (T1) and end (T2) of the fall semester. Guided by Dörrenbächer and Perels's (2016b) work, several existing instruments were utilized to measure five different dimensions of students' SRL strategies that are aligned with Zimmerman's cyclical phase model of SRL (Zimmerman & Moylan, 2009). Specifically, for the forethought phase, two subscales were included: *goal setting and planning* and *self-efficacy for learning and performance*. Goal setting and planning was assessed with four items from the Academic Self-Regulated Learning Scale (ASRLS; Magno, 2009). Each item measures the extent to which students set learning goals and make specific plans for completing those goals; e.g., "I make a timetable of all the activities I have to complete." and "I use a planner

to keep track of what I am supposed to accomplish.” Self-efficacy was assessed with four items borrowed from the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1991). Each item measures the extent to which students believe their abilities to learn or perform in their courses at desired levels (e.g., “I'm confident I can do an excellent job on the assignments and tests in my course.”, “I'm confident I can understand the basic concepts taught in my courses.”). For the performance phase, two subscales taken from the Learning and Study Strategies Inventory (LASSI; Weinstein, Palmer, & Acee, 2016) were used: *information processing* and *time management*. Four items of information processing assessed the extent to which students use elaboration and strategies to link their previous knowledge and experiences with new information (e.g., “I try to find relationships between what I am learning and what I already know.”, “I try to relate what I am studying to my own experiences.”). Four items of time management measure the extent to which students adhere to their study plans and schedules. Sample items are “When it comes to studying, procrastination is a problem for me.” (reverse-coded) and “I end up ‘cramming’ for every test.” (reverse-coded). For the last phase, self-reflection, one subscale was used: *self-evaluation.* Three items taken from the Metacognitive Awareness Inventory (MAI; Schraw & Dennison, 1994) assessed the extent to which students reflect and evaluate their own performance and learning goals (e.g., “I ask myself if I learned as much as I could have once I finish a task.”, “I ask myself how well I accomplished my goals once I'm finished.”) All 19 items were rated on a 5-point Likert-type scale (1 - very untrue of me to 5 – very true of me). Appendix B presents the entire questionnaires. Appendix C (Table C1) presents the factor loadings of the 19

items obtained from exploratory factor analyses (EFAs) for each year for each sample, respectively.

For the first set of research questions, the latent factor structure of this 19-item questionnaire was tested using confirmatory factor analyses (CFAs) with the full sample (N=626) at each time point (T1 and T2), separately. The overall model fit was evaluated based on the root mean square error of approximation (RMSEA), the comparative fit index (CFI), the Tucker–Lewis Index (TLI), and the standardized root mean square residual (SRMR). Cutoff values of 0.05 and 0.08 are recommended for RMSEA and SRMR, respectively (Hu & Bentler, 1999). Values of CFI and TLI above 0.95 were considered good model fit, and values between 0.90 and 0.95 indicated acceptable fit (Kline, 2005).

For the full sample at T1, the model with the 19 subscales as five first-order latent factors showed an acceptable fit to the data: χ^2 (142) = 327.19, $p < 0.001$, RMSEA = 0.046, (90% confidence interval [CI] = [0.040, 0.053], CFI = 0.95, TLI = 0.94, SRMR = 0.047. The model with one second-order factor (Overall SRL) also revealed an acceptable fit: χ^2 (147) = 393.89, $p < 0.001$, RMSEA = 0.052 (90% CI = [0.046, 0.059]), CFI = 0.94, TLI = 0.93, SRMR = 0.064. With the same sample at T2, the first-order model fit the data well: χ^2 (142) = 317.23, $p < 0.001$, RMSEA = 0.054 (90% CI = [0.046, 0.062]), CFI = 0.95, TLI = 0.94, SRMR = 0.048 and the second-order model also showed an acceptable fit: χ^2 (147) = 358.40, $p < 0.001$, RMSEA = 0.058 (90 % CI = [0.051, 0.066]), CFI = 0.94, TLI = 0.93, SRMR = 0.067.

For the second set of research questions of this study, longitudinal CFAs with the SI attendee sample (N=352) were conducted to ensure that the SRL questionnaire measured

the same underlying constructs over time (i.e., factorial invariance). Equality constraints on the model parameters were successively placed: Configural (i.e., baseline model), weak (i.e., equivalent factor loadings), and strong (i.e., equivalent factor loadings and intercepts) measurement invariance. Cutoff values of 0.01 and 0.015 are suggested for ΔCFI and ΔRMSEA, respectively, for the test of invariance (Chen, 2007). The configural invariance model showed an acceptable fit: χ^2 (620) = 1137.26, $p < 0.001$, RMSEA = 0.049 (90% CI = [0.045, 0.054]), CFI = 0.90, TLI = 0.88, SRMR = 0.056. The weak invariance model also fit the data acceptably: χ^2 (634) = 1154.50, $p < 0.001$, RMSEA = 0.049 (90% CI = [0.044, 0.053], CFI = 0.90, TLI = 0.89, SRMR = 0.060, ΔCFI = 0.001, ΔRMSEA = 0. In addition, the strong invariance model likewise represented an acceptable fit: χ^2 (648) = 1236.26, $p <$ 0.001, RMSEA = 0.051 (90% CI = [0.047, 0.056], CFI = 0.88, TLI = 0.87, SRMR = 0.063, ΔCFI = 0.014, ΔRMSEA = 0.002. Given that the changes in the values of CFI and RMSEA were acceptable across all successive models, it was assumed that the same constructs were measured through the SRL questionnaire across the two time points.

SI Program-related Variables

Frequency of SI Session Attendance

Participants' frequency of attending to the SI study sessions throughout the semester obtained at the end of the semester (T2) by ASC administrative records. Given the positively skewed distribution of this data (M = 4.53, SD = 4.39, Min = 1, Max = 25, See Figure 1), the values were coded into ordinal categories: (1) low (attending only one study session; 25.3% of the SI attendee sample), (2) moderate (attending 2-4 study sessions; 41.8%), and (3) high (attending 5-25 study sessions; 33%).

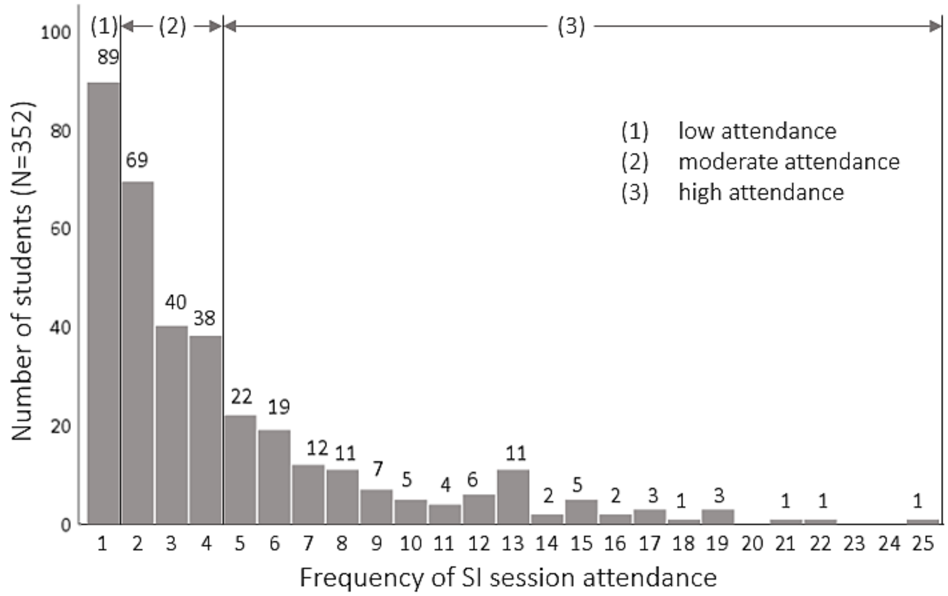


Figure 1. Frequency distribution for SI attendance

<u>Perceived Beliefs about SI Program</u>

Participants' levels of beliefs regarding the benefits of attending the SI study sessions were assessed at the end of the semester (T2) with five items borrowed from a questionnaire used to evaluate SI at other institutions (Malm et al., 2015). Each item was scored on a 5-point Likert-type scale (1 - very untrue to 5 - very true). Sample items of this scale are: "The SI sessions have trained me in my ability to critically review covered materials/questions/solutions in the course by discussion in groups." and "The SI sessions have developed my problems solving skills." See Appendix A for the full questionnaires.

<u>Reasons for Attending SI Study Sessions</u>

Participants' levels of purpose in attending the SI study sessions were measured at the end of the semester (T2) with two items taken from Malm and colleagues' (2015) instrument. Students were asked to use a 5-point Likert-type scale (1 - very untrue of me

to 5 – very true of me) to rate a set of four items with the following stem, “Why did you attend SI sessions?” The individual items include “To pass the course” and “To understand the subject better.” Each item was individually used for the analysis.

Academic Achievement (Post-SI Program)

Participants’ academic achievement, including their final grades in the courses to which the SI program was attached and overall GPAs, was obtained from the university’s registrar office at the end of the fall semester and represented on a 5-point scale (i.e., A/ A^- = 5, B^+/B^-/B = 4, C^+/C^-/C = 3, D^+/D = 2, F = 1).

Procedures

During the first two weeks of the fall semester of 2018 (T1), study recruitment emails (see Appendix D) were sent to undergraduate students (N = 5518) who enrolled in any SI-attached course. The students who agreed and signed consent forms (see Appendix E) were directed to Qualtrics for completing the initial online survey packet, comprised of the self-regulated learning and demographic questionnaires. This initial survey took approximately 15-20 minutes. In the last week of the semester (T2), the participants received the second survey packet electronically that comprised self-regulated learning (same as the initial survey) and SI-related experience questionnaires. This second survey also required approximately 15-20 minutes. Of the participants who completed both surveys, twenty names were selected at random for gift cards worth $100 as incentive for their participation. After the semester ended, additional student data were

obtained from the Academic Success Center and registrar records. These data included SI attendance frequency, prior academic achievement, and fall semester performance.

Data Analyses

In general, the focus of variable-centered approaches is “the relation between individuals' positions on latent dimensions, statistically studied across individuals” (Magnusson, 2003, p.14), in accordance with the assumption that “the population is homogeneous with respect to how the predictors operate on the outcome” (Laursen & Hoff, 2006, p. 379). In contrast, the goal of person-centered approaches is “the identification of groups of individuals who function in a similar way at the organism level and in a different way relative to other individuals at the same level” (Magnusson, 2003, p. 16). The assumption is these approaches is that the population is heterogeneous with respect to how the predictors operate on the outcome” (Laursen & Hoff, 2006, p. 379). Thus, while variable-centered analyses are suited for discerning the extent to which particular variables account for variance in other variables, person-centered analyses are appropriate to determine the individual discrepancies in relationships among variables (Laursen & Hoff, 2006).

Recently, growing attention has been devoted to person-centered approaches to SRL research because they are a useful tool to disaggregate individual students according to their patterns of SRL behaviors (Abar & Loken, 2010; Barnard-Brak et al., 2010; Broadbent & Fuller-Tyszkiewicz, 2018; Dörrenbächer & Perels, 2016b; Fryer & Vermunt, 2018; Greene et al., 2019; Liu et al., 2014; Ning & Downing, 2015;

Vanslambrouck et al., 2019). These studies demonstrate the existence of distinct subpopulations among college students with respect to their patterns of SRL strategy use. Some of these studies have identified groups of students that are only quantitatively different from one another (e.g., Valle et al., 2008; Vanslambrouck et al., 2019). For instance, Vanslambrouck et al. (2019) found three SRL subgroups: low SRL profile, average SRL profile, and high SRL profile.

On the other hand, other studies identified SRL subgroups that differ both quantitatively and qualitatively (e.g., Barnard-Brak et al., 2010; Dörrenbächer & Perels, 2016b; Ning & Downing, 2015). For example, Ning and Downing (2015) classify final-year university students into four different groups: *competent self-regulated learners*, *cognitive-oriented self-regulated learners*, *behavioral-oriented self-regulated learners*, and *minimal self-regulated learners*. Students in the *competent self-regulated learners* profile scored higher on all of the SRL indicators than those in the *minimal self-regulated learners* profile. In contrast, students in the *cognitive-oriented self-regulated learners* profile were different from their peers who belong in the *behavioral-oriented self-regulated learners* profile in terms of their patterns of strategy use. *Cognitive-oriented self-regulated learners* scored higher on concentration, selecting main ideas, time management, and testing strategies but lower on self-testing, study aids, and information processing in comparison to *behavioral-oriented self-regulated learners*. Consequently, latent profile analysis was used as an exploratory technique to identify emergent characteristics within the larger sample.

Integration of Latent Profile Analysis (LPA) and Propensity Score Matching (PSM)

The first portion of the study attempted to discern the effects of attending an SI program on students' SRL development as a function of latent profile membership. Profiles were determined by participants' self-reported SRL strategy use patterns prior to attending the SI program. A combination of latent profile analysis (LPA) and propensity score matching (PSM) was applied for this purpose.

LPA is a special case of latent class analysis (LCA), which allows for continuous indicators. LPA is a latent variable mixture model for identifying unobserved subgroups in a population with respect to subjects' responses to observed variables (Muthén & Muthén, 2000; Vermunt & Magidson, 2002). LPA has proved to be superior to other traditional clustering techniques (e.g., K-means) in that it is a probabilistic and model-based approach (Magidson & Vermunt, 2002; Stanley, Kellermanns, & Zellweger, 2017; Vermunt & Magidson, 2002).

Although recent evidence identifies unique subgroups characterized by SRL strategy use patterns (e.g., Barnard-Brak et al., 2010; Broadbent & Fuller-Tyszkiewicz, 2018), little is known about how membership in these subgroups is differentially associated with intervention effects. For the current study, the subgroups were created based on pre-intervention (i.e., before attending SI program) measures of SRL variables, and these variables were primary outcomes following the intervention (i.e., after attending an SI program).

While estimating intervention effects in a person-centered framework can be valuable, one challenge inherent to this approach is a lack of random assignment to the

treatment and control conditions. That is, given that student attendance in SI programs is completely voluntary, the presence of potential imbalances of baseline covariates could threaten the existence of a valid inference regarding the intervention effects. In fact, the self-selected and voluntary nature of SI has been one of the biggest challenges faced by previous researchers (Dawson et al., 2014).

To overcome this self-selection bias, some studies examined the SI effects while adjusting for students' previous academic performance or/and demographic characteristics using traditional statistical approaches, such as analysis of covariance (ANCOVA) (e.g., Fayowski & MacMillan, 2008). However, many researchers have criticized these traditional approaches, for not being statistically strong enough to minimize possible imbalances in observed covariates at baseline between the treated and non-treated groups. They have thus suggested statistical matching techniques proven as more powerful alternatives, such as propensity score matching (PSM; Fan & Nowell, 2011; Rosenbaum & Rubin, 1983) and coarsened exact matching (CEM; Iacus, King, & Porro, 2009, 2012). Surprisingly few attempts have been made to employ these alternative approaches to SI research, with only a couple of exceptions (Guarcello et al., 2016; Stock et al., 2013).

The current study utilized PSM, which is a matching method for pre-processing data to reduce potential imbalances of covariates at the baseline between treated and control groups in order to estimate casual effects (Rosenbaum & Rubin, 1983). Within subgroups determined by LPA, SI-attending students were matched to non-SI attending students using propensity scores. The specific analysis procedures for this LPA-PSM

combined analysis were guided by Haviland and colleagues' (2007, 2008) work. Confirmatory factor analyses and LPAs were conducted using Mplus 8.1 (Muthén & Muthén, 1998-2017), while descriptive statistics, PSM, and *t*-tests were performed using SPSS 25. In particular, PSM was done using the PS matching program, which is an SPSS R extension based on the *MatchIt* package in R.

Step 0: Preliminary Data Analysis

Descriptive statistics and correlations for all study variables were calculated. Values for missing data for subsequent analyses were handled using full information maximum likelihood (FIML) approach under the assumption that the data for this study is missing at random (MAR, Little & Rubin, 1990). In addition, confirmatory factor analyses were performed to assess the underlying factor structure of the SRL questionnaire administered to the whole sample (i.e., both SI and non-SI attending students) at T1. The results of confirmatory factor analyses are presented in the "Measures" section.

Step 1: Creating Heterogeneous SRL Profiles before SI Program using LPA

The first step of the LPA-PSM integrated analysis involved latent profile modeling of the means of the five SRL indicators. An LPA model estimates two types of model parameters: profile (i.e., class)-specific means (or variance/covariance) of the observed variables and profile probabilities (i.e., the relative prevalence of each profile). The LPA model for the current study has the form

$$f(y_i) = \sum_{k=1}^{K} P(c = k)\, f(y_i | c = k)$$

Here, y_i is the vector of scores for individual i on the set of the SRL indictors, and the categorical latent variable *c* has *K* profiles ($c = k$; k = 1, 2, 3, . . ., *K*). For y_i, the multivariate normal distribution is used for $f(y_i|c\ = k)$ (e.g., within profile normality) with profile-specific means (and variances/covariance). Figure 2 is a diagram of the final LPA model fitted in this study. Variables in boxes represent the five SRL indictors (GP = goal setting and planning; SEF = self-efficacy; IP = information processing; TM = time management; SEV = self-evaluation). The circled variable, *C*, represents the latent profile variable with *K* categories. Models with up to six categories were estimated, and each model allowed the SRL indicators to be uncorrelated within profile, constraining the variances of the indicators to be equal across profiles (default condition in Mplus). Relaxing this default condition has been found to yield less biased parameter estimates and may provide more realistic solutions (Meyer, & Morin, 2016; Peugh & Fan, 2013). However, since estimating too many parameters freely in a model often leads to convergence problems (i.e., fewer profile solutions found before nonconvergence; Muthén & Muthén (1998-2017), LPA models were fitted per the default setting for the current study.

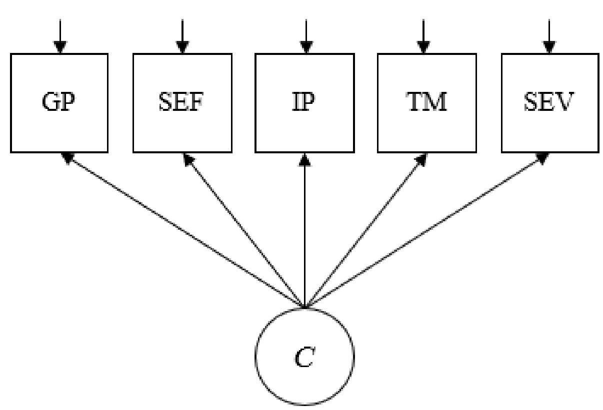


Figure 2. LPA model estimated in the study

In order to determine the LPA model with the most appropriate number of profiles, two approaches were used: (1) comparing statistical model fit across competing models and (2) considering theoretical/practical interpretability of the profile solution. For example, the Bayesian Information Criterion (BIC; Schwartz, 1978), which is defined as

$$BIC = -2 \log L + p \log(n),$$

where L is the log likelihood of the model, p is the number of free model parameter, and n is the sample size, is a descriptive measure for comparing competing models (e.g., 3- vs. 4-profile solutions). While other ICs (e.g., Akaike Information Criteria [AIC; Akaike, 1987], adjusted BIC [Sclove, 1987]) are also commonly used for class enumeration, BIC performs better than other IC statistics (Nylund, Asparouhov, & Muthén, 2007). Overall, smaller values of BIC indicate better fit. In addition to BIC, the current study also used entropy (Celeux & Soromenho, 1996), a standardized measure of the accuracy with which individuals are assigned to each profile; values close to 1 indicate better profile assignments. However, it is possible that these statistical indicators support a model in which the number of profiles or profile sizes may not be theoretically meaningful or readily interpretable (Nylund, 2007). Thus, both statistical and theoretical/practical aspects were considered jointly in order to select the final LPA model. Once the final LPA was determined, each participant was assigned to the most likely profile based on probabilities of latent profile membership. Profile membership was used for subsequent analyses.

Step 2: Matching on the Propensity Score and Assessing Covariate Balance

The next step of the LPA-PSM analysis was to match each treated individual (i.e., SI attendee) with one untreated individual (i.e., non-SI attendee) using the propensity score matching method (Rosenbaum & Rubin, 1983). The goal of this step is to reduce the potential imbalance in baseline covariates due the self-selected nature of SI attendance. Propensity scores were calculated using logistic regression to predict the probability of being in the treatment group (i.e., SI attendees), given the set of specified covariates. Sixteen covariates were selected based on previous studies on SI (e.g., Dawson et al., 2014; Guarcello et al., 2017), including students' socio-demographic features (e.g., age, major, first-generation student status) and pre-college academic performance (e.g., high school GPA, ACT score). Since these covariates included missing values, multiple imputation was used to handle the missing values, resulting in five datasets. Propensity scores were estimated across the five imputed datasets. Following propensity score estimation, students were matched using the 1:1 nearest neighbor matching within calipers of 0.075. Students in the treatment group were matched with students in the non-treatment group who possessed the closest propensity score. The matching was performed separately within each of the SRL profiles created by the LPAs in Step 1, as well as within the full sample across the five imputed datasets.

After matching, the balance of the covariates in the matched sample was evaluated by computing standardized bias statistics for the full sample and each SRL profile across the five imputed datasets. The absolute standardized differences for the unmatched (d_X) and matched samples (d_{Xm}) were calculated:

$$d_X = \frac{|\, M_{X_t} - M_{X_p} |}{\sqrt{(S^2{}_{X_t} + S^2{}_{X_c})/2}} \text{ and } d_{\mathrm{Xm}} = \frac{|\, M_{X_t} - M_{X_c} |}{\sqrt{(S^2{}_{X_t} + S^2{}_{X_c})/2}}$$

where M_{X_t}, M_{X_p}, and M_{X_c} are the means for a covariate X for SI attending students, non-SI attending students before matching, and non-SI attending students after matching, respectively, and S_{X_t} and S_{X_c} are the standard deviations of a covariate X for SI attending students and non-SI attending students before matching. An absolute standardized difference close to 0 represents an excellent covariate balance, and values greater than 0.2 or 20% indicate a significant covariate imbalance (Haviland et al., 2008).

<u>Step 3: Estimating SI Program Effects on SRL Development</u>

The last step of the LPA-PSM analysis was to estimate the treatment effects (i.e., the effects of SI program) with the matched sample. All imputed datasets in which the covariate balance was successfully achieved were included in the analysis (Kupzyk & Beal, 2017). Within each SRL profile as well as within the full sample, the two-sample *t*-tests were first conducted to examine if there were differences between SI attendees and non-SI attendees in the overall SRL means at T2 (i.e, after SI program) as well as in the fall semester cumulative GPAs. Subsequent paired *t*-tests were next performed to determine whether there were significant increases in the overall SRL means over the course of the semester within each intervention group (SI and non-SI attendees) for each profile. The results (e.g., *p*-value) across the imputations were combined based on Rubin’s (1987) rules.

Latent Profile Transition Analysis (LPTA)

While the first part of the study was aimed at comparing students exposed to SI intervention with those who were not exposed, the second part was focused solely on characterizing trends of students exposed to SI intervention. Specifically, the second set of research questions in this study investigates the stability and mobility of SRL profiles in SI attendees over the course of a semester. It also examines the extent to which stability or mobility is associated with a range of SI-related factors, such as attendance frequency, reasons for attending SI study sessions, and perceived benefits of the SI program. To address these objectives, latent profile transition analysis (LPTA), an extension of LPA to accommodate repeated measures was used (Martinent & Decret, 2015). In an LPA model, latent profile can represent states or stable sets of SRL strategies. However, in an LPTA model, individual students may move between SRL latent profiles over time (Lanza, Patrick, & Maggs, 2010).

Although the analysis of college students' SRL strategies in a group-based framework (e.g., LPA) has recently received considerable attention (e.g., Barnard-Brak et al., 2010; Broadbent & Fuller-Tyszkiewicz, 2018; Dörrenbächer & Perels, 2016b), surprisingly few attempts have been made to explore how student SRL profile membership changes over time.

In the current study, the specific analysis procedures for building LPTA models were guided by Nylund's (2007) work. All analyses were conducted using Mplus 8.1 (Muthén & Muthén, 1998-2017), while the descriptive statistics and multivariate analyses of variance (MANOVA) were performed using SPSS 25. Given that SI-attending

students were distributed across 34 courses (10 students per course), the results of LPTAs and multinomial logistic regression analyses accounted for this nested nature of the data by adjusting the standard errors using a sandwich estimator (type=complex).

Step 0: Preliminary Data Analysis

Descriptive statistics and correlations for all study variables were calculated. Values for missing data for subsequent analyses were handled using full information maximum likelihood (FIML) approach under the assumption that the data for this study is missing at random (MAR, Little & Rubin, 1990). In addition, confirmatory factor analyses were conducted to test the underlying factor structure of the items regarding participants' beliefs about SI program benefits administered to SI attending students at T2. Given that the second set of research questions was designed to examine changes in SRL profiles in SI attending students over time, longitudinal confirmatory factor analyses were also performed to verify whether participants perceived the SRL questionnaire in the same way at each time point (i.e., factorial invariance; Widaman & Reise, 1997). Configural (i.e., baseline model), weak (i.e., constraining the factor loadings to be equal over time), and strong (i.e., constraining the factor loadings and intercepts to be equal over time) invariance models were tested. The results of confirmatory factor analyses are presented in the "Measures" section.

Step 1: Cross-sectional SRL Profiles

The first step of LPTA involved latent profile modeling of the means of the five SRL indicators separately at each time point (T1 and 2). The LPA model specification

and selection were performed in the same way as did in the first part of the study. The final LPA models were used as the measurement models for the following LPTA models.

Step 2: Estimating LPTA Models without Covariates

Once the most appropriate number of profiles has been determined at each time point, the next step was latent profile transition modeling. An LPTA model estimates three sets of parameters that include a set of profile-specific means of the observed variables (at each time point), profile probabilities (i.e., the relative prevalence of each profile at each time point), and transition probabilities (i.e., the probability of transitioning from a particular profile at time *t* to another profile at time *t*+1).

Figure 3 is a diagram of the LPTA model fitted in this study. The five SRL indicators were used at each of the two time points, and they were allowed to be correlated across time (e.g., goal setting at T1 is correlated with goal setting at T2).

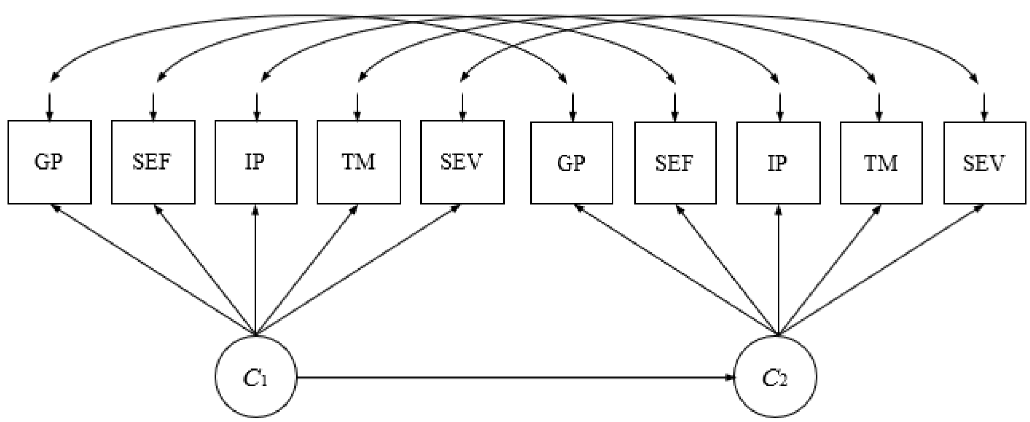


Figure 3. LPTA model estimated in the study

As seen in the Figure 3, the categorical latent profile variable at T1 is regressed on the latent profile variable at T2 (i.e., C_2 on C_1). Transition probabilities of the model is then calculated as follows:

$$\tau_{ikm} = \mathrm{P}\ (C_{\mathrm{it}} = k \mid C_{i(\mathrm{t}\text{-}1)} = \mathrm{m})$$

where τ_{ikm} is the transition probability for individual *i* to be in latent profile *k* (*k* = 1, …, *S*) at time point *t*, given that the individual was in latent profile *m* (*m* = 1, …, *S*) at the previous time point, *t - 1*.

In general, there can be different specifications for LPTA models, which include measurement invariance (i.e., within-profile means are consistent across time points), stationary transitions (i.e., transition probabilities are consistent across transition points), and higher-order effects (Nylund, 2007). Given that this study estimated LPTA models for two time points, only testing for measurement invariance was considered. A model with full measurement invariance was compared to a model with full measurement noninvariance using BIC, with a lower value representing better fit. In this study, full measurement invariance implies that within-profile means on the five SRL indicators are the same across the two time points, while full measurement noninvariance does not hold that assumption. If full measurement invariance holds, the transition probabilities are straightforward to interpret, because the meanings of the SRL profiles are the same across time. Once the final LPTA model was determined, each participant was assigned to the most likely profile based on probabilities of latent profile transition membership, and this membership (i.e., a categorical variable) was then used for subsequent analyses.

Step 3: Exploring SI-related Predictors Associated with SRL Profile Transition

Multinomial logistic regression analyses were conducted to examine the extent to which SI-related variables predict students' SRL profile transition while adjusting for a set of confounding factors (e.g., ACT composite score, high school GPA). The SI-related variables included the frequency of SI attendance, scores relating to four different purposes of attending SI study sessions, and perceptions about the SI benefits. The students' profile transition as an outcome variable was examined in two ways: 1) SRL profiles at T2 based on the final LPTA model and 2) SRL transition patterns.

Step 4: Exploring Outcomes of SRL Profile Transition

Multivariate analyses of variance (MANOVA) determined the extent to which SRL profile transition was associated with students' outcomes. The student outcomes included final grades in the SI-attached course and fall semester cumulative GPAs. Students' profile transition as a predictor variable was examined in two ways: 1) SRL profiles at T2 based on the final LPTA model and 2) SRL transition patterns.

CHAPTER VI

RESULTS

The results of this study are presented in two major sections. The first section reports the extent to which the Supplement Instruction (SI) program has an effect on students' development of self-regulated learning (SRL) and how such an effect differs as a function of individual student membership in the baseline profiles of SRL. The second section reports how the SRL profiles of students attending the SI program change over the course of the semester and how such changes are associated with the SI-related predictors and outcomes.

Heterogeneous Treatment Effects on SRL Development

Descriptive Analyses

Table 2 presents the descriptive statistics and zero-order correlations for the variables used in the first part of this dissertation. Among the five SRL indicators, the mean score on information processing was highest (M = 4.10, SD = 0.68), followed by self-efficacy for learning and performance (M = 3.98, SD = 0.75). In addition, the mean score on time management was lowest, falling near the middle of the response range (M = 2.74, SD = 0.99). This result indicates that the current sample reported frequently using strategies to connect their previous knowledge and experiences with new information. They also felt highly confident with their learning and performance. However, these students reported managing their time and study schedules only at a moderate level.

Table 2

Descriptive statistics and correlations among variables used in the first part of the study

	1	2	3	4	5	6	7	8	9
1. Gender	–								
2. Race	.00	–							
3. ITNS	.10*	.00	–						
4. FG	-.07	.02	-.04	–					
5. Major	-.01	-.02	.02	-.01	–				
6. YIS	-.02	.01	-.03	.04	.10*	–			
7. SIATT	-.03	-.04	.02	-.08	.08*	-.14**	–		
8. Age	.10*	.05	-.02	.18**	-.07	.39**	-.13**	–	
9. HSGPA	-.20**	.00	.00	-.18**	.06	.06	.15**	-.29**	–
10. ACT score	.06	.03	-.01	-.24**	.04	.01	-.06	-.21**	.48**
11. GP (T1)	-.25**	-.02	-.01	.00	-.01	.06	.09*	-.01	.17**
12. SEF (T1)	.18**	.00	.06	-.11**	.09*	.09*	.00	-.02	.15**
13. IP (T1)	-.01	.03	.05	-.03	.05	.09*	.02	-.04	.08
14. TM (T1)	.04	-.04	-.01	.02	.02	.03	.11**	.04	.14**
15. SEV (T1)	.02	.02	.06	-.03	-.01	-.01	.02	-.03	.00
16. OSRL (T1)	-.03	-.01	.04	-.05	.03	.08	.08	.01	.18**
17. OSRL (T2)	-.05	-.07	-.03	-.14**	-.04	.01	.03	-.06	.18**
N	596	593	593	592	621	594	626	594	560
M	–	–	–	–	–	–	–	20.51	3.71
SD	–	–	–	–	–	–	–	3.72	0.37
Min	0	1	0	0	1	1	0	17	2
Max	1	4	1	1	5	4	1	46	4
Missing rate (%)	4.8	5.3	5.3	5.4	0.8	5.1	0.0	5.1	10.5

Note. ITNS = international student status; FG = first-generation student status; YIS = year in school; SIATT = whether to attend the SI program (0 = no, 1 = yes); HSGPA = high school GPA; ACT score = American College Testing (ACT) score; GP = goal setting and planning; SEF = self-efficacy; IP = information processing; TM = time management; SEV = self-evaluation; OSRL = overall score of the five SRL indicators; T1 = Time 1; T2 = Time 2. Internal consistency reliability coefficients (Omega; McDonald, 1970) are reported on the diagonal in bold.

* $p < .05$, ** $p < .01$

Table 2

Descriptive statistics and correlations among variables used in the first part of the study

	10	11	12	13	14	15	16	17
1. Gender								
2. Race								
3. ITNS								
4. FG								
5. Major								
6. YIS								
7. SIATT								
8. Age								
9. HSGPA								
10. ACT score	–							
11. GP (T1)	.01	**.80**						
12. SEF (T1)	.31**	.11**	**.83**					
13. IP (T1)	.12**	.21**	.31**	**.77**				
14. TM (T1)	.04	.35**	.35**	.15**	**.84**			
15. SEV (T1)	-.02	.25**	.21**	.35**	.21**	**.60**		
16. OSRL (T1)	.14**	.65**	.60**	.57**	.71**	.61**	**.83**	
17. OSRL (T2)	.12*	.52**	.48**	.33**	.55**	.42**	.73**	**.86**
N	550	595	595	597	594	594	587	438
M	26.55	3.76	3.98	4.10	2.74	3.35	3.59	3.56
SD	4.44	0.97	0.75	0.68	0.99	0.80	0.53	0.57
Min	12	1	1	1	1	1	2.02	1.20
Max	36	5	5	5	5	5	4.93	4.95
Missing rate (%)	12.1	5.0	5.0	4.6	5.1	5.1	6.2	30.0

Note. ITNS = international student status; FG = first-generation student status; YIS = year in school; SIATT = whether to attend the SI program (0 = no, 1 = yes); HSGPA = high school GPA; GP = goal setting and planning; SEF = self-efficacy; IP = information processing; TM = time management; SEV = self-evaluation; OSRL = overall score of the five SRL indicators; T1 = Time 1; T2 = Time 2. Internal consistency reliability coefficients (Omega; McDonald, 1970) are reported on the diagonal in bold.

* $p < .05$, ** $p < .01$

Creating Heterogeneous SRL Profiles before SI Program

LPA Model Selection

A series of LPAs were performed to create distinct student subgroups characterized by their SRL skills before attending the SI program (T1). LPA models with up to six latent profiles were estimated while allowing the SRL indicators to be uncorrelated within profile and constraining the variances of the indicators to be equal across profiles. To determine the best-fitting LPA model, statistical fit indices were first considered (Table 3). The values of BIC consistently decreased as the number of profiles increased, within which the smallest values may be not preferred for model selection. As such, a scree plot was used as an alternative means of selection for the best-fitting LPA model. The plot line slope flattened noticeably at the three-profile model (see Figure 4), suggesting that a three-profile model would provide the best fit with the data (Meyer & Morin, 2016; Nylund-Gibson, Grimm, Quirk, & Furlong, 2014). Examination of profile sizes indicated that the two- and three-profile solutions seem adequate while the other solutions include a profile whose size is very small (e.g., N = 31, [5%]; N = 20, [3.2%]; N = 2, [0.3%]). However, the two-profile model had a very low entropy value (E = 0.58). Further, the mean posterior probabilities for the most likely profile membership of the three-profile model ranged from 0.788 to 0.889, suggesting that students were assigned to each profile with high prediction. In addition to these statistical criteria, the theoretical interpretability of each profile was also considered. The profiles of the three-profile model allowed clearer and easier interpretation based on SRL theory. Taken together, the three-profile model was selected and used for further analyses.

Table 3

Fit indices for LPA models

Model	BIC	Profile Sizes (N)	Entropy
1- profile	7576.410		
2- profile	7351.982	282/333	0.58
3- profile	**7296.185**	**159/134/322**	**0.70**
4- profile	7263.228	155/31/134/295	0.74
5- profile	7239.010	66/20/223/197/109	0.74
6- profile	7214.242	69/193/219/2/20/112	0.77

Note. Statistics for the selected LPA model are in bold type.

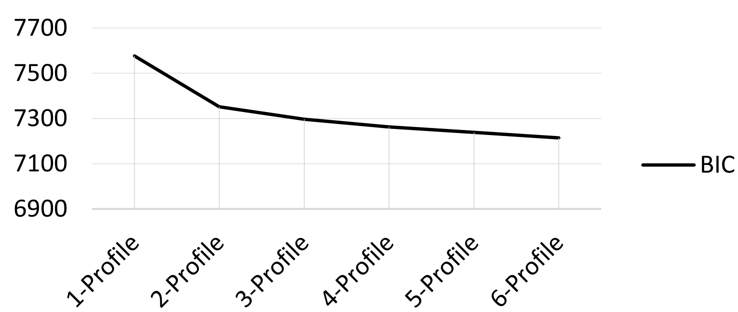


Figure 4. Scree plot of information criteria for model comparisons

<u>Describing the Profiles</u>

Figure 5 illustrates the within-profile means of the five SRL indicators for each of the three SRL latent profiles. Students in Profile 1 reported having high scores on three SRL strategies, including goal setting and planning, self-efficacy, and information processing. Their scores on time management and self-evaluation were moderate, but relatively higher than those of students in the other profiles. This profile, therefore, was labelled *competent regulator,* with 52.4% (N = 322) of the sample belonging to it. Students in Profile 2 showed moderate scores on self-evaluation and low scores on goal setting and planning and time management, while their scores on self-efficacy and

information processing remained high. Thus, Profile 2 was named *self-confident regulator* (N = 159; 25.8%). Students in Profile 3 exhibited levels of information processing, time management, and self-evaluation quite similar to those of the students in Profile 2. However, their scores on goal setting and planning were high, while their self-efficacy scores remained moderate. Based on this pattern, Profile 3 was named *goal-oriented regulator* (N =134; 21.8%).

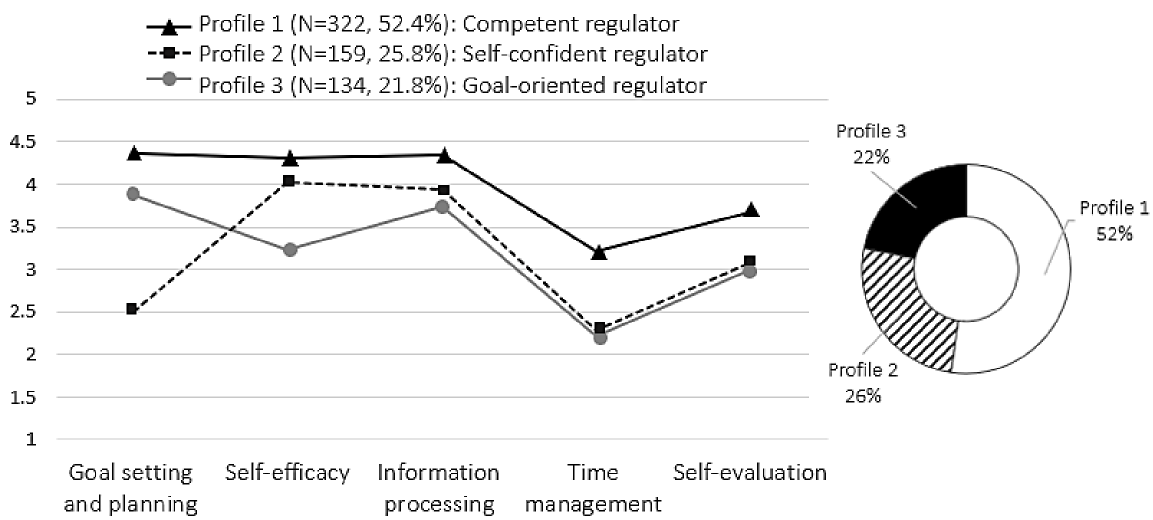


Figure 5. Three SRL profiles obtained from LPA

Validating the Profiles

To validate this profile classification, the association between students' SI attendance rates and their SRL membership was tested (Table 4 and Figure 6). The chi-squire test revealed that the rates of student attendance in the SI program differed significantly depending on their membership in SRL profiles, χ^2 (2) = 11.452, p = 0.003, Cramer's V = 0.136. Specifically, more than half of the students in the c*ompetent*

regulator (61.5 %) and *goal-oriented regulator* (54.5%) profiles attended at least one SI study sessions during the semester. This was also the case for the full sample; 55.8% of the entire participants attended the SI program. However, the students in the *self-confident regulator* profile showed an opposite pattern; more than half of these students (54.7%) did not attend any SI study sessions.

Table 4

SI attendance by SRL membership

	Total	SI attendees (%)	Non-SI attendees (%)	χ^2
Full sample	615	343 (55.8)	272 (44.2)	
Profile 1: competent regulator	322	198 (61.5)	124 (38.5)	11.452^{**}
Profile 2: self-confident regulator	159	72 (45.3)	87 (54.7)	
Profile 3: goal-oriented regulator	134	73 (54.5)	61 (45.5)	

** $p < .01$

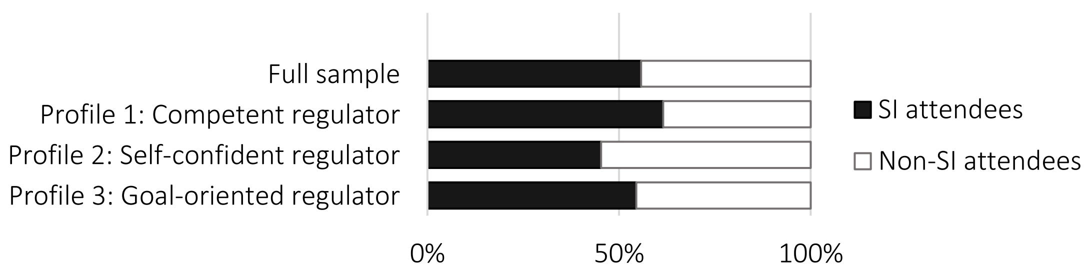


Figure 6. SI attendance by SRL membership

Matching on the Propensity Score and Assessing Covariate Balance after Matching

Propensity score matching analyses were conducted to match SI attending students with non-SI attending students based on the 16 pre-treatment (i.e., SI program) covariates within the full sample, as well as within each SRL profile, across the five imputed data sets. The covariate balance was assessed after matching. Table 5 present the standardized bias statistics for intervention (SI-attendees) and control groups (non-SI

attendees) before and after matching for each of the 16 covariates with one of the five imputed datasets. An absolute standardized difference close to 0 represents an excellent covariate balance, and values greater than 0.2 or 20% indicate a significant covariate imbalance (Haviland et al., 2008). As shown in Table 5, prior to matching, the full sample included 4 out of 16 covariates that had mean standardized differences greater than 0.2 and 3 covariates that had mean standardized differences greater than 0.1. Overall, the average covariate was imbalanced by 11% of a standard deviation, and the logit of the propensity score was imbalanced by 69% of a standard deviation. After matching, however, covariate balance was successfully achieved in the full sample; the absolute standardized differences in the covariate means and the logit of the propensity score decreased to 3% and 5%, respectively. This result indicated that the SI attendee and non-SI attendee groups in the full sample became substantially equivalent with respect to the given set of covariates. The same trends of this result were apparent across the three SRL profiles. More specifically, before matching, the average covariate was imbalanced by 13%, 14%, and 21% of a standard deviation in Profile 1, 2, and 3, respectively, but these values decreased to 6%, 8%, and 5% after matching. Similarly, the logit of the propensity score had a standardized difference of 66%, 95%, and 130% in absolute value in the three profiles before matching but these values decreased to 5%, 2%, and 4% after matching. Appendix F presents the results for the covariance balance across the other four imputed datasets. In addition, given the fact that the covariate balance was achieved across all the five imputations (see Table 6), all matched imputed datasets were used for further analyses (Kupzyk & Beal, 2017).

Table 5

Covariate balance before and after matching for each SRL profile (Imputed dataset 1)

	Full sample		Profile 1: competent regulator		Profile 2: self-confident regulator		Profile 3: goal-oriented regulator	
	d_X	d_{Xm}	d_X	d_{Xm}	d_X	d_{Xm}	d_X	d_{Xm}
Gender[a]	0.01	0.03	0.06	0.17	0.09	0.05	0.06	0.15
Race								
Asian[b]	0.09	0.03	0.14	0.00	0.03	0.15	0.12	0.00
White[b]	0.04	0.02	0.07	0.12	0.13	0.09	**0.22**	0.00
Other[b]	0.01	0.05	0.14	0.14	0.04	0.00	0.12	0.00
International student status	0.01	0.00	0.03	0.00	0.15	0.00	0.00	0.00
First-generation student status	0.12	0.01	0.07	0.02	0.02	0.19	**0.57**	0.00
Year in school								
Sophomore[c]	**0.21**	0.01	0.12	0.09	**0.35**	0.06	0.09	0.13
Junior[c]	0.03	0.01	0.00	0.07	0.10	0.09	**0.22**	0.00
Senior[c]	**0.26**	0.08	**0.25**	0.06	0.18	0.00	**0.29**	0.00
Major								
Social science[d]	0.16	0.09	0.06	0.00	0.15	0.06	**0.41**	0.14
Engineering[d]	0.00	0.00	0.10	0.06	**0.23**	0.18	0.05	0.10
Science[d]	0.02	0.06	0.05	0.03	0.20	0.09	**0.31**	0.00
Exploratory[d]	0.14	0.08	0.16	0.00	0.08	0.05	**0.30**	0.18
Age	**0.22**	0.02	**0.41**	0.14	0.03	0.04	**0.40**	0.01
High school GPA	**0.40**	0.02	**0.38**	0.06	**0.35**	0.02	0.08	0.08
ACT composite score	0.05	0.03	0.02	0.13	0.15	0.00	0.04	0.01
Overall SRL score at T1	0.12	0.02	0.08	0.00	0.12	**0.21**	0.10	0.05
Average covariate balance	0.11	0.03	0.13	0.06	0.14	0.08	**0.21**	0.05
Logit propensity score	**0.69**	0.05	**0.66**	0.05	**0.95**	0.02	**1.30**	0.04

Note: d_X = Absolute standardized difference in covariate means before matching; d_{Xm} = Absolute standardized difference in covariate means after matching

Values greater than 0.2 are presented in bold type.

[a]Reference group: Female

[b]Reference group: Hispanic

[c]Reference group: Freshman

[d]Reference group: Art & Humanities

Table 6

Overall covariate balance before and after matching across all imputed data sets

	Full sample		Profile 1: competent regulator		Profile 2: self-confident regulator		Profile 3: goal-oriented regulator	
	d_X	d_{Xm}	d_X	d_{Xm}	d_X	d_{Xm}	d_X	d_{Xm}
Imputed dataset 1								
Average covariate balance	0.11	0.03	0.13	0.06	0.14	0.08	0.21	0.05
Logit propensity score	0.69	0.05	0.66	0.05	0.95	0.02	1.30	0.04
Imputed dataset 2								
Average covariate balance	0.12	0.03	0.17	0.04	0.13	0.06	0.22	0.08
Logit propensity score	0.66	0.04	0.77	0.04	0.94	0.03	1.24	0.04
Imputed dataset 3								
Average covariate balance	0.12	0.03	0.11	0.06	0.13	0.09	0.23	0.08
Logit propensity score	0.65	0.05	0.71	0.06	0.93	0.04	1.29	0.03
Imputed dataset 4								
Average covariate balance	0.12	0.02	0.15	0.06	0.14	0.06	0.22	0.09
Logit propensity score	0.66	0.04	0.70	0.05	1.03	0.03	1.34	0.03
Imputed dataset 5								
Average covariate balance	0.13	0.03	0.11	0.07	0.14	0.08	0.21	0.09
Logit propensity score	0.64	0.04	0.71	0.05	0.95	0.03	1.19	0.04

Note: d_X = Absolute standardized difference in covariate means before matching; d_{Xm} = Absolute standardized difference in covariate means after matching

Analyzing SI Program Effects on SRL Development

With the matched datasets created by the propensity score analyses, the effects of the SI program on students' SRL development were finally estimated. The analyses were conducted on each of the five imputed datasets for the full sample as well as for each of the three SRL profiles, and the results were combined according to Rubin's (1987) rules. The two-sample *t*-tests were first performed to determine if there were differences between SI attendees and non-SI attendees in the overall SRL means after the SI program, as well as in the fall semester cumulative GPAs. Levene's tests for equality of variance were not violated across the samples and the imputed data sets. The results

indicated that although SI attendees exhibited higher mean scores on those two outcomes than non-SI attendees did in the full sample as well as across the three profiles, none of these differences were statistically significant (Table 7 and Figure 7).

Follow-up paired *t*-tests were then carried out to examine whether there were significant increases in the overall SRL means over the course of the semester within treatment group (SI and non-SI attendees) for each profile (Table 8). Levene's tests for equality of variance were not violated across the samples and the imputed data sets. The results showed different patterns across the samples. Specifically, for the full sample, both SI and non-SI attendees showed a decrease in the overall SRL scores over time but such a decrease was statistically significant only in non-SI attendees ($t = -2.24$. $p < 0.05$). These decreasing trends were also observed in students in the *competent regulator* profile. Within this profile, however, both SI and non-SI attendees' overall SRL scores significantly decreased over the course of the semester ($t = -3.23$. $p < 0.01$, $t = -4.72$. $p < 0.001$). In addition, within the *self-confident regulator* profile, pre-post descriptive comparisons of the overall SRL scores revealed an improvement for SI-attendees but not for non-SI attendees. None of these comparisons, however, were statistically significant. Lastly, within the *goal-oriented regulator* profile, both SI and non-SI attendees' overall SRL scores increased but these increases were not significant.

Table 7

Descriptive statistics and SI program effects on SRL and semester GPA

	N	M(SD)	*t*	*p*-value	95% CI
SRL scores at T2 (post-SI program)					
Full sample					
SI attendees	225	3.58 (0.57)	1.29	0.21	[-0.05, 0.23]
Non-SI attendees	225	3.49 (0.60)			
Profile 1: competent regulator					
SI attendees	101	3.89 (0.49)	1.28	0.21	[-0.06, 0.29]
Non-SI attendees	101	3.78 (0.54)			
Profile 2: self-confident regulator					
SI attendees	43	3.20 (0.55)	0.74	0.46	[-0.19, 0.40]
Non-SI attendees	43	3.09 (0.50)			
Profile 3: goal-oriented regulator					
SI attendees	34	3.30 (0.43)	0.19	0.85	[-0.22, 0.27]
Non-SI attendees	34	3.28 (0.44)			
Fall semester cumulative GPAs					
Full sample					
SI attendees	225	3.35 (0.72)	1.48	0.14	[-0.04, 0.30]
Non-SI attendees	225	3.22 (0.86)			
Profile 1: competent regulator					
SI attendees	101	3.43 (0.73)	1.08	0.28	[-0.10, 0.36]
Non-SI attendees	101	3.31 (0.88)			
Profile 2: self-confident regulator					
SI attendees	43	3.34 (0.80)	0.91	0.36	[-0.20, 0.55]
Non-SI attendees	43	3.17 (0.89)			
Profile 3: goal-oriented regulator					
SI attendees	34	3.28 (0.64)	0.91	0.37	[-0.19, 0.52]
Non-SI attendees	34	3.12 (0.70)			

Note. 95% CI = 95% confidence intervals of the difference

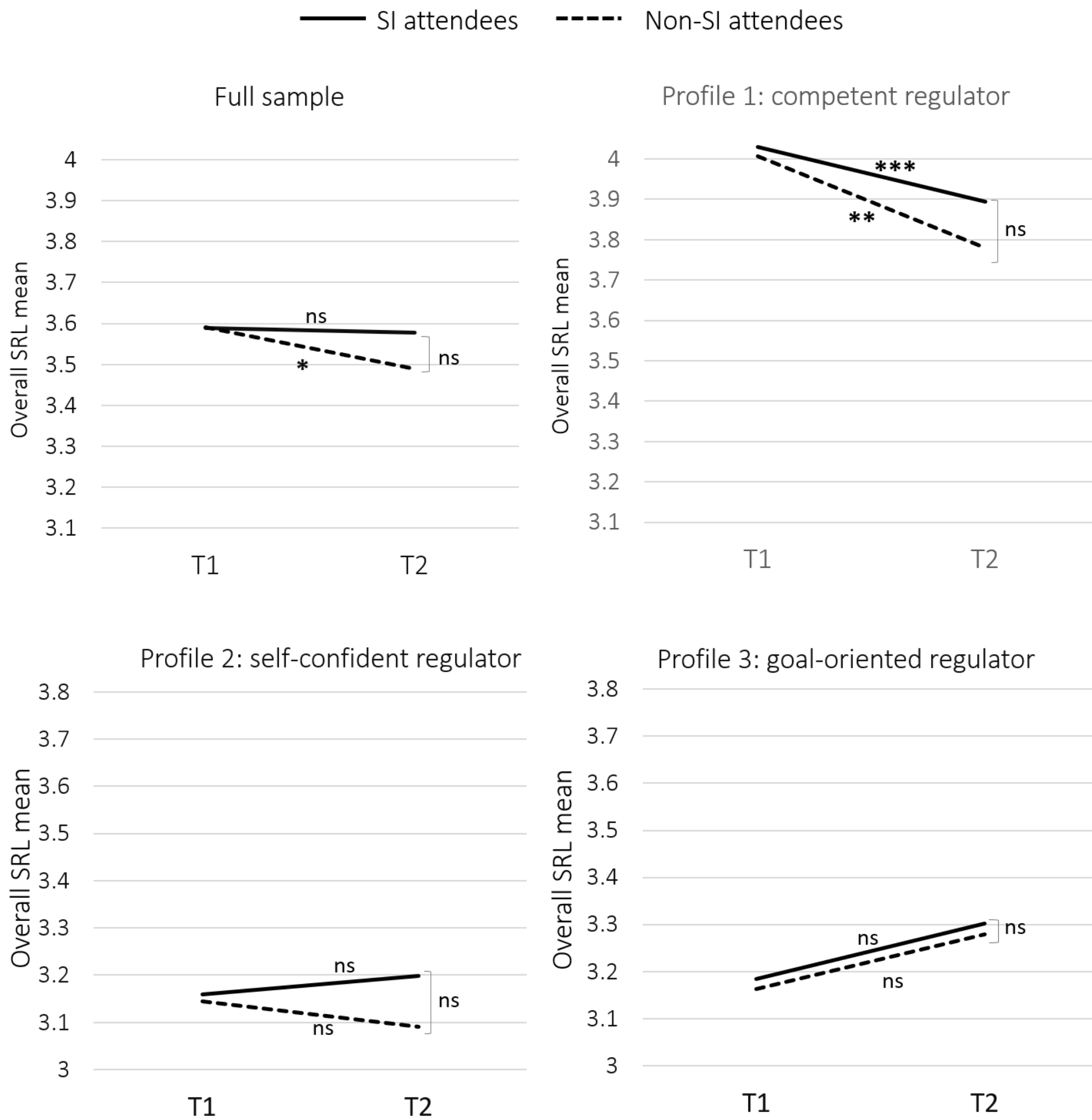
Table 8

Descriptive statistics and SI program effects on SRL gain

	N	SRL at T1 M(SD)	SRL at T2 M(SD)	Diff. (SD)	*t*	*p*	95% CI
Full sample							
SI attendees	225	3.59 (0.55)	3.58 (0.57)	-0.01 (0.40)	-0.34	0.74	[-0.08, 0.05]
Non-SI attendees	225	3.59 (0.53)	3.49 (0.60)	-0.10 (0.45)	-2.24	0.04*	[-0.20, -0.00]
Profile 1: competent regulator							
SI attendees	101	4.03 (0.31)	3.89 (0.49)	-0.14 (0.40)	-3.23	0.00**	[-0.21, -0.05]
Non-SI attendees	101	4.01 (0.32)	3.78 (0.54)	-0.23 (0.43)	-4.72	0.00***	[-0.32, -0.13]
Profile 2: self-confident regulator							
SI attendees	43	3.16 (0.38)	3.20 (0.55)	0.04 (0.47)	0.46	0.65	[-0.13, 0.21]
Non-SI attendees	43	3.14 (0.39)	3.09 (0.50)	-0.05 (0.45)	-0.74	0.46	[-0.20, 0.09]
Profile 3: goal-oriented regulator							
SI attendees	34	3.18 (0.29)	3.30 (0.43)	0.12 (0.37)	1.31	0.21	[-0.07, 0.31]
Non-SI attendees	34	3.16 (0.31)	3.28 (0.44)	0.12 (0.38)	1.35	0.19	[-0.06, 0.29]

Note. 95% CI = 95% confidence intervals of the difference

* p < .05, ** p < .01, *** p < .001



*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns = non-significant

Figure 7. SI program effects on SRL development

Stability and Change in SRL Profiles

Descriptive Statistics and Correlations

Table 9 presents the descriptive statistics and zero-order correlations for the variables used in the second part of this research. The pattern of mean scores on the five SRL indicators for SI attendees at T1 was quite similar to that for the full sample at T1 (Table 2). Specifically, the mean score on information processing was highest (M = 4.12, SD = 0.65), followed by self-efficacy for learning and performance (M = 3.98, SD = 0.74). The lowest mean score was observed in time management (M = 2.84, SD = 0.99). In addition, by the end of the semester (T2), the relative magnitude of the mean scores across the five indicators remained the same. However, there was a decrease found in the mean on time management while the other four indicators' scores increased. These findings indicate that the current sample of college students who attended the SI program seemed to be most vulnerable in their ability to effectively manage time and adhere to study schedules among a range of SRL strategies examined in the study.

In terms of students' reasons for attending the SI study sessions, the mean score on the reason 'to understand the subject better' (M = 4.69, SD = 0.53) was greater in comparison to the reason 'to pass the course' (M = 4.45, SD = 0.96).

In addition, the biggest benefit from attending the SI sessions seemed to be an increased self-confidence in learning (M = 4.10, SD = 0.89), followed by study skill development. However, the mean score on improved group work skills was lowest (M = 3.27, SD = 1.14).

Table 9

Descriptive statistics and correlations among variables used in the second part of the study

	1	2	3	4	5	6	7	8	9	10	11	12
1. Major	–											
2. YIS	-.06	–										
3. HSGPA	-.11*	-.02	–									
4. ACT	-.12*	-.05	.49**	–								
5. NSIATT	.01	.02	.01	-.14*	–							
6. PPC	.15*	-.05	-.02	-.12	.05	–						
7. PUS	.00	.04	-.01	-.01	.15*	.34**	–					
8. BSC	-.04	-.02	-.09	-.02	.20**	.13	.36**	–				
9. BSK	.13	-.20*	-.10	-.14	.24**	.26**	.29**	.51**	–			
10. BCT	.05	-.08	-.07	-.15*	.08	.16*	.09	.40**	.47**	–		
11. BPS	-.09	.04	-.01	-.01	.11	.11	.22**	.47**	.48**	.46**	–	
12. BGW	.03	.00	-.20**	-.29**	.18*	.08	.07	.30**	.39**	.52**	.49**	–
13. GP (T1)	.12*	.10	.10	.01	.03	.15*	.13	.16*	.08	.10	.13	.11
14. SEF (T1)	-.14*	.10	.17**	.32**	-.08	-.12	-.02	.00	.00	.17*	.19**	.07
15. IP (T1)	-.07	.10	.06	.12*	-.08	.00	-.01	-.01	.03	.11	.15*	-.12
16. TM T1)	-.05	.10	.18**	.07	.08	.01	.03	.12	.07	.05	.21**	.13
17. SEV (T1)	-.04	.02	.00	.02	.02	-.05	.21**	.20**	.18*	.23**	.37**	.28**
18. GP (T2)	.14*	-.01	.19**	.03	.06	.01	.21**	.23**	.14*	.14	.10	.12
19. SEF (T2)	-.14*	.06	.23**	.32**	.03	-.10	.16*	.18*	.07	.22**	.23**	.09
20. IP (T2)	-.10	.05	.10	.15*	-.01	.04	.26**	.15*	.11	.13	.13	.07
21. TM T2)	-.06	.02	.16*	-.01	.15*	-.03	.06	.16*	.10	.12	.19**	.14
22. SEV (T2)	-.02	-.10	.07	.03	.01	.01	.22**	.12	.13	.19**	.28**	.25**
23. FGC	-.14*	-.02	.45**	.44**	.09	-.14*	-.01	.08	-.09	-.02	-.10	-.18*
24. FCGPA	-.13*	-.11*	.50**	.44**	.12*	-.06	.09	.05	-.05	-.01	-.07	-.15*
N	350	329	321	318	352	192	192	191	192	192	192	192
M	–	–	3.76	26.34	4.53	4.45	4.69	4.10	4.07	3.85	3.93	3.27
SD	–	–	0.31	4.34	4.39	0.96	0.53	0.89	0.94	0.97	0.97	1.14
Min	1	1	2	17	1	1	3	1	1	1	1	1
Max	5	4	4	36	25	5	5	5	5	5	5	5
Missing rate (%)	0.6	6.5	8.8	9.7	0	45.5	45.5	45.7	45.5	45.5	45.5	45.5

Note. YIS = year in school; HSGPA = high school grade point average (GPA); ACT = ACT composite score; NSIATT = the number of attending SI study sessions during the semester; PPC = purpose of SI attendance - to pass the course; PUS = purpose of SI attendance - to understand the subject better; BSC = Perceived SI benefit – increased self-confidence; BSK = Perceived SI benefit – increased study skills; BCT = Perceived SI benefit – increased critical thinking skills; BPS = Perceived SI benefit – increased problem- solving skills; BGW = increased group work skills; GP = goal setting and planning; SEF = self-efficacy; IP = information processing; TM = time management; SEV = self-evaluation; FGC = final grade in the SI-supported course; FCGPA = fall semester cumulative GPA; T1 = Time 1; T2 = Time 2. Internal consistency reliability coefficients (Omega; McDonald, 1970) are reported on the diagonal in bold.
* $p < .05$, ** $p < .01$

Table 9

Descriptive statistics and correlations among variables used in the second part of the study

	13	14	15	16	17	18	19	20	21	22	23	24
1. Major												
2. YIS												
3. HSGPA												
4. ACT												
5. NSIATT												
6. PPC												
7. PUS												
8. BSC												
9. BSK												
10. BCT												
11. BPS												
12. BGW												
13. GP (T1)	**.80**											
14. SEF (T1)	.13*	**.81**										
15. IP (T1)	.19**	.33**	**.73**									
16. TM T1)	.34**	.36**	.19**	**.84**								
17. SEV (T1)	.23**	.24**	.31**	.29**	**.64**							
18. GP (T2)	.67**	.05	.08	.32**	.28**	**.85**						
19. SEF (T2)	.12	.60**	.30**	.28**	.25**	.10	**.83**					
20. IP (T2)	.22**	.19**	.56**	.17**	.35**	.29**	.35**	**.83**				
21. TM T2)	.32**	.31**	.14*	.75**	.31**	.30**	.28**	.14*	**.88**			
22. SEV (T2)	.19**	.15*	.23**	.18**	.60**	.31**	.29**	.45**	.20**	**.73**		
23. FGC	.00	.25**	.10	.21**	-.05	.01	.48**	.15*	.22**	-.01	–	
24. FCGPA	.05	.24**	.05	.23**	-.02	.07	.48**	.16*	.25**	.09	.81**	–
N	330	331	331	329	329	251	252	250	253	253	342	351
M	3.85	3.98	4.12	2.84	3.37	3.87	4.09	4.22	2.61	3.60	4.18	3.40
SD	0.94	0.74	0.65	0.99	0.81	0.96	0.74	0.64	1.06	0.83	0.97	0.68
Min	1	1	2	1	1	1	2	2	1	1	1	0
Max	5	5	5	5	5	5	5	5	5	5	5	4
Missing rate (%)	6.3	6.0	6.0	6.5	6.5	28.7	28.4	29.0	28.1	28.1	2.8	0.3

Note. YIS = year in school; HSGPA = high school GPA; ACT = ACT composite score; NSIATT = the number of attending SI study sessions during the semester; PPC = purpose of SI attendance - to pass the course; PUS = purpose of SI attendance - to understand the subject better; BSC = Perceived SI benefit – increased self-confidence; BSK = Perceived SI benefit – increased study skills; BCT = Perceived SI benefit – increased critical thinking skills; BPS = Perceived SI benefit – increased problem- solving skills; BGW = increased group work skills; GP = goal setting and planning; SEF = self-efficacy; IP = information processing; TM = time management; SEV = self-evaluation; FGC = final grade in the SI-supported course; FCGPA = fall semester cumulative GPA; T1 = Time 1; T2 = Time 2. Internal consistency reliability coefficients (Omega; McDonald, 1970) are reported on the diagonal in bold.

* $p < .05$, ** $p < .01$

Cross-Sectional SRL Profiles

LPA Model Selection

Separate LPAs at T1 (pre-SI) and T2 (post-SI) were first performed to identify unobserved subgroups from the SI attendee sample distinguished by their SRL strategies at each time point. The same criteria used in the first part of this study were applied to specify the LPA models and determine the optimal numbers of latent profiles. Both statistical and theoretical examinations favored the three-profile solution at T1 as well as T2 (Table 10). The selected three-profile LPA models were used as the measurement models for the further LPTAs.

Table 10

Fit indices for cross-sectional LPA models at T1 and T2

Model	BIC	Profile Sizes (N)	Entropy
Time 1 (pre-SI program) (N=343)			
1- profile	4178.887		
2- profile	4053.661	140/203	0.60
3- profile	**4030.913**	**74/183/86**	**0.70**
4- profile	4024.669	128/17/69/129	0.70
5- profile	4009.468	16/62/25/120/120	0.76
6- profile	4020.053	44/16/51/47/117/68	0.74
Time 2 (post-SI program) (N=254)			
1- profile	3195.594		
2- profile	3085.711	64/190	0.74
3- profile	**3077.190**	**47/167/40**	**0.81**
4- profile	3078.819	110/31/18/95	0.81
5- profile	3077.920	31/48/71/70/34	0.75
6- profile	3086.374	27/76/20/17/77/37	0.77

Note. Statistics for the selected LPA model are in bold type.

Describing the Profiles

As shown in Figure 8, the structure of SI attendees' SRL profiles emerged from cross-sectional LPAs was very similar to that of the full sample's profiles at T1 (Figure 5). Each profile accordingly was labeled as it was for the full sample: 1) *competent regulator* with high scores on goal setting and planning , self-efficacy, and information processing and moderate scores on time management and self-evaluation, which represented 53.3 % and 65.8% of the SI attendee sample for T1 and T2, respectively; 2) *self-confident regulator* (21.6% and 18.5%) with high scores on self-efficacy and information processing, moderate scores on self-evaluation, and low scores on goal setting and planning and time management; and 3) *goal-oriented regulator* (25.1% and 15.7%) with high scores on goal setting and planning and moderate scores on information processing and self-efficacy, and low scores on time management and self-evaluation.

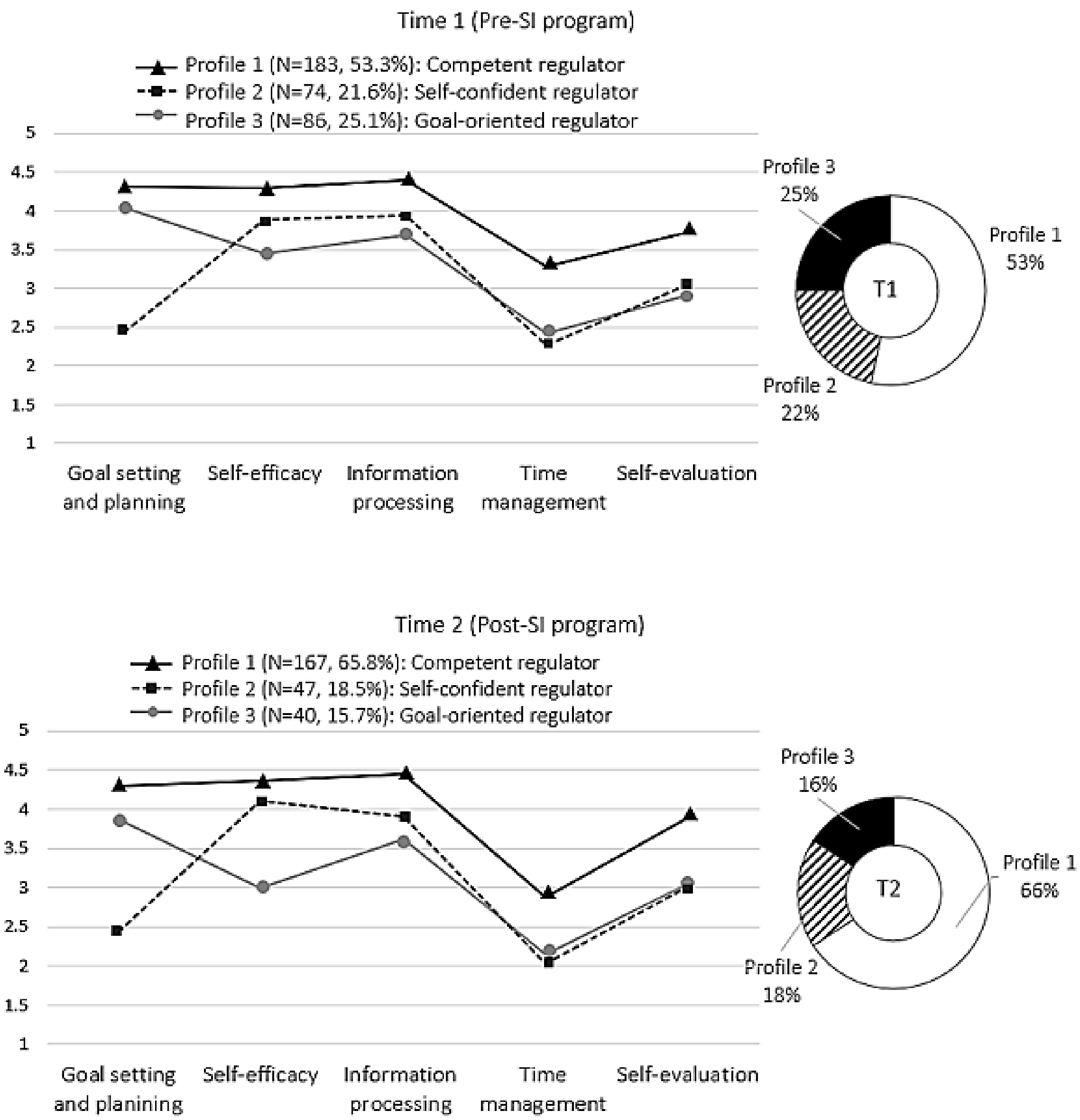


Figure 8. Cross-sectional LPAs at T1 and T2

Validating the Profiles

To validate the profile classification for each time point, the associations between students' membership in the three SRL profiles and four covariates were tested. The covariates included students' pre-college academic performance (ACT composite scores and high school GPAs) and their demographic characteristics (e.g., year in school and major). Table 11 presents the descriptive statistics for the three profiles based on the covariates. For example, students in the *competent regulator* profile had the highest scores on both ACT composites and high school GPAs than those in the other two profiles across two time points. In addition, students in the *self-confident regulator* profile had slightly higher ACT composites but lower high school GPAs than those in the *goal-oriented regulator* profile at both T1 and T2. The demographic distribution of the profiles also showed patterns. For instance, freshman students accounted for the highest portion in the *self-confident regulator* profile among the three profiles at T1 (62.5%), whereas their percentage was the highest in the *goal-oriented regulator* profile at T2 (56.8%). In addition, at T1, students majoring in engineering accounted for the lowest portion in the *goal-oriented regulator* profile (5.8%) among the three profiles, while students majoring in science covered the highest portion in the same profile. At T2, however, the percentage of science majors was highest in the *self-confident regulator* profile (48.9%), while engineering majors still covered the lowest portion in the *goal-oriented regulator* profile (10.0%).

Table 11

Descriptive distribution in each of covariates by latent profile at each time point

	Profile 1: competent regulator	Profile 2: self-confident regulator	Profile 3: goal-oriented regulator
Time 1 (pre-SI program)			
ACT score (M/SD)	26.99 (4.46)	26.09 (4.26)	24.86 (4.60)
High school GPA (M/SD)	3.80 (0.28)	3.69 (0.32)	3.73 (0.35)
Year in school (N/%)			
Senior/Junior	38 (21.6%)	9 (12.2%)	11 (13.6%)
Sophomore	46 (26.1%)	18 (25.0%)	25 (30.9%)
Freshman	92 (52.3%)	45 (62.5%)	45 (55.5%)
Major (N/%)			
Art & Humanities / Social science	58 (32.0%)	19 (25.7%)	22 (25.6%)
Engineering	24 (13.3%)	17 (23.0%)	5 (5.8%)
Science	82 (45.3%)	31 (41.9%)	47 (54.7%)
Exploratory	7 (9.4%)	7 (9.4%)	12 (13.9%)
Time 2 (post-SI program)			
ACT score (M/SD)	27.38 (4.24)	26.29 (4.31)	24.59 (3.65)
High school GPA (M/SD)	3.84 (0.26)	3.67 (0.35)	3.69 (0.31)
Year in school (N/%)			
Senior/Junior	33 (20.4%)	10 (21.7%)	3 (8.1%)
Sophomore	43 (26.5%)	13 (28.3%)	13 (35.1%)
Freshman	86 (53.1%)	24 (51.0%)	21 (56.8%)
Major (N/%)			
Art & Humanities / Social science	47 (28.5%)	11 (23.4%)	11 (27.5%)
Engineering	21 (12.7%)	11 (23.4%)	4 (10.0%)
Science	79 (47.9%)	23 (48.9%)	18 (45.0%)
Exploratory	18 (10.9%)	2 (4.3%)	7 (17.5%)

Table 12 shows the results of multinomial logistic regression analyses for predicting the SRL profile membership by each covariate. Students' pre-college academic achievement scores were significantly related to the SRL profile membership at both T1 and T2. Specifically, higher levels of ACT composite scores predicted an increased likelihood of membership in the *competent regulator* profile relative to the *goal-oriented regulator* profile at T1 (OR = 1.51). This was also the case for the second

measurement occasion (T2); students with higher ACT scores were nearly twice as likely to belong to the *competent regulator* profile relative to the *goal-oriented regulator* profile (OR = 1.89). Similarly, higher ACT scores also increased the likelihood of entry into the *self-confident regulator* profile relative to the *goal-oriented regulator* profile at T2 (OR = 2.09). Further, higher levels of high school GPAs were associated with a greater likelihood of membership into the *competent regulator* profile relative to the *self-confident regulator* profile at both T1 (OR = 1.38) and T2 (OR = 2.00). Unlike students' pre-college performance, their school-level and major were found not to be significantly associated with the profile membership.

Table 12

Effects of the predictors on profile membership at each time point

	Competent vs. self-confident regulator		Competent vs. Goal-oriented regulator		Self-confident vs. Goal-oriented regulator	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Time 1 (pre-SI program)						
ACT score	0.04 (0.18)	1.04	0.41 (0.14)**	**1.51**	0.37 (0.24)	1.45
High school GPA	0.32 (0.12)**	**1.38**	0.04 (0.23)	1.04	-0.28 (0.24)	0.75
Non-freshman	0.47 (0.31)	1.60	0.25 (0.25)	1.29	-0.22 (0.30)	0.80
Engineering or Science major	-0.37 (0.32)	0.69	-0.19 (0.22)	0.83	0.18 (0.28)	1.20
Time 2 (post-SI program)						
ACT score	-0.10 (0.16)	0.90	0.63 (0.23)**	**1.89**	0.74 (0.25)**	**2.09**
High school GPA	0.69 (0.26)**	**2.00**	0.28 (0.21)	1.32	-0.42 (0.24)	0.66
Non-freshman	0.04 (0.36)	1.04	0.41 (0.41)	1.50	0.36 (0.47)	1.44
Engineering or Science major	-0.63 (0.35)	0.53	0.11 (0.31)	1.12	0.75 (0.44)	2.11

Note: When X vs. Y, Y was the reference group; OR= odds ratio; SE = standard error of the coefficient

* p < .05, ** p < .01

Transitions Between SRL Profiles

Measurement Invariance of SRL Profiles across Time

After selecting and validating the number of latent profiles, measurement invariance of the profiles across time was tested. Two alternative models were examined: 1) one with full measurement invariance in which the profile-specific means on the LPA indicators were constrained to be equal across time (Model A) and 2) one with full measurement noninvariance in which the profile-specific means were allowed different across time (Model B). For both models, the SRL indicators were allowed to correlate across time. The results revealed Model A (BIC = 6621.774) provided a better fit than Model B (BIC = 6638.116) based on a lower BIC value, indicating that the invariance of the latent profiles across time can be assumed and applied to the final LPTA model. This result support the equivalent nature and meaning of each profile across time.

Changes in Profile Size over Time

Figure 9 displays within-profile means of each of the five SRL indicators for the three SRL profiles and profile sizes based on the final LPTA model. Examining the changes in profile sizes over time, there are several patterns to note. First, the relative profile according to size remains the same; that is, the *competent regulator* profile was always the largest, followed by the *self-confident regulator* profile, and the *goal-oriented regulator* profile was the smallest across time. In addition, the size of the *competent regulator* profile increased from 56.9% at T1 to 65.9% at T2, while the sizes of the other two profiles decreased over time; the *self-confident regulator* profile decreased from 22.6% to 20.5% and the *goal-oriented regulator* profile decreased from 20.5% to 13.6%.

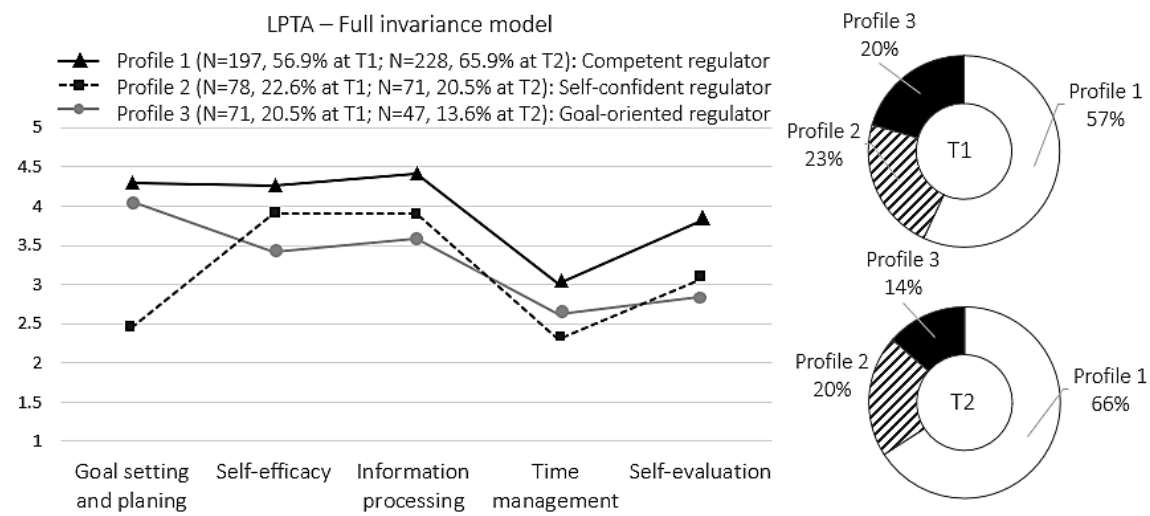


Figure 9. Final LPTA model

Transition Probabilities

Table 13 presents the transition probabilities estimated based on the final LPTA model. These parameters indicate the probability of individuals transitioning to a particular SRL profile at time *t*+1 conditional on time *t* SRL profile. Diagonal elements of the matrix indicate the proportion of individuals belonging to the same profile at both measurement points. Figure 10 illustrates the transition probabilities graphically.

The transition matrix highlights several notable observations. First, students in the c*ompetent regulator* profile were the most stable over time; those starting in this profile at the beginning of the semester (T1: pre-SI program) were most likely to stay in the same profile by the end of the semester (T2: post-SI program) (91.7%). Only 3.8% and 4.6% of the students in this profile moved to the *self-confident regulator* and *goal-oriented regulator* profiles, respectively. On the other hand, students starting in the *goal-oriented regulator* profile were least stable over time; 53.7% at T1 remained in the same

profile at T2, while 46.3% moved to other profiles. Notably, however, these participants were more likely to move to the *competent regulator* profile (42.6%) rather than the *self-confident regulator* profile (3.7%). Lastly, 74.5% of the students who belonged to the *self-confident regulator* profile at T1 stayed in the same profile at T2. In addition, these students' mobility toward the *competent regulator* profile (16.9%) was twice the rate of mobility toward the *goal-oriented regulator* profile (8.7%). This result indicated that students were less likely to move between the *self-confident regulator* and *goal-oriented regulator* profiles across time than they moved to the c*ompetent regulator* profile from these two profiles.

Table 13

Transition probabilities based on the final LPTA model

		Time 2 (Post-SI program)		
		Profile 1: competent regulator	Profile 2: self-confident regulator	Profile 3: goal-oriented regulator
Time 1 (Pre-SI program)	Profile 1	0.917	0.038	0.046
	Profile 2	0.169	0.745	0.087
	Profile 3	0.426	0.037	0.537

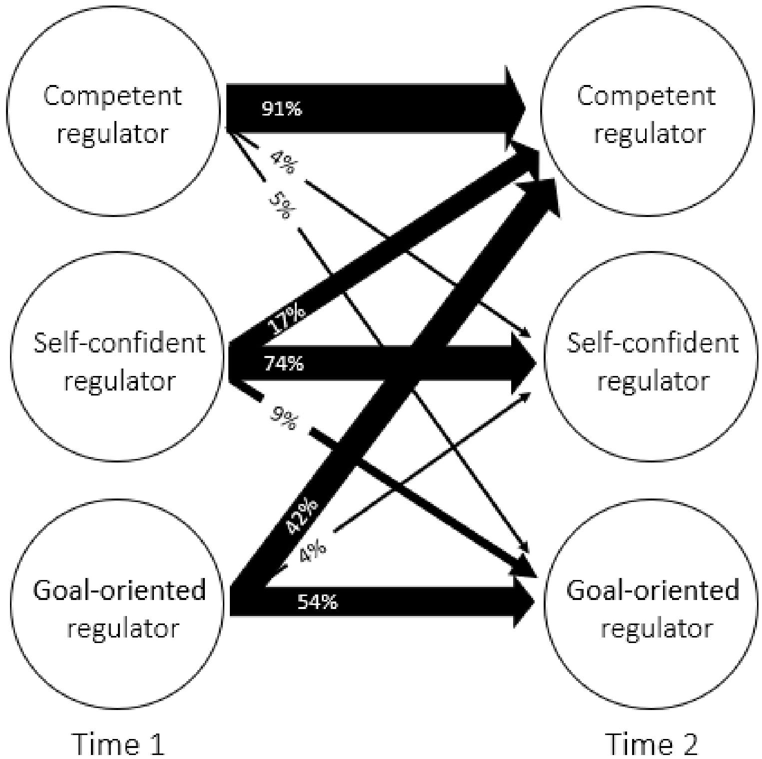


Figure 10. SRL profile transition from T1 to T2

Transition Patterns

Table 14 details the transition patterns of SI attendees' SRL profiles over time based on the final LPTA model. All nine possible transition patterns were observed. Overall, the results showed that the vast majority of students remained in the same SRL profile over the course of the semester (between pre- and post-SI program) (N = 283, 81.8%).

According to their transition patterns, students were grouped into six different categories for further analyses. Specifically, the most common transition pattern was to remain in the *competent regulator* profile across time. This Group 1 student was accordingly labelled as *remaining competent regulator* (N = 184, 53.2%). The next two

most common patterns included two groups of students who stayed in the *self-confident regulator* profile (Group 2: *remaining self-confident regulator*; N = 64, 18.5%) or who stayed in the *goal-oriented regulator* profile all the time (Group 3: *remaining goal-oriented regulator*; N = 35, 10.1%).

In addition to these stable student groups (Group 1, 2, and 3), the transitioning groups were also identified (Group 4, 5, and 6). For instance, Group 4 included those who moved to the c*ompetent regulator* profile at T2 from either the *self-confident regulator* or the *goal-oriented regulator* profile at T1. This student group student was therefore referred to *becoming competent regulator* (N = 44, 12.7%). In contrast, Group 5 included those who showed the opposite pattern; these students moved to either the *self-confident regulator* or the *goal-oriented regulator* profile at T2 from the c*ompetent regulator* profile at T1 (N = 13, 3.7%). Lastly, the remaining six students (1.7%) were labelled as *never became competent regulator*, since they moved between the *self-confident regulator* and the *goal-oriented regulator* profiles across time.

Table 14

SRL transition patterns and new variables

Transition Pattern	# of students (%)	New variables labelled
Profile 1 → Profile 1	184 (53.2%)	Group 1: remaining competent regulator
Profile 2 → Profile 2	64 (18.5%)	Group 2: remaining self-confident regulator
Profile 3 → Profile 3	35 (10.1%)	Group 3: remaining goal-oriented regulator
Profile 3 → Profile 1	35 (10.1%)	Group 4: becoming competent regulator
Profile 2 → Profile 1	9 (2.6%)	Group 4: becoming competent regulator
Profile 1 → Profile 3	7 (2.0%)	Group 5: no longer competent regulator
Profile 1 → Profile 2	6 (1.7%)	Group 5: no longer competent regulator
Profile 2 → Profile 3	5 (1.5%)	Group 6: never became competent regulator
Profile 3 → Profile 2	1 (0.2%)	Group 6: never became competent regulator
Total	346 (100.0%)	

Note. Profile 1: competent regulator; Profile 2: self-confident regulator; Profile 3: goal-oriented regulator

SI-related Predictors of SRL Profile Transition

Multinomial logistic regression analyses were conducted to examine the extent to which SI program-related variables affect students' SRL profile transition when adjusting for confounding factors, including ACT composite scores and high school GPAs. The SI program-related variables included the frequency of SI attendance, scores relating to two purposes of attending SI study sessions, and perceived benefits of SI. The students' profile transition as an outcome variable was examined in two ways: 1) SRL profiles at T2 based on the final LPTA model and 2) SRL transition patterns.

<u>Effects of SI-related Variables on SRL Profiles at T2</u>

Table 15 presents the descriptive statistics of the three SRL profiles at T2 (post-SI program) based on the SI program-related variables. For instance, the portion of students with high SI attendance (i.e., attending 5 to 25 SI study sessions during the entire semester) was highest in the *goal-oriented regulator* profile (38.3%), followed by the

competent regulator profile (33.8%). This pattern was also observed from students with moderate SI attendance (i.e., attending 2 to 4 SI study sessions). However, the portion of students with low SI attendance (i.e., attending only one session) was highest in the *self-confident regulator* profile (32.4%), followed by the *competent regulator* profile (24.1%).

In terms of students' own purpose of attending SI sessions, students in the *competent regulator* profile had the highest scores on the item, 'to understand the subject better', while those in the *goal-oriented regulator* profile had the highest scores on the item, 'passing the course'.

In addition, with regard to students' perceived benefits of SI, students in the *competent regulator* profile had the highest scores on four aspects of the benefits of the program except for group work development. The mean score on group work development was highest in the *goal-oriented regulator* profile.

Table 15

Descriptive statistics for SI-related predictors by SRL profile at T2

	Profile 1: competent regulator	Profile 2: self-confident regulator	Profile 3: goal-oriented regulator
Number of SI attendance (N/%)			
5-25 (high)	77 (33.8%)	19 (26.8%)	18 (38.3%)
2-4 (moderate)	96 (42.1%)	29 (40.8%)	21 (44.7%)
1 (low)	55 (24.1%)	23 (32.4%)	8 (17.0%)
Purpose of SI attendance (M/SD)			
To pass the course	4.46 (1.00)	4.38 (0.97)	4.56 (0.68)
To understand the subject better	4.77 (0.45)	4.54 (0.54)	4.52 (0.69)
Perceived benefits of SI			
Self-confidence	4.24 (0.79)	3.88 (1.00)	3.77 (0.97)
Study skills	4.14 (0.95)	3.88 (0.89)	4.04 (0.90)
Critical thinking skills	3.97 (0.95)	3.63 (1.03)	3.62 (0.84)
Problem- solving skills	4.06 (0.91)	3.73 (0.96)	3.62 (1.11)
Group work skills	3.33 (1.12)	3.00 (1.23)	3.39 (1.04)
ACT score (M/SD)	26.72 (4.29)	26.23 (4.42)	24.68 (4.01)
High school GPA (M/SD)	3.80 (0.29)	3.67 (0.33)	3.66 (0.34)
Year in school (N/%)			
Senior/Junior	43 (19.6%)	10 (14.7%)	5 (11.9%)
Sophomore	59 (26.9%)	17 (25.0%)	13 (31.0%)
Freshman	117 (53.4%)	41 (60.3%)	24 (57.1%)
Major (N/%)			
Art & Humanities / Social science	65 (28.8%)	18 (25.4%)	16 (34.0%)
Engineering	27 (11.9%)	16 (22.5%)	3 (6.4%)
Science	106 (46.9%)	31 (43.7%)	25 (53.2%)
Exploratory	28 (12.4%)	6 (8.5%)	3 (6.4%)

Table 16 presents the results of multinomial logistic regression analyses for predicting the SRL profile membership at T2 by the SI-related variables when controlling for previous academic achievement. Overall, SI program-related variables were associated with student membership into the SRL profiles. For example, students with high SI attendance (i.e., attending 5 to 25 study sessions) were more likely than those with low SI attendance (i.e., attending only one study session during the entire semester) to fall into the *goal-oriented regulator* profile relative to the *competent regulator* or *self-*

confident regulator profile, with significant odds ratios (ORs) of 2.50 (95% confidence interval [CI] = [1.11, 5.56]) and 2.84 (95% CI = [1.00, 8.05]), respectively.

In terms of students' reasons for attending SI sessions, the reason 'to pass the course' was not statistically significant in predicting the SRL profile membership. However, students who had higher scores on the reason 'to understand the subject better' were significantly more likely to end up in the *competent regulator* profile relative to both the *self-confident regulator* (OR = 1.55, 95% CI = [1.03, 2.31]) or *goal-oriented regulator* (OR = 1.69, 95% CI = [1.07, 2.68]) profile.

Lastly, higher perceptions about increased self-confidence as a benefit from attending the SI sessions significantly predicted an improved likelihood of membership into the *competent regulator* profile relative to the *goal-oriented regulator* profile (OR = 1.79, 95% CI = [1.39, 2.30]). This was also the case for critical thinking skill development; students who more strongly believed that the SI study sessions developed their critical thinking skills tended to belong to the *competent regulator* profile relative to the *goal-oriented regulator* profile (OR = 1.90, 95% CI = [1.19, 3.01]). In addition, higher perceptions about group work skill development as a benefit from the SI program predicted an increased likelihood of membership of being in the *goal-oriented regulator* profile relative to the *self-confident regulator* profile (OR = 1.93, 95% CI = [1.04, 3.58]). However, increased study skills did not appear to be significantly associated with the transition membership.

Table 16

Effects of SI-related variables on SRL profile at T2

	competent vs. self-confident regulator		competent vs. goal-oriented regulator		goal-oriented vs. self-confident regulator	
	Coef. (SE)	Odds Ratio [95% CI]	Coef. (SE)	Odds Ratio [95% CI]	Coef. (SE)	Odds Ratio [95% CI]
SI-related predictors						
Number of SI attendance						
5-25 vs. 2-4	0.15 (0.27)	1.16 [0.69-1.96]	0.04 (0.42)	1.04 [0.46-2.36]	0.11 (0.42)	1.12 [0.49-2.52]
5-25 vs. 1	0.13 (0.33)	1.14 [0.60-2.16]	-0.92* (0.41)	**0.40** [0.18-0.90]	1.05* (0.53)	**2.84** [1.00-8.05]
2-4 vs. 1	-0.01 (0.33)	0.98 [0.52-1.88]	-0.95 (0.56)	0.40 [0.13-1.15]	0.94 (0.55)	2.55 [0.86-7.55]
Purpose of SI attendance						
To pass the course	-0.11 (0.27)	0.90 [0.54-1.51]	-0.29 (0.33)	0.75 [0.39-1.44]	0.18 (0.23)	1.21 [0.77-1.87]
To understand the subject better	0.44* (0.21)	**1.55** [1.03-2.31]	0.53* (0.24)	**1.69** [1.07-2.68]	-0.09 (0.19)	0.91 [0.63-1.32]
Perceived benefits of SI						
Self-confidence	0.35 (0.27)	1.42 [0.84-2.40]	0.58*** (0.13)	**1.79** [1.39-2.30]	-0.23 (0.29)	0.79 [0.45-1.39]
Study skills	-0.15 (0.21)	0.86 [0.57-1.30]	-0.52 (0.33)	0.59 [0.31-1.14]	0.37 (0.29)	1.45 [0.83-2.55]
Critical thinking skills	0.28 (0.17)	1.32 [0.96-1.83]	0.64* (0.24)	**1.90** [1.19-3.01]	-0.36 (0.24)	0.70 [0.44-1.11]
Problem- solving skills	-0.03 (0.25)	0.97 [0.59-1.58]	0.36 (0.38)	1.44 [0.68-3.03]	-0.40 (0.40)	0.67 [0.31-1.45]
Group work skills	0.29 (0.30)	1.33 [0.75-2.37]	-0.37 (0.27)	0.69 [0.40-1.17]	0.66* (0.31)	**1.93** [1.04-3.58]
Control variables						
ACT score	-0.05 (0.23)	0.95 [0.60-1.50]	0.30 (0.26)	1.35 [0.81-2.27]	-0.35 (0.33)	0.70 [0.37-1.33]
High school GPA	0.59*** (0.15)	**1.80** [1.35-2.41]	0.45* (0.23)	**1.56** [1.00-2.44]	0.14 (0.22)	1.15 [0.75-1.77]

Note: When X vs. Y, Y was the reference group; SE = standard error of the coefficient; 95% CI = 95% confidence interval
* $p < .05$, *** $p < .001$

Effects of SI-related Variables on SRL Transition Patterns

Table 17 presents the descriptive statistics of the six SRL transition groups based on the SI program-related variables. For example, the portion of students with high SI attendance (i.e., attending 5 to 25 SI study sessions during the entire semester) was

highest in the *never became competent regulator* group (66.6%). These students' proportions were quite similar in the *remaining competent regulator* (33.7%), *remaining goal-oriented regulator* (34.3%), and *becoming competent regulator* (34.1%) groups. Further, students with low SI attendance (i.e., attending only one session) accounted for the highest proportion in the no longer competent regulator group (38.5%), followed by the *remaining self-confident regulator* (29.7%) and *becoming competent regulator* (29.5%) groups.

With respect to the purpose of attending the SI study sessions, students in the *remaining competent regulator* group had the highest score on the reason, 'to understand the subject better', while the mean on the reason, 'passing the course' was highest in the *remaining goal-oriented regulator* group.

Further, with regard to students' perceived benefits of SI, students in the *becoming competent regulator* group had the highest scores on increased self-confidence in learning and study skills, while the *remaining competent regulator* group had the highest scores on developed critical thinking and problem-solving skills. The mean score on group skill development was highest in the *remaining goal-oriented regulator* group.

Table 17

Descriptive statistics for SI-related predictors by transition group

	Transition Pattern					
	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Number of SI attendance (N/%)						
5-25 (high)	62 (33.7%)	18 (28.1%)	12 (34.3%)	15 (34.1%)	3 (23.1%)	4 (66.6%)
2-4 (moderate)	80 (43.5%)	27 (42.2%)	17 (48.6%)	16 (36.4%)	5 (38.5%)	1 (16.7%)
1 (low)	42 (22.8%)	19 (29.7%)	6 (17.1%)	13 (29.5%)	5 (38.5%)	1 (16.7%)
Purpose of SI attendance (M/SD)						
To pass the course	4.48 (1.03)	4.32 (1.02)	4.65 (0.57)	4.35 (0.85)	4.10 (0.54)	4.50 (0.87)
To understand the subject better	4.78 (0.46)	4.59 (0.55)	4.70 (0.56)	4.75 (0.43)	4.20 (0.60)	4.00 (0.71)
Perceived benefits of SI (M/SD)						
Self-confidence	4.22 (0.76)	3.85 (1.03)	3.79 (0.77)	4.35 (0.96)	4.00 (0.82)	3.50 (1.66)
Study skills	4.14 (0.95)	3.91 (0.89)	4.05 (0.89)	4.15 (0.96)	4.00 (0.77)	3.50 (1.12)
Critical thinking skills	3.96 (0.89)	3.62 (1.06)	3.58 (0.75)	4.00 (1.18)	3.70 (1.10)	3.75 (0.43)
Problem- solving skills	4.12 (0.86)	3.74 (1.01)	3.63 (1.13)	3.70 (1.10)	3.90 (0.83)	3.00 (0.71)
Group work skills	3.31 (1.13)	2.97 (1.22)	3.53 (0.94)	3.45 (1.02)	3.20 (1.25)	2.75 (1.09)
ACT score (M/SD)	26.79 (4.38)	26.38 (4.41)	23.97 (3.81)	26.44 (3.86)	26.31 (4.58)	25.00 (2.89)
High school GPA (M/SD)	3.79 (0.30)	3.68 (0.33)	3.62 (0.36)	3.83 (0.21)	3.69 (0.31)	3.80 (0.16)
Year in school (N/%)						
Senior/Junior	33 (19.3%)	6 (10.0%)	5 (16.6%)	4 (9.5%)	2 (16.7%)	0 (0.0%)
Sophomore	44 (25.7%)	15 (25.0%)	8 (26.7%)	15 (35.7%)	6 (50.0%)	1 (16.7%)
Freshman	94 (51.0%)	39 (65.0%)	17 (56.7%)	23 (54.8%)	4 (33.3%)	5 (83.3%)
Major (N/%)						
Art & Humanities / Social science	55 (30.2%)	15 (23.4%)	10 (28.6%)	10 (22.7%)	6 (46.2%)	3 (50.0%)
Engineering	23 (12.6%)	15 (23.4%)	1 (2.9%)	4 (9.1%)	0 (0.0%)	0 (0.0%)
Science	82 (45.1%)	28 (43.8%)	22 (62.9%)	24 (54.5%)	6 (46.2%)	3 (50.0%)
Exploratory	22 (12.1%)	6 (9.4%)	2 (5.7%)	6 (13.7%)	1 (7.6%)	0 (0.0%)

Note. Group 1= remaining competent regulator; Group 2 = remaining self-confident regulator; Group 3 = remaining goal-oriented regulator; Group 4 = becoming competent regulator; Group 5 = no longer competent regulator; Group 6 = never became competent regulator

Table 18 presents the results of multinomial logistic regression analyses for predicting the SRL transition group membership by the SI-related variables while adjusting for previous academic achievement. Students in the *never became competent regulator* group were excluded from the analysis, since the number of these students was too small (N = 6). Overall, the SI program-related variables were widely significant in predicting student membership in the transition groups. First, students with moderate SI attendance (i.e., attending 2 to 4 study sessions during the entire semester) were more likely than those with low SI attendance (i.e., attending only one study session) to fall into the *remaining goal-oriented regulator* group relative to the *becoming competent regulator* group (OR = 5.88, 95% CI = [1.28, 25.00]).

Regarding students' reasons for attending SI sessions, the reason 'to pass the course' was not statistically significant in predicting membership into the transition group. However, students with higher levels on the reason 'to understand the subject better' were significantly less likely to belonging to the *no longer competent regulator* group relative to the other four groups.

In terms of students' perceptions regarding the five different aspects of the SI program's benefits, students who more strongly believed that attending the SI sessions helped them feel more confident in their studies were more likely to end up in the *becoming competent regulator* (OR = 2.95, 95% CI = [1.39, 6.27]) or *remaining competent regulator* group (OR = 1.82, 95% CI = [1.23, 2.71]) relative to the *remaining goal-oriented regulator* group. The same patterns were observed for critical thinking skill development. That is, higher perceptions about increased critical thinking skills as a

benefit from attending the SI sessions significantly predicted a higher likelihood of membership into the two most desirable transition groups (*becoming competent regulator* and *remaining competent regulator* groups) relative to the *remaining goal-oriented regulator* group.

Students' higher scores on group work skill development as a result of attending the SI sessions significantly were predictive of improved likelihoods of being in the *becoming competent regulator* (OR = 2.10, 95% CI = [1.03, 4.31]) or *remaining goal-oriented regulator* (OR = 2.86, 95% CI = [1.20, 6.79]) group relative to the *remaining self-confident regulator* group. They were also significantly associated with a decreased likelihood of membership into the *remaining competent regulator* group relative to the *remaining goal-oriented regulator* group (OR = 0.46, 95% CI = [0.21, 0.98]).

However, problem-solving skills developed by the SI program predicted students' SRL transition differently; they tended to be associated with an increased likelihood of membership into less desirable groups. For instance, students who more highly believed that the SI study sessions improved their problem-solving abilities tended to be in the *no longer competent regulator* group relative to the *remaining goal-oriented regulator* (OR = 2.33, 95% CI = [1.08, 5.00]) or *becoming competent regulator* (OR = 2.94, 95% CI = [1.64, 5.26]) group. They were also more likely to fall into the *remaining self-confident regulator* (OR = 2.22, 95% CI = [1.40, 3.57]) or *remaining competent regulator* (OR = 2.44, 95% CI = [1.54, 3.88]) group relative to the *becoming competent regulator* group.

Lastly, study skill development did not seem to significantly related to membership into the different SRL transition groups.

Table 18

Effects of SI-related variables on SRL transition pattern

	Group 1 vs. 2		Group 1 vs. 3		Group 1 vs. 4		Group 1 vs. 5		Group 2 vs. 5	
	Coef. (SE)	Odds Ratio [95% CI]	Coef. (SE)	Odds Ratio [95% CI]	Coef. (SE)	Odds Ratio [95% CI]	Coef. (SE)	Odds Ratio [95% CI]	Coef. (SE)	Odds Ratio [95% CI]
SI-related predictors										
Number of SI attendance										
5-25 vs. 2-4	0.13	1.14	0.42	1.52	-0.14	0.87	0.17	1.18	0.03	1.03
	(0.29)	[0.64-2.03]	(0.54)	[0.53-4.34]	(0.35)	[0.44-1.72]	(0.69)	[0.30-4.58]	(0.74)	[0.24-4.42]
5-25 vs. 1	0.04	1.05	-0.73	0.48	0.50	1.66	0.81	2.25	0.76	2.15
	(0.37)	[0.50-2.17]	(0.50)	[0.18-1.29]	(0.53)	[0.59-4.66]	(0.58)	[0.72-7.04]	(0.68)	[0.56-8.18]
2-4 vs. 1	-0.09	0.91	-1.14	0.32	0.65	1.91	0.64	1.90	0.73	2.08
	(0.40)	[0.41-2.01]	(0.75)	[0.07-1.40]	(0.54)	[0.67-5.48]	(0.76)	[0.42-8.48]	(0.86)	[0.39-11.23]
Purpose of SI attendance										
To pass the course	0.02	1.03	-0.22	0.80	0.12	1.13	-0.49	0.61	-0.52	0.60
	(0.28)	[0.59-1.78]	(0.30)	[0.45-1.43]	(0.24)	[0.71-1.80]	(0.55)	[0.21-1.8]	(0.43)	[0.26-1.38]
To understand the subject better	0.34	1.40	0.17	1.18	0.06	1.06	1.22**	**3.40**	0.89*	**2.42**
	(0.24)	[0.88-2.24]	(0.29)	[0.67-2.09]	(0.26)	[0.64-1.75]	(0.46)	[1.38-8.35]	(0.40)	[1.11-5.30]
Perceived benefits of SI										
Self-confidence	0.41	1.51	0.60**	**1.82**	-0.48	0.62	0.03	1.03	-0.38	0.68
	(0.26)	[0.91-2.48]	(0.20)	[1.23-2.71]	(0.35)	[0.31-1.23]	(0.28)	[0.60-1.77]	(0.46)	[0.28-1.67]
Study skills	-0.24	0.78	-0.59	0.56	-0.05	0.95	-0.51	0.60	-0.27	0.77
	(0.21)	[0.52-1.19]	(0.48)	[0.22-1.41]	(0.28)	[0.56-1.63]	(0.54)	[0.21-1.73]	(0.51)	[0.28-2.09]
Critical thinking skills	0.26	1.30	0.84**	**2.30**	-0.08	0.93	0.52	1.68	0.26	1.29
	(0.19)	[0.89-1.90]	(0.28)	[1.33-3.98]	(0.39)	[0.43-2.01]	(0.32)	[0.90-3.15]	(0.33)	[0.68-2.46]
Problems solving skills	0.09	1.09	0.66	1.93	0.89***	**2.44**	-0.19	0.82	-0.28	0.76
	(0.28)	[0.64-1.88]	(0.46)	[0.79-4.72]	(0.24)	[1.54-3.88]	(0.34)	[0.42-1.61]	(0.33)	[0.40-1.44]
Group work skills	0.27	1.31	-0.78*	**0.46**	-0.47	0.62	0.31	1.36	0.04	1.04
	(0.30)	[0.73-2.35]	(0.39)	[0.21-0.98]	(0.25)	[0.38-1.02]	(0.68)	[0.36-5.15]	(0.70)	[0.26-4.10]
Control variables										
ACT score	-0.06	0.95	0.47	1.61	0.05	1.05	-0.15	0.87	-0.09	0.92
	(0.21)	[0.63-1.43]	(0.27)	[0.95-2.71]	(0.17)	[0.76-1.46]	(0.41)	[0.39-1.93]	(0.35)	[0.46-1.82]
High school GPA	0.54***	**1.72**	0.39	1.47	-0.45	0.64	0.53	1.69	-0.02	0.98
	(0.14)	[1.31-2.26]	(0.22)	[0.96-2.27]	(0.25)	[0.39-1.03]	(0.28)	[0.98-2.93]	(0.28)	[0.57-1.70]

Note. Group 1= remaining competent regulator; Group 2 = remaining self-confident regulator; Group 3 = remaining goal-oriented regulator; Group 4 = becoming competent regulator; Group 5 = no longer competent regulator; Group 6 = never became competent regulator; SE = standard error of the coefficient; 95% CI = 95% confidence interval
When X vs. Y, Y was the reference group. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table 18

Effects of SI-related variables on SRL transition pattern

	Group 3 vs. 2		Group 3 vs. 5		Group 4 vs. 2		Group 4 vs. 3		Group 4 vs. 5	
	Coef. (SE)	Odds Ratio [95% CI]	Coef. (SE)	Odds Ratio [95% CI]	Coef. (SE)	Odds Ratio [95% CI]	Coef. (SE)	Odds Ratio [95% CI]	Coef. (SE)	Odds Ratio [95% CI]
SI-related predictors										
Number of SI attendance										
5-25 vs. 2-4	-0.28	0.76	-0.25	0.78	0.28	1.32	0.56	1.75	0.31	1.36
	(0.53)	[0.27-2.12]	(0.77)	[0.17-3.55]	(0.44)	[0.56-3.11]	(0.47)	[0.70-4.38]	(0.70)	[0.35-5.32]
5-25 vs. 1	0.77	2.16	1.53	4.64	-0.46	0.63	-1.23	0.29	0.31	1.36
	(0.68)	[0.57-8.25]	(0.84)	[0.90-23.91]	(0.59)	[0.20-2.01]	(0.77)	[0.07-1.32]	(0.76)	[0.30-6.06]
2-4 vs. 1	1.05	2.86	1.78	5.95	-0.74	0.48	-1.79*	**0.17**	-0.01	0.99
	(0.75)	[0.66-12.41]	(1.03)	[0.79-45.02]	(0.55)	[0.16-1.40]	(0.78)	[0.04-0.78]	(1.01)	[0.14-7.22]
Purpose of SI attendance										
To pass the course	0.25	1.28	-0.26	0.77	-0.10	0.91	-0.35	0.71	-0.62	0.54
	(0.23)	[0.82-2.00]	(0.48)	[0.30-1.96]	(0.36)	[0.45-1.85]	(0.42)	[0.31-1.60]	(0.58)	[0.17-1.68]
To understand the subject better	0.17	1.19	1.06*	**2.88**	0.28	1.33	0.11	1.12	1.17**	**3.21**
	(0.33)	[0.62-2.26]	(0.48)	[1.13-7.32]	(0.30)	[0.73-2.40]	(0.30)	[0.63-2.00]	(0.45)	[1.34-7.72]
Perceived benefits of SI										
Self-confidence	-0.19	0.83	-0.57	0.56	0.89	2.44	1.08**	**2.95**	0.51	1.66
	(0.32)	[0.45-1.53]	(0.35)	[0.28-1.13]	(0.47)	[0.97-6.12]	(0.39)	[1.39-6.27]	(0.37)	[0.80-3.47]
Study skills	0.34	1.41	0.08	1.08	-0.19	0.82	-0.54	0.58	-0.46	0.63
	(0.42)	[0.62-3.19]	(0.64)	[0.31-3.81]	(0.24)	[0.52-1.31]	(0.51)	[0.21-1.60]	(0.54)	[0.22-1.83]
Critical thinking skills	-0.57	0.57	-0.31	0.73	0.34	1.40	0.91*	**2.48**	0.60	1.81
	(0.31)	[0.31-1.04]	(0.43)	[0.32-1.69]	(0.37)	[0.68-2.89]	(0.43)	[1.07-5.76]	(0.513)	[0.67-4.92]
Problems solving skills	-0.57	0.57	-0.85*	**0.43**	-0.81**	**0.45**	-0.24	0.79	-1.09***	**0.34**
	(0.49)	[0.22-1.47]	(0.40)	[0.20-0.93]	(0.24)	[0.28-0.71]	(0.46)	[0.32-1.93]	(0.31)	[0.19-0.61]
Group work skills	1.05*	**2.86**	1.09	2.96	0.74*	**2.10**	-0.31	0.74	0.78	2.18
	(0.44)	[1.20-6.79]	(0.73)	[0.70-12.47]	(0.37)	[1.03-4.31]	(0.49)	[0.28-1.90]	(0.72)	[0.53-8.91]
Control variables										
ACT score	-0.53	0.59	-0.62	0.54	-0.11	0.90	0.42	1.53	-0.19	0.82
	(0.31)	[0.32-1.09]	(0.53)	[0.19-1.53]	(0.29)	[0.51-1.58]	(0.29)	[0.87-2.69]	(0.49)	[0.31-2.17]
High school GPA	0.16	1.17	0.14	1.15	1.00***	**2.71**	0.84*	**2.32**	0.98**	**2.67**
	(0.22)	[0.76-1.80]	(0.32)	[0.62-2.14]	(0.27)	[1.60-4.60]	(0.33)	[1.23-4.40]	(0.32)	[1.43-4.97]

Note. Group 1= remaining competent regulator; Group 2 = remaining self-confident regulator; Group 3 = remaining goal-oriented regulator; Group 4 = becoming competent regulator; Group 5 = no longer competent regulator; Group 6 = never became competent regulator; SE = standard error of the coefficient; 95% CI = 95% confidence interval
When X vs. Y, Y was the reference group. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Outcomes of SRL Profile Transition

Multivariate analyses of variance (MONOVAs) were carried out to examine the extent to which SRL profile transition is associated with students' outcomes. The student outcome included the final grades in SI-supported courses and the fall semester cumulative GPAs. Students' profile transition as a predictor variable was examined in two ways: 1) SRL profiles at T2 based on the final LPTA model and 2) SRL transition patterns. Among the five transition groups, students in the *never became competent regulator* group were excluded from the analysis, since the number of these students was insufficient for analysis (N = 6).

Associations between SRL Profiles at T2 and Student Outcomes

The results (Table 19 and Figure 11) indicated the combined outcome variable was significantly influenced by student membership in the three SRL profiles (Pillai's trace = 0.05, $F[4, 666] = 4.28$, $p = 0.002$). Further, subsequent univariate analyses for each outcome revealed that there was a significant difference in the final grades in the course to which the SI program was attached among the profiles ($F[(2, 333] = 6.21$, $p = 0.002$). Scheffe's post hoc tests indicated that students ending up in the *competent regulator* profile and *self-confident regulator* profile at T2 had significantly higher final grades than those in the *goal-oriented regulator* profiles, respectively. A significant difference among the profiles was also found in the fall semester cumulative GPAs ($F[2, 333] = 6.35$, $p = 0.002$). Post hoc comparisons revealed that students in the *competent regulator* profile had significantly higher GPAs than those in the *goal-oriented regulator* profile.

Table 19

Means and standard deviations of student outcomes across SRL profiles at T2

	Final course grade		Cumulative GPA	
	M(SD)	95% CI	M(SD)	95% CI
Profile 1: competent regulator	4.28 (0.89)	[4.15, 4.41]	3.50 (0.59)	[3.41, 3.58]
Profile 2: self-confident regulator	4.19 (1.03)	[3.96, 4.41]	3.33 (0.75)	[3.16, 3.47]
Profile 3: goal-oriented regulator	3.73 (1.04)	[3.46, 4.01]	3.16 (0.81)	[2.96, 3.34]
Significant difference of post hoc tests	Profile 1, 2 > 3		Profile 1 > 3	

Note. 95% CI = 95% confidence intervals of the difference

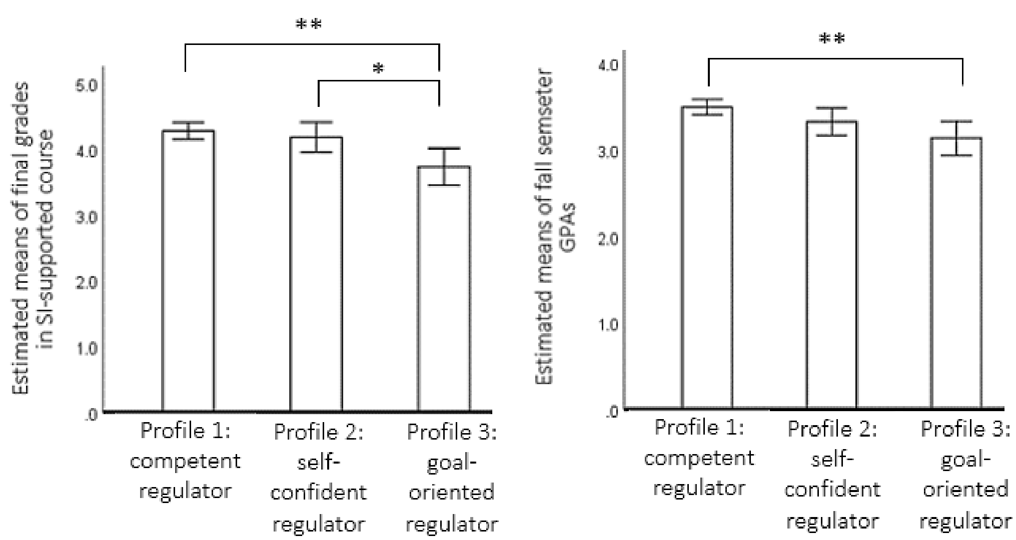


Figure 11. Student outcomes across SRL profiles at T2

Associations between SRL Transition Patterns and Student Outcomes

Students' transition pattern was significantly associated with the combined outcome variable (Pillai's trace = 0.07, $F[8, 650] = 2.79$, $p = 0.005$). In addition, univariate analyses for each outcome showed that the group effect was statistically significant in the final grades in the SI-supported course ($F[4, 325] = 3.22$, $p = 0.013$). However, none of the pairs among the five transition groups showed a significant difference in the final course grades. In terms of the fall semester cumulative GPAs, a

significant group difference was found (F[4, 325] = 4.51, p = 0.001). Post hoc analyses revealed that students in the *remaining competent regulator* group had significantly higher cumulative GPAs than students in the *no longer competent regulator* group (Table 20 and Figure 12).

Table 20

Means and standard deviations of student outcomes across SRL transition groups

	Final course grade		Cumulative GPA	
	M(SD)	95% CI	M(SD)	95% CI
Group 1	4.32 (0.87)	[4.19, 4.45]	3.51 (0.60)	[3.42, 3.60]
Group 2	4.21 (1.06)	[3.94, 4.47]	3.33 (0.78)	[3.13, 3.52]
Group 3	3.85 (0.99)	[3.51, 4.20]	3.23 (0.62)	[3.01, 3.45]
Group 4	4.10 (1.01)	[3.78, 4.42]	3.42 (0.57)	[3.24, 3.59]
Group 5	3.58 (1.24)	[2.80, 4.37]	2.88 (1.19)	[2.16, 3.60]
Significant difference of post hoc tests	None		Group 1 > 5	

Note. Group 1= remaining competent regulator; Group 2 = remaining self-confident regulator; Group 3 = remaining goal-oriented regulator; Group 4 = becoming competent regulator; Group 5 = no longer competent regulator; 95% CI = 95% confidence intervals of the difference

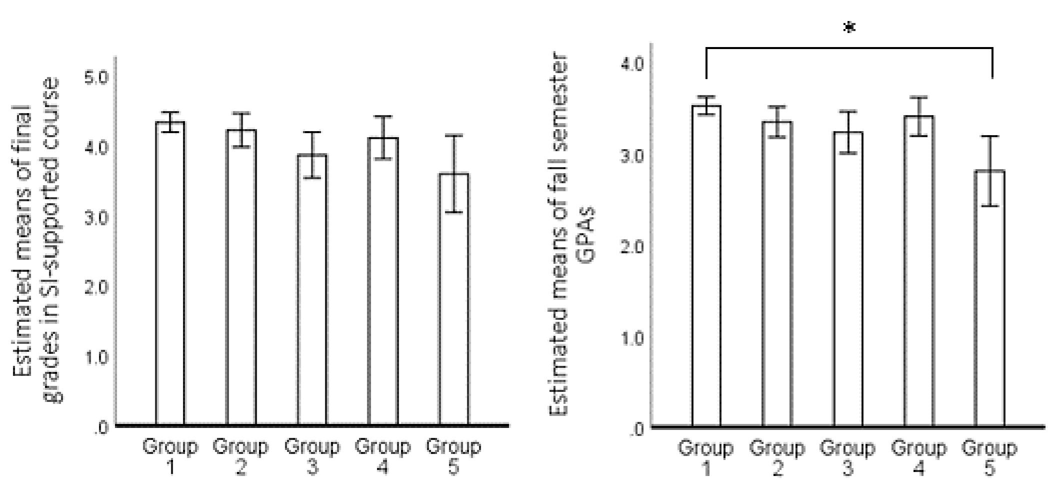


Figure 12. Student outcomes across SRL transition groups

CHAPTER V

DISCUSSION

The overall goal of this dissertation was to examine the development of college students' self-regulated learning (SRL) strategies through Supplemental Instruction (SI), a peer-led academic support program, using a person-centered framework. Specifically, the first part of the study investigated the differential effects of the SI program on students' SRL development. The second part of the study explored the heterogeneity of longitudinal stability and change in students' SRL. These two goals were accomplished by combining latent profile analysis (LPA) with propensity score matching (PSM) and by applying latent profile transition analysis (LPTA), respectively.

This chapter synthesizes and interprets the key findings emerging for each group of research questions. The discussions of both theoretical and practical implications are also presented. Finally, the chapter ends with the study limitations and suggestions for further research.

Heterogeneous Treatment Effects on SRL Development

Students' SRL Profiles

The first set of research questions sought to evaluate the extent to which participation in the SI program affects the development of SRL across individual students in different baseline SRL profiles. In order to achieve this aim, LPAs were first performed to construct distinct hidden subgroups according to the constellation of SRL strategies measured at the beginning of the semester (T1). Based on the findings of

previous studies taking a person-centered approach, it is hypothesized that there will be at least three latent profiles emerging with respect to their patterns of use of different SRL strategies. The results were consistent with expectations, revealing the presence of three SRL profiles: competent regulator, self-confident regulator, and goal-oriented regulator.

These three profiles differed both quantitatively and qualitatively. Specifically, students in the *competent regulator* profile were characterized by high levels of goal setting and planning, self-efficacy, and information processing. Their scores in time management and self-evaluation were moderate, but relatively higher than those of students in the other profiles. The size of this profile was largest, consisting of approximately half of the entire sample (N = 322; 52.4%). Students in the other two profiles, *self-confident regulator* and *goal-oriented regulator,* were differentiated quantitatively from those in the *competent regulator* profile; in other words, these scored lower on all the SRL indicators compared to the those in the *competent regulator* profile. However, these two profiles were different qualitatively from each other. the *self-confident regulator* featured high levels of self-efficacy and low levels of goal setting and planning, while the *goal-oriented regulator* profile was characterized by high levels of goal setting and planning and moderate levels of self-efficacy. These two profiles' scores on the remaining three SRL indicators (information processing, time management, and self-evaluation) remained similar. The profile representing the fewest students was the *goal-oriented regulator* (N = 134; 21.8%), but its size difference from the *self-confident regulator* (N = 159; 25.8%) was not notable.

The *competent regulator* profile emerging from the current findings was similar to the profile identified in many previous studies that have taken a person-centered approach to analysis of college students' SRL (e.g., Barnard-Brak et al., 2010; Broadbent & Fuller-Tyszkiewicz, 2018; Dörrenbächer & Perels, 2016b; Liu et al., 2014; Valle et al., 2008). Although other researchers have not explicitly identified the *self-confident* and *goal-oriented regulator* profiles as separate profiles, similar profiles have been observed in their studies. For example, Dörrenbächer and Perels (2016b) found a profile (named *conflicting SRL with high motivation*) that featured high levels of self-efficacy and other motivational constructs, low levels of time planning, self-evaluation, and procrastination, and moderate levels of the remaining indicators. In addition, Barnard-Brak et al. (2001) identified a profile (named *forethought-endorsing self-regulators*) that was characterized high scores on goal setting and environment structuring and relatively lower scores on task strategies, time management, help seeking, and self-evaluation. These results suggest that motivational constructs may function as critical separators that qualitatively discriminate between SRL profiles. They also imply that qualitative differences in SRL profiles tend to occur within the forethought phase of Zimmerman's cyclical SRL model, reflecting the crucial roles of the forethought components in the whole SRL process (Schunk, 1990).

These profiles were further validated using a cross-tab chi-squire test, which revealed that the rates of students' voluntary attendance in the SI program differed significantly as a function of their membership in SRL profiles. Specifically, students in the *competent regulator* (61.5 %) profile were more likely to attend the SI study sessions

than students in other two profiles. In addition, about 45.3% of the students who were *self-confident regulators* attended at least one SI study session during the semester, while 54.7% of them did not. However, students in the *goal-oriented regulators* profile showed an opposite pattern; while 54.5% of these students participated in the SI program, 45.5 % did not. These results suggest that students with more adaptive SRL strategies tended to use existing academic resources more actively. In addition, the high rate of non-attendance in the *self-confident regulator* profile implies that some of students in this profile may be over-confident. They may overestimate the likelihood of success in their courses, which in turn causes them to perceive no need for additional resources and support. The notion of overconfidence and its negative influence on further study decisions and performance has been extensively studied in the research on metacognition (e.g., Dunlosky & Rawson, 2012).

Heterogeneous Effects of SI Program on SRL Development

After matching SI attendees to comparable non-SI attendees using PSM, two-sample *t*-tests were conducted to discern the effects of students' involvement in the SI program on their overall SRL scores at the end of the semester (T2) and fall semester cumulative GPAs. These treatment effects were first estimated by comparing SI attendees with non-SI attendees in these two outcomes within the full sample. They were also compared within each of the three SRL profiles. As hypothesized, descriptive comparisons indicated that students attending the SI study sessions showed higher mean values on both outcomes relative to students not attending for the full sample as well as across the three profiles. In addition, the biggest score gaps in overall SRL scores were

observed in the *competent* and *self-confident regulators* profile, followed by the full sample and *goal-oriented regulator* profile. Differences in fall semester cumulative GPAs were largest in the *self-confident regulator* profile, followed by the *goal-oriented regulator* profile, full sample, and the *competent regulator* profile. However, significance tests did not support these differences.

Next, subsequent paired *t*-tests were conducted to determine whether there was significant improvement in the overall SRL means over the course of the semester (T1-T2) for SI and non-SI attendee groups, separately. Like previous analyses, these analyses were performed within the full sample as well as within each SRL profile. For the full sample, contrary to hypotheses, the results indicate that while both SI and non-SI attendee groups showed a decreasing trend in overall SRL scores over the semester, such trend was statistically significant only for non-SI attendees. This result suggests that attending the SI study sessions may help prevent students from decreasing the use of SRL strategies over time, reflecting a positive, albeit limited, effect of the SI program on students' SRL. This finding is generally in agreement with the previous evidence that SI is a promising tool for college students to develop their learning strategies and competence (e.g., Malm et al., 2012, 2015; Ning & Downing, 2015). However, this association with preventing decrease rather than fostering increase was unexpected.

When the effects of the SI program were analyzed with the disaggregated sample obtained by LPAs, different results were obtained. For the *competent regulator* profile, both SI and non-SI attendees showed a significant decrease in the overall SRL scores over time. However, given that SI-attendees' score decrease was relatively smaller, it

could be said that the SI program is helpful for these students in the *competent regulator* profile in terms of their SRL development., which conflicts with the hypothesis that more desirable profiles would reflect less growth. The smaller score decrease in highly self-regulated students was also observed in Dörrenbächer and Perels's (2016b) work, although the score change was not statistically significant in their study. Dörrenbächer and Perels suggested the possible existence of a ceiling effect for these students, stating, "As this group scored high on SRL before the training, they have less potential to show a development than the other SRL profile groups." (p. 239). With regard to the *goal-oriented regulator* profile, although both the overall SRL scores increased for both SI and non-SI attendees, these changes were not significant. Within the *self-confident regulator* profile, while SI attendees' SRL scores increased, non-SI attendees' scores decreased. However, these trends were not statistically significant. These results suggest that a group-based analysis can provide more detailed information about who could benefit from an intervention program.

Stability and Change in SRL Profiles

Cross-sectional SRL Profiles

The second set of research questions intended to examine the extent to which SI attendees stay and change between SRL profiles before (T1) to after (T2) participating in the SI program. It also sought to scrutinize the extent to which such stability and change were influenced by a range of SI-related factors, such as attendance frequency, reasons for attending SI study sessions, and perceived benefits of the SI program. For these goals,

cross-sectional LPAs were first fit to identify a set of latent profiles from the SI attendee sample with respect to the interaction of the five SRL indicators both at T1 and T2, separately. As expected, the SRL profiles emerging from the LPAs appeared constant across the two time points in terms of the number of profiles and mean structures. These profiles were also very similar to those in the first part of the study, which resulted in being labeled in the same way: competent regulator, self-confident regulator, and goal-oriented regulator.

The profile classification was further validated for each time point. The results showed that students in the most adaptive profile (competent regulator) had the highest scores on both ACT composites and high school GPAs compared to those in the other two profiles across two time points. These findings are consistent with existing literature on the relationship between previous academic achievement and SRL (e.g., Dörrenbächer & Perels, 2016b; Lee & Choi, 2010).

Transitions between SRL Profiles

Based on the three-profile solutions obtained by the cross-sectional LPAs, LPTA was used to examine the stability and mobility of the profiles over time. The statistical test for the measurement invariance of the profiles across time indicated that the substantive structure and meaning of the three SRL profiles remained invariant across the two time points, allowing a straightforward interpretation of the profile transitions.

Results indicated that the relative prevalence of profiles changed over time. Specifically, the size of the *competent regulator* profile increased from 56.9% at T1 to 65.9% at T2, while the sizes of the other two profiles decreased over time; the *self-*

confident regulator profile decreased from 22.6% to 20.5% and the *goal-oriented regulator* profile decreased from 20.5% to 13.6%. This finding suggests that students attending SI study sessions tended to move to a more desirable profile (*competent regulator*) over the course of one semester.

The transition probabilities estimated by the LPTA offered a more nuanced picture of the profile transitions. First, the most stable profile over time was the *competent regulator* profile; 91.7% of students starting in this profile at the beginning of the semester (T1: pre-SI program) remained in the same profile by the end of the semester (T2: post-SI program). On the other hand, students starting in the *goal-oriented regulator* profile were most mobile; 53.7% at T1 stayed in the same profile at T2, while 46.3% moved to other profiles. Notably, however, these movers mainly shifted to the *competent regulator* profile (42.6%) rather than the *self-confident regulator* profile (3.7%). Compared to the *goal-oriented regulator* profile, the *self-confident regulator* profile tended to be more stable; 74.5% of the students remained in the same profile over time. In addition, these students' mobility toward the *competent regulator* profile (16.9%) was 2.5 times less than the *goal-oriented regulator* profile. These results were in the line with the previous longitudinal studies showing the overall stability of college students' self-regulatory learning strategies over time (e.g., Coertjens et al., 2017; De Clercq et al., 2013). Further, these findings also indicate that students who attended the SI program tended to become more sophisticated self-regulated learners over time. In addition, it is also noted that goal setting and strategic planning may play a more important role relative to self-efficacy in developing a comprehensive set of SRL strategies.

These transition patterns were further classified into six different groups in order to explore potential predictors and outcomes of the transitions: *remaining competent regulator* (N = 184, 53.2%), *remaining self-confident regulator* (N = 64, 18.5%), *remaining goal-oriented regulator* (N = 35, 10.1%), *becoming competent regulator* (N = 44, 12.7%), *no longer competent regulator* (N = 13, 3.7%), and *never became competent regulator* (N = 6, 1.7%). The first three transition groups described student groups who stayed in each of the three SRL profiles by the end of the semester. The *becoming competent regulator* group represented students who moved from the *goal-oriented regulator* and *self-confident regulator* profiles at T1 to the *competent regulator* profile at T2. The *no longer competent regulator* profile showed the opposite patterns (*competent regulator* at T1 → *goal-oriented regulator* or *self-confident regulator* at T2). The last group, *never became competent regulator*, described students who moved between the *goal-oriented regulator* and *self-confident regulator* profiles over time. This classification provides a finer-grained description of longitudinal trajectories of students' SRL development.

SI-related Predictors of SRL Profile Transition

Results of multinomial logistic regression analyses showed that overall, the SI program-related factors examined in this study had unique contributions to predicting students' SRL profile transitions while controlling for the effects of prior academic achievement (e.g., ACT composite score, high school GPA).

One notable finding was that, as hypothesized, a mastery-oriented reason for attending SI sessions was positively associated with students' development of SRL, but

this effect was not observed when participants cited performance or outcome-oriented reasons for attendance. Specifically, students attending the SI study sessions in order to understand the subject better were more likely to fall into to the *competent regulator* profile relative to the *self-confident regulator* or *goal-oriented regulator* profiles after the SI program had ended. Citing an objective of understanding the subject better also predicted an increased likelihood of membership in all other transition groups relative to the *no longer competent regulator* groups. However, contrary to expectations, no relationship was found between students' attendance at the SI sessions for the purpose of passing their course and their SRL profile transitions. These findings can be understood through the achievement goal literature, which has provided evidence that mastery goals, as opposed to performance goals, are linked to greater effort and persistence (Grant & Dweck 2003; Sideridis & Kaplan, 2011), positive engagement with adaptive self-regulatory strategies (Al-Harthy & Was, 2010; Middleton & Midgley, 1997), and deep learning approaches (Elliot, McGregor, & Gable, 1999).

Next, students' perceived benefits obtained from attending the SI sessions were found to be significant predictors of their transitions between SRL profiles. These benefits included increased academic self-confidence, critical thinking development, and improved group work skills. Students' increasing self-confidence predicted a greater likelihood of membership in the *competent regulator* profile relative to the *goal-oriented regulator* profile at the end of the semester. Similarly, it also had positive effects on the likelihoods of belonging to the *remaining competent regulator* and *becoming competent regulator* groups relative to the *remaining goal-oriented regulator* group. These findings

are intuitively reasonable, as the *goal-oriented regulator* profile was mainly characterized by relatively lower levels of self-efficacy for learning. These findings also imply that the SI program may help students to increase their academic self-confidence, which can lead to a positive change in their SRL strategy use. The critical role of self-efficacy beliefs in self-regulated learning processes have been highlighted by social cognitive researchers (Bandura, 1997; Pajares, 2008; Pintrich & De Groot, 1990; Schunk, 1990). Pajares (2008) explained, "Confident students monitor their academic work time effectively, persist when confronted with academic challenges, do not reject correct hypotheses prematurely, and solve conceptual problems" (p. 120).

Critical thinking skill development through the SI study sessions was also a significant determinant of SRL transitions. Students who perceived that the SI sessions improved their ability to critically review course materials and solutions were more likely to be in the most desirable profile or groups (*competent regulator, remaining competent regulator,* and *becoming competent regulator*) relative to the *goal-oriented regulator* profile or *remaining goal-oriented regulator* groups. These findings are in line with previous studies showing that critical thinking as a cognitive practice facilitates students' adoption of deep processing skills in their learning (e.g., Leung & Kember, 2003).

Students' group work skills fostered by the SI sessions predicted an increased likelihood of being in the *goal-oriented regulator profile* relative to the *self-confident regulator* profile. Such group work skills were also positively associated with the likelihoods of being in the *becoming competent regulator* and *remaining goal-oriented regulator* groups relative to the *remaining self-confident regulator* group. These findings

imply that group activities may make a stronger contribution to goal setting and planning than they do to self-efficacy for learning. Through working and interacting in groups, students had the opportunity to use their peers' goals, knowledge, and skills to help them refine and attain their own goals. The current findings are also in the line with Fitch and colleagues' (2012) study that demonstrated a positive effect of a group goal setting intervention on college students' improvement in overall SRL skills.

Problem-solving skills developed through the SI program appeared to have somewhat negative impacts on the transitions to more desirable SRL profiles. Specifically, students who reported that the SI sessions improved their problem-solving skills were more likely to fall in the *no longer competent regulator* group relative to the *remaining goal-oriented regulator* or *becoming competent regulator* groups. They also tended to belong to the *remaining self-confident regulator* or *remaining competent regulator* relative to the *becoming competent regulator* group. These results may contrast with previous studies that have shown that problem-based learning (PBL) approaches promote students' SRL skills (e.g., Malan et al., 2014; Sungur & Tekkaya, 2006). One possible reason for the current findings is that the SI sessions examined in this study might not have explicitly adopted the principles of PBL (Savery & Duffy, 1995) or adopted them poorly. In either of the two conditions, students could not have received the opportunity to develop their SRL, since problems often impede students' self-regulated efforts during problem solving (Schunk, 1995). Further, the effects of PBL on students' self-regulated learning (SRL) development can especially be limited for those who are poor self-regulators. Ertmer et al. (1996) have found that veterinary students with low

self-regulation did not value problem-based instruction as highly as their peers with high self-regulation. The students with low SRL also tended to focus on learning facts, while the high SRL students were likely to focus on analyzing the problems and reflecting on their thinking. With regard to this issue, Hmelo-Silver (2004) stated, “For students who are poor self-regulated learners, problem-based learning (PBL) is likely to pose difficulties without appropriate scaffolding for students trying to develop SDL [self-directed learning] skills” (p. 257).

Unexpectedly, no significant association was found between students’ frequency of attending the SI study sessions and their improvement in SRL. Rather, frequency of attendance significantly predicted a higher likelihood of membership in the *goal-oriented regulator* profile. More specifically, students with high SI attendance (i.e., attending 5 to 25 SI study sessions during the entire semester) were more likely than those with low SI attendance (i.e., attending only one session) to fit the *goal-oriented regulator* profile relative to the other two profiles at the end of semester. In addition, they were also more likely to be in the *remaining goal-oriented regulator* group relative to the *becoming competent regulator* group. These findings conflict with previous work that has shown that attendance frequency at SI sessions positively influences student outcomes (Malm et al., 2011, 2012, 2015). The current findings suggest that students’ frequency of attending the SI sessions is closely related to their goal-related behaviors but not their self-efficacy.

Outcomes of SRL Profile Transition

The last research question of the second part of the study was to examine the extent to which SRL profile transition is associated with students’ outcomes. Results of

MANOVAs showed that students' academic performance (e.g., final course grades, semester cumulative GPAs) differed depending on their membership in SRL profiles assigned at the end of semester. More specifically, the more adaptive profile (*competent regulator*) had higher scores in both outcomes than the less adaptive profile (*goal-oriented regulator*). These findings generally concur with the previous evidence of a positive association between SRL strategies and academic achievement that has been obtained by both variable-centered (e.g., Broadbent & Poon, 2015; Richardson, Abraham, & Bond, 2012) and person-centered analyses (e.g., Barnard-Brak et al., 2010; Broadbent & Fuller-Tyszkiewicz, 2018). Interestingly, however, students in the *self-confident regulator* profile did not underperform those in the *competent regulator* profile, despite their relatively lower levels on all the five SRL indicators compared with the *competent regulator* profile. These findings may reflect a relatively stronger influence of self-efficacy on academic performance or there may be other SRL strategies associated with this profile (*self-confident regulator*) that led students to have similar levels of outcomes as with the *competent regulator* profile. Further, the current findings also showed that students in the *remaining competent regulator* transition group outperformed those in the *no longer competent regulator* group in fall semester GPAs, suggesting that students' negative changes in SRL over time disadvantaged them in terms of their performance across course they were taking in the semester.

Implications for SI and SRL Literature

This research's findings make several important contributions to the current bodies of SI and SRL literature. There has been a longstanding concern regarding the possible impact of self-selection bias on the validity of impact estimates (Dawson et al., 2014). The current results provide more robust evidence regarding the effectiveness of SI programs by employing a PSM analysis, which is considered more appropriate for minimizing baseline covariate imbalance compared to other adjustment approaches, such as analysis of covariance (ANCOVA) (Fan & Nowell, 2011; Rosenbaum & Rubin, 1983).

Existing SI research largely focuses on final course grades and course completion as the main outcomes for assessing SI's effects (Dawson et al., 2014) with only a few exceptions (e.g., Malm et al., 2015; Ning & Downing, 2010). The current study attempted to fill this gap by examining students' SRL development as the primary outcome of interest. The findings suggest that SI attendees benefit from the SI program a limited amount more than non-SI attendees in terms of improving their SRL strategies over time. Further, from a group-based framework, the current study also showed that such an effect differed as a function of students' initial membership into different SRL profiles. This study is the first to apply LPAs to examine the effectiveness of SI, an approach which provides novel insights into individual differences in response to this particular peer-learning intervention.

Another novel finding of this dissertation was that students with mastery-oriented goals (i.e., attending the SI sessions to better understand course content) are more likely

to show a positive change in their SRL development. Since the SI program relies on voluntary participation, it is important to understand why students attend SI sessions and how students' motivation for attending SI sessions impacts their leaning outcomes in the SI program.

By applying LPA/LPTA, the current study contributes to the understanding of the multi-dimensional nature of students' SRL. In particular, the findings extend previous person-centered studies on SRL (e.g., Broadbent & Fuller-Tyszkiewicz, 2018; Dörrenbächer & Perels, 2016b) by investigating longitudinal stability and mobility of SRL profile membership. As expected, students who already use highly sophisticated SRL strategies (*competent regulators*) seem to maintain their good standing easily over time. In addition, students who were characterized by high levels of self-efficacy and information processing (*self-confident regulators*) were more stable than those who were characterized by high levels of goal-setting and planning (*goal-oriented regulators*). Understanding such individual differences in stability and mobility might be useful for identifying and supporting students who are at risk for academic difficulty and failure.

This study also examined potential predictors of membership changes, and these predictors were related to a peer-led academic support intervention (SI). All previous person-centered research on SRL other than Dörrenbächer and Perels (2016b) investigated general demographic or psychological constructs (e.g., gender, automaticity, personality) as predictors of membership in an SRL profile. As such, the current findings offer much more substantive information about how students can develop their SRL strategies, especially in the context of peer learning. For example, an increase in

students' self-confidence, critical thinking skills, and group work skills after attending the intervention program predicted greater likelihoods of membership in the more adaptive and desirable SRL profile (*competent regulator*) and transition groups (*remaining competent regulator* and *becoming competent regulator*).

Practical Implications

From a practical standpoint, this research offers several critical implications for university leaders, administrators, and educators. In general, this study demonstrates the potential of the SI program as a platform for enhancing students' SRL. The findings should encourage universities to invest more time and resources in this kind of peer learning-related intervention. It is also recommended that faculty and instructors actively incorporate group activities and social interaction components into their teaching.

In addition, the current findings highlight the importance of recognizing that students may respond heterogeneously to an intervention program. They may also differ in the ways in which they implement SRL strategies over time. The LPA/LPTA modeling approach used in this study informs how individualized teaching methods and intervention practices may help students to develop their SRL. For instance, educators should be especially attentive to students with high levels of self-efficacy without corresponding levels of goal setting and planning, as these students tend not to attend SI study sessions. Even if they spontaneously engage in the SI sessions, students in this group are less likely to move to the more adaptive profile. The results suggest that additional academic or motivational support may be needed for students in the *remaining*

goal-oriented regulator and *no longer competent regulator* group, as these students seem to be at-risk for poor academic performance. In terms of the *remaining goal-oriented regulator* group, lower performance may be attributed to goals that are too high or unrealistic (Schunk, 1990), so educators should have these students reflect upon and refine their goals.

The current results found that students who more mastery-oriented in terms of their purpose of attending the SI study sessions were likely to advance to more desired groups relative to the *no longer competent regulator* group over time. This result suggests that educators should make an effort to establish a more mastery-oriented learning environment to facilitate student engagement in and development of SRL (Ames, 1992).

Students' perceptions of having gained benefits from attending the SI sessions, such as increased self-confidence, critical thinking skills development, and improved group work skills, were positively associated with their membership in more desired transition groups (*remaining competent regulator* and *becoming competent regulator*). These findings also give valuable information about how SI leaders should facilitate their sessions in order to develop their students' SRL.

Further, to help students develop their SRL skills more effectively, direct instruction of SRL phases and processes should be incorporated into the current curriculum of SI interventions. Reviewing general findings of SRL training programs, Greene (2018) stresses that successful SRL interventions typically include explicit explanations of all SRL processes and strategies before, during, and after learning, rather than just showing or modeling relevant techniques. Such instruction includes "what to

do" to regulate learning effectively, as well as "when and why to do it" (Greene, 2018, p. 117). He also highlights that direct and explicit teaching in SRL should occur within the specific context (e.g., task, subject, domain), followed quickly by practice with peers and feedback from both peers and educators. Learning from these findings of SRL interventions, the SI programs should provide students with more explicit guidance regarding how to effectively regulate learning.

Limitations and Suggestions for Future Research

While this study shed light on the current understanding of SRL in important ways, the findings should be interpreted in the context of several limitations. Some these limitations include methodological/statistical issues, while the others concern theoretical/practical facets. Each limitation suggests directions for further research, and additional suggestions for future investigations are also discussed.

The principal limitations of this study stem from its reliance on a self-reported questionnaire as a means of measuring SRL strategies. Although researchers have often used self-reported instruments to assess SRL in the field (see Roth, Ogrin, & Schmitz [2016] for a recent review), these methods have recently faced a barrage of criticism. Researchers have pointed out that self-reported responses are limited in terms of their accuracy in assessing corresponding behaviors; respondents' memories of what and how they actually did while learning are inherently imprecise (Veenman, 2011; Winne, 2010). In addition, these measures are typically trait or component-oriented. They are limited in their ability to capture the procedural and dynamic aspects of SRL (Panadero, Klug, &

Järvelä, 2016; Schunk & Mullen 2013). Further, the SRL questionnaire used in this study is domain-general in nature rather than domain-specific, so it fails to tackle the situated, contextual aspects of SRL. Despite these shortcomings, self-reported instruments are still valuable in that they reflect students' own perceptions and interpretations about their SRL habits and behaviors. As such, future research should extend this work by taking a multimodal approach that simultaneously utilizes various data sources which can be subjective or/and objective (e.g., Greene et al., 2019). Subjective data may include self-reported instruments or interviews while objective data could include log data, classroom observations, or physiological measures.

Several other limitations of this study were attributed to issues related to the sample. Specifically, the study site was confined to one university, and the majority of the participants were white (89.1% of the whole sample, 87.8% of the SI attendee sample) and domestic students (94.2% of the whole sample, 92.9% of the SI attendee sample). The sample's homogeneity may threaten the generalizability of the study's findings. To confirm the generalizability of the findings, future studies are needed that replicate this study's findings with different samples from various regions and racial-ethnic groups. Further, given the increasing attention to cultural differences in SRL strategies (Loong, 2012; McInerney & King, 2018), future research could explore cross-cultural comparisons of the effects of the SI program on SRL development or differences in latent profile transitions of SRL across different cultural groups. Another sample-related limitation in the study was the relatively small sample size, which may limit the external validity of the findings. Future investigations with larger samples are needed.

It should also be acknowledged that one semester might not be a sufficient duration to detect significant changes in SRL strategies as a result of attendance at the SI program. The one semester period might be too short to fully understand the stability and mobility of SRL profile membership. Future studies should take this issue into account. In addition, the LPTA conducted in this study was based on only two measurement occasions, which were limited to explore various LPTA model specifications (e.g., higher-order effects, stationary transitions). Further studies with multiple occasions of measurement would allow a thorough examination of the dynamic nature of SRL development.

Some analytic limitations of the study should also be addressed. In the current study, LPA and LPTA models were estimated using manifest variables as SRL profile indicators (e.g., using the summed score of the four items for the *goal setting and planning* indicator). This method may be problematic, as manifest variables inevitably contain measurement errors, which may cause imprecise estimates of model parameters. However, the use of latent variables as LPA/LPTA model indicators would require a larger sample size. Thus, future studies may need to include a larger sample and to take a complete latent approach to LPA/LPTA modeling. Such an approach would help achieve unbiased results by correcting errors in measurement.

In addition, in order to examine the predictors and outcomes of the profiles, the present study extracted the most likely profile membership and used it as a categorical variable for further analyses (e.g., multinomial logistic regressions, MANOVAs). While this is a straightforward approach to interpreting the results, it ignores uncertainty in

latent profile membership, which may lead to bias in the results in terms of estimating covariate effects related to profile membership (Lanza, Tan, & Bray, 2013). Further studies may benefit from adding covariates directly to the models to obtain a more precise estimation of covariate effects.

It should also be noted that the current study estimated LPA and LPTA solutions under assumptions that may not be realistic: the equal variances of the SRL indicators across profiles and the uncorrelations between the SRL indicators within profile. Since some of the LPA solutions estimated in this study failed to converge when these assumptions were relaxed, holding those rigid assumptions was unavoidable. This non-convergence problem may be due to the relatively small sample size of the study. Estimating a larger number of parameters required after abandoning the assumptions requires a larger sample size. This issue should be taken into account in further studies.

Lastly, despite the fact that participants were nested within 34 SI-supported courses, this study did not employ particular modeling techniques (e.g., multi-level LPA or LPTA) that explicitly take into account the clustered nature of the data. This was primarily because the intraclass correlation coefficients (ICC) values for the SRL indicators were very low, ranging from 0.001 (self-efficacy at T1) to 0.028 (goal setting and planning at T3), indicating marginal between-cluster variance (Hox, 2010). Future studies may benefit from applying multilevel modeling approaches that are able to obtain a more nuanced and complete picture of SI-related phenomena by exploring cluster-level factors (e.g., SI leaders' expertise, SI session structure).

In a similar vein, given that courses and disciplines inherently differ in knowledge structure and how they should be taught, SI instruction and activities may vary by course or discipline. This is the underlying reason why Supplemental Instruction (SI) interventions are typically operated by course, providing students with course-specific practices and strategies rather than focusing on generic learning skills (Court & Molesworth, 2008). Further, self-regulated learning (SRL) has also been considered context-sensitive; students regulate and manage their learning differently depending on the task, subject or situation (Pintrich, 2000; Winne, 2010). In this regard, the current analyses aggregating the sample as a whole may have their limits in deeper understanding of SI practices related to SRL. Therefore, future analysis should be undertaken in a course- or discipline-specific manner by restricting the sample to students taking certain SI-supported courses.

In terms of the LPA-PSM combined analysis used in the first part of this study, a causal interpretation of the findings should only be made carefully. Although PSM has been known as a potential tool for making causal inferences in nonexperimental design or observational research, the validity of that causal inferences would not be achieved if relevant covariates were omitted (Baser, 2006). The current analysis included sixteen covariates that were selected based on previous SI studies and data availability in the situation of this study. However, there may be other relevant covariates (e.g., students' socioeconomic status) that were not included in this study that are associated with SI attendance. As such, additional explorations of relevant covariates are needed before establishing a valid causal relationship between SI programs and SRL development.

While students' SRL development was the primary outcome of interest in this study, students' final grades in the SI-attached course and fall semester cumulative GPAs were also examined as additional outcomes. In particular, the second part of this study confirmed the predictive role of students' SRL transition group membership on their final course grades and fall semester GPAs. However, the analyses in this study were insufficient to determine potential mediating or moderating effects of SRL group membership on relations between SI attendance or relevant factors and student outcome (e.g., final course grades, course completion). For instance, using a structural equation modeling approach, Ning and Downing (2010) found that increased study skills and competence partially mediated the positive impact of SI attendance on academic performance (e.g., GPAs). Future study should extend the current findings by exploring mediating or moderating roles of SRL development in the SI program's effects on student outcomes using person-centered analyses. These analyses may lead to a more comprehensive understanding of how the SI program leads to positive changes in students' academic achievement.

One of the key features of the SI program is that students to have the opportunity to interact socially with their fellow students and to study collaboratively in small groups. However, in this study, these social or peer learning aspects of the SI program were not examined directly, which merits consideration in future studies. While this is an understudied area of SI research, previous studies have offered evidence that students benefited from the social or peer learning facets of attending SI sessions (e.g., Dobbie & Joyce, 2008). Further, researchers studying SRL have recently become greatly interested

in social forms of regulation of learning, such as socially shared regulated learning (SSRL) and co-regulated learning (CoRL) (Hadwin, Järvelä, & Miller, 2018; Panadero, & Järvelä, 2015). For example, CoRL refers to “the dynamic metacognitive processes through which [individual] self-regulation and shared regulation [in groups] of cognition, behavior, motivation, and emotions are transitionally and flexibly supported and thwarted” (Hadwin et al., 2018, p. 83). Incorporating these socially regulated learning aspects into assessments of SI program effects may be a promising area of future research.

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APPENDICES

Appendix A

Institutional Review Board (IRB) Certificate

Institutional Review Board

USU Assurance: FWA#00003308

UtahState University
OFFICE OF RESEARCH AND GRADUATE STUDIES

Exemption #1

Certificate of Exemption

FROM:

Melanie Domenech Rodriguez, IRB Chair

Nicole Vouvalis, IRB Administrator

To:	David Feldon, Soojeong Jeong
Date:	July 17, 2018
Protocol #:	9531
Title:	College Students' Self-Regulated Learning Profiles And Their Transitions: Exploring The Role Of Supplemental Instruction

The Institutional Review Board has determined that the above-referenced study is exempt from review under federal guidelines 45 CFR Part 46.101(b) category #1:

> Research conducted in established or commonly accepted educational settings, involving normal educational practices, such as (i) research on regular and special education instructional strategies, or (ii) research on the effectiveness of or the comparison among instructional techniques, curricula, or classroom management methods.

This exemption is valid for three years from the date of this correspondence, after which the study will be closed. If th research will extend beyond three years, it is your responsibility as the Principal Investigator to notify the IRB before the study's expiration date and submit a new application to continue the research. Research activities that continue beyond the expiration date without new certification of exempt status will be in violation of those federal guidelines which permit the exempt status.

As part of the IRB's quality assurance procedures, this research may be randomly selected for continuing review durir the three year period of exemption. If so, you will receive a request for completion of a Protocol Status Report during the month of the anniversary date of this certification.

In all cases, it is your responsibility to notify the IRB prior to making any changes to the study by submitting an Amendment/Modification request. This will document whether or not the study still meets the requirements for exempt status under federal regulations.

Upon receipt of this memo, you may begin your research. If you have questions, please call the IRB office at (435) 797 1821 or email to irb@usu.edu.

The IRB wishes you success with your research.

Appendix B

Survey Questionnaires

Self-regulated Learning Strategies (1 - very untrue of me to 5 – very true of me)

Goal setting and planning (GP)

1. I make a detailed schedule of my daily activities.
2. I make a timetable of all the activities I have to complete
3. I plan the things I have to do in a week.
4. I use a planner to keep track of what I am supposed to accomplish

Self-efficacy for learning and performance (SEF)

1. I believe I will receive an excellent grade in my courses.
2. I'm confident I can understand the basic concepts taught in my courses.
3. I'm confident I can understand the most complex material presented by the instructor in my courses.
4. I'm confident I can do an excellent job on the assignments and tests in my courses.

Information processing (IP)

1. I try to find relationships between what I am learning and what I already know.
2. To help me learn the material presented in my classes, I relate it to my own general knowledge.
3. I try to see how what I am studying would apply to my everyday life.
4. I try to relate what I am studying to my own experiences.

Time management (TM)

1. I find it hard to stick to a study schedule.
2. When it comes to studying, procrastination is a problem for me.
3. I put off studying more than I should.
4. I end up “cramming” for every test.

Self-evaluation (SEV)

1. I ask myself if I learned as much as I could have once I finish a task.
2. I ask myself if I have considered all options after I solve a problem.
3. I ask myself how well I accomplished my goals once I'm finished.

Supplemental Instruction (SI) Experience (1 - very untrue to 5 - very true)

Why did you attend SI sessions?

  - To pass the course
  - To understand the subject better

What are the benefits you have achieved from SI attendance?

  - I achieved better self confidence in my studies by attending SI sessions.
  - The SI sessions have developed my way of studying. I will also have use of this in other courses.
  - The SI sessions have developed my way of studying.
  - I will also have use of this in The SI sessions have developed my problems solving skills.
  - The SI sessions have developed my ability to work and interact in groups.

General Demographic Information

Gender

- Male
- Female

Age (e.g., 21): ____

Year in school

- Freshman
- Sophomore
- Junior
- Senior

Race/Ethnicity background

- Latino/Hispanic (not white)
- Asian/Asian-American
- White
- Other

What was the highest degree obtained by your father/mother (sperate items)?

- Some High School
- High School Diploma/GED
- Some College
- A.A./A.A.S.
- B.A./B.S.
- Master's Degree
- Professional Doctorate (e.g., M.D., J.D., Ed.D.)
- Ph.D.

Are you an international student?

- Yes
- No

What department or program are you in (e.g., Math & Statistics)? ____

Appendix C

Factor Loadings of the Self-regulated Learning Scales

Table C1

Results of exploratory factor analyses with geomin

Items	Factor	Factor loading T1/T2	
		Full sample	SI attendee sample
GP1	GP	0.812/0.840	0.853/0.873
GP2		0.604/0.688	0.523/0.712
GP3		0.597/0.738	0.574/0.750
GP4		0.728/0.715	0.732/0.671
SEF1	SEF	0.808/0.749	0.793/0.769
SEF2		0.697/0.610	0.725/0.601
SEF3		0.631/0.636	0.595/0.666
SEF4		0.825/0.876	0.808/0.874
IP1	IP	0.702/0.710	0.636/0.774
IP2		0.616/0.725	0.540/0.737
IP3		0.561/0.490	0.561/0.519
IP4		0.774/0.767	0.752/0.782
TM1	TM	0.562/0.681	0.602/0.660
TM2		0.901/0.951	0.901/0.974
TM3		0.789/0.840	0.827/0.813
TM4		0.591/0.694	0.559/0.663
SEV1	SEV	0.526/0.702	0.482/0.775
SEV2		0.613/0.683	0.760/0.595
SEV3		0.532/0.635	0.480/0.584

Note. GP = goal setting and planning; SEF = self-efficacy; IP = information processing; TM = time management; SEV = self-evaluation

Appendix D

Recruitment Letter

UtahState University
Department of Instructional Technology
& Learning Sciences
2830 Old Main Hill
Logan UT 84322-6720
Telephone: (435) 797-0556

Recruitment Letter

Dear [student],

We hope that you have had a great start to the semester! With the support of the Academic Success Center, we are currently conducting a research study on how college students develop their learning strategies. We are contacting you, because you are enrolled in a course for which Supplemental Instruction (SI) is offered. This study has been reviewed and approved by the Institutional Review Board of Utah State University (Protocol # 9531).

Participation in this research study is voluntary. If you agree to participate in this research study, you will be asked to complete three online surveys during the fall semester of 2018. Each survey session requires 20 to 30 minutes of your time. In addition, you will authorize the researchers to have access to your educational records, including your ACT scores, your high school GPA, the final grade(s) you obtained in the course(s) that are supported by SI study sessions, your decision to drop out of the course(s) that are supported by SI study sessions, your fall semester overall GPA, and your record of attendance at SI sessions from the Academic Success Center at USU.

All participants who complete the three survey sessions will be entered into a drawing to win one of twenty $100 gift cards. If you have any questions, please feel free to contact David Feldon at david.feldon@usu.edu or Soojeong Jeong at soojeong.jeong@aggiemail.usu.edu. We greatly appreciate your consideration and time.

Please use the below link if you are interested in participating in this study.
[https://usu.co1.qualtrics.com/jfe/form/SV_3QJiihNdb0aPJE9]

Sincerely,

David Feldon
Professor, Principal Investigator
Department of Instructional Technology and Learning Sciences

Soojeong Jeong
Student Investigator

Appendix E

Informed Consent

OFFICE of RESEARCH and GRADUATE STUDIES
UtahStateUniversity
INSTITUTIONAL REVIEW BOARD

IRB Approval Date:
Consent Document Expires:
IRB Password Protected per IRB X

v.8.3; May2017

Informed Consent

College students' self-regulated learning profiles and their transitions: Exploring the role of Supplemental Instruction

Purpose

You are invited to participate in a research study conducted by Dr. David Feldon, a professor in the Instructional Technology and Learning Sciences, and Soojeong Jeong, a Ph.D. student, at Utah State University. The purpose of this research is to investigate how college students' learning strategies develop over time through Supplemental Instruction (SI). This research is conducted in cooperation with the Academic Success Center at USU that administers and runs the SI program.

This form includes detailed information on the research to help you decide whether to participate in this research. Please read it carefully and ask any questions you have before you agree to participate.

Procedures

If you agree to participate in this research study, you will be asked to complete three online surveys during the fall semester of 2018. You will receive the initial survey during the first week of the semester (Time 1) that will ask questions about your learning strategies (40 items) and background (8 items). The survey will require approximately 25 minutes. You will receive the second survey during the ninth week of the semester (Time 2) that will ask the same questions about your learning strategies (40 items; 20 minutes) as well as additional questions about your experience with SI study sessions (20 items; 10 minutes). The third survey will be set to you with the same items used in the second survey during the last week of the semester (Time 3). However, for the second and third survey, the question items about SI experience are only for those who have attended at least one of the SI study sessions; if you did not attend any of SI study sessions during the given period (Time 1-2, Time 2-3), you will not need to answer to those questions.

In compliance with the Family Education Right to Privacy Act (FERPA), it is the policy of the Utah State University to maintain the confidentiality of students' records. If you agree to participate in this study, you authorize the researchers to gather information about your ACT scores, your high school GPA, the final grade(s) you obtained in the course(s) that are supported by SI study sessions, your decision to drop out of the course(s) that are supported by SI study sessions, your fall semester overall GPA, and your record of attendance at SI sessions from the Academic Success Center at USU. Once the information from these records is linked to your survey responses, your identifying information will be removed from the record to protect your privacy.

Risks

This is a minimal risk research study. That means that the risks of participating are no more likely or serious than those you encounter in everyday activities. The foreseeable risks or discomforts include a small risk of loss of confidentiality but we will take steps to reduce this risk. However, your name will be immediately removed from all data you provide and assigned a unique numeric identifier in order to maintain your confidentiality. At no time will any personally identifiable information be shared with anyone outside the research team conducting the study. If you have a bad research-related experience or are injured in any way during your participation, please contact the principal investigator of this study right away at (435)797-0556 or david.feldon@usu.edu.

Benefits

There is no direct benefit to you for participating in this research study. More broadly, this study will help the researchers learn more about the development of college students' learning strategies and may help the 3 Success Center and future researchers design new interventions to help students develop their academic skills.

Confidentiality

The researchers will make every effort to ensure that the information you provide as part of this study remains confidential. Your identity will not be revealed in any publications, presentations, or reports resulting from this research study.

We will collect your information through online surveys (Qualtrics) and the Academic Success Center at USU. Only the principal investigator and the student researcher directly involved in this study will have access to the data, which will be securely stored in a restricted-access folder on Box.com, an encrypted, cloud-based storage system. Therefore, responses to survey items cannot be traced back to any individual participant.

To protect your privacy, personal, identifiable information (e.g., name, A-Number and e-mail) will be removed from study records and replaced with a study identifier.

It is unlikely, but possible, that others (Utah State University or state or federal officials) may require us to share the information you give us from the study to ensure that the research was conducted safely and appropriately. We will only share your information if law or policy requires us to do so.

The research team works to ensure confidentiality to the degree permitted by technology. It is possible, although unlikely, that unauthorized individuals could gain access to your responses because you are responding online. However, your participation in this online survey involves risks similar to a person's everyday use of the internet.

The researchers will make every effort to ensure that the information you provide as part of this study remains confidential. Your identity will not be revealed in any publications, presentations, or reports resulting from this research study.

Voluntary Participation & Withdrawal

Your participation in this research is completely voluntary. If you agree to participate now and change your mind later, you may withdraw at any time by emailing Soojeong Jeong (soojeong.jeong@aggiemail.usu.edu) with the subject "study withdraw". If you choose to withdraw after we have already collected information about you in any of the study phases, all information will be deleted immediately after receiving the withdraw email.

Compensation

If you complete all the three survey sessions, you will become eligible for a drawing to win one of twenty $100 gift cards. Should your name be drawn, Soojeong Jeong will contact you to arrange delivery of the gift card.

IRB Review

The Institutional Review Board (IRB) for the protection of human research participants at Utah State University has reviewed and approved this study. If you have questions about the research study itself, please contact the Principal Investigator at (435) 797-0556 or david.feldon@usu.edu. If you have questions about your rights or would simply like to speak with someone other than the research team about questions or concerns, please contact the IRB Director at (435) 797-0567 or irb@usu.edu.

David Feldon
Principal Investigator
(435) 797-0556; david.feldon@usu.edu

Soojeong Jeong
Student Investigator
(435) 754-9648; soojeong.jeong@aggiemail.usu.edu

Informed Consent

By typing your full name and the date below, you agree to participate in this study. You indicate that you understand the risks and benefits of participation, and that you know what you will be asked to do. You also agree that you have asked any questions you might have, and are clear on how to stop your participation in the study if you choose to do so. Please be sure to retain a copy of this form for your records.

Appendix F

Covariate Balance Before and After Matching for Each SRL Profile

Table F1

Covariate balance before and after matching for each SRL profile (Imputed dataset 2)

	Full sample		Profile 1: competent regulator		Profile 2: self-confident regulator		Profile 3: goal-oriented regulator	
	d_X	d_{Xm}	d_X	d_{Xm}	d_X	d_{Xm}	d_X	d_{Xm}
Gender[a]	0.05	0.01	0.08	0.07	0.09	0.05	0.03	0.00
Race								
Asian[b]	0.05	0.06	**0.39**	0.00	0.03	0.14	0.02	0.00
White[b]	0.07	0.04	0.19	0.00	0.13	0.09	0.19	0.17
Other[b]	0.02	0.00	**0.21**	0.00	0.03	0.00	0.12	0.13
International student status	0.11	0.02	**0.27**	0.00	0.17	0.00	0.00	0.00
First-generation student status	0.19	0.03	0.10	0.00	0.01	0.06	**0.51**	0.00
Year in school								
Sophomore[c]	0.14	0.02	0.12	0.00	**0.42**	0.06	0.12	0.00
Junior[c]	0.06	0.08	0.01	0.07	0.10	0.00	0.09	0.07
Senior[c]	**0.26**	**0.00**	**0.25**	0.13	0.08	0.12	**0.58**	**0.22**
Major								
Social science[d]	0.17	0.02	0.07	0.07	0.15	0.00	**0.41**	0.12
Engineering[d]	0.00	0.04	0.10	0.09	0.20	0.06	0.05	0.09
Science[d]	0.02	0.01	0.05	0.03	0.20	0.09	**0.31**	0.07
Exploratory[d]	0.15	0.03	0.17	0.06	0.06	0.10	**0.30**	0.10
Age	**0.26**	**0.02**	**0.36**	0.01	0.03	0.14	**0.37**	0.17
High school GPA	**0.36**	**0.06**	**0.44**	0.04	**0.38**	0.08	0.17	0.08
ACT composite score	0.08	0.00	0.00	0.03	0.08	0.05	0.00	0.05
Overall SRL score at T1	0.11	0.01	0.09	0.05	0.13	0.04	**0.20**	0.01
Average covariate balance	0.12	0.03	0.17	0.04	0.13	0.06	**0.22**	0.08
Logit propensity score	**0.66**	**0.04**	**0.77**	0.04	**0.94**	0.03	**1.24**	0.04

Note: d_X = Absolute standardized difference in covariate means before matching; d_{Xm} = Absolute standardized difference in covariate means after matching

Values greater than 0.2 are presented in bold type.

[a]Reference group: Female

[b]Reference group: Hispanic

[c]Reference group: Freshman

[d]Reference group: Art & Humanities

Table F2

Covariate balance before and after matching for each SRL profile (Imputed dataset 3)

	Full sample		Profile 1: competent regulator		Profile 2: self-confident regulator		Profile 3: goal-oriented regulator	
	d_X	d_{Xm}	d_X	d_{Xm}	d_X	d_{Xm}	d_X	d_{Xm}
Gender[a]	0.04	0.01	0.07	0.04	0.09	0.05	0.00	0.07
Race								
Asian[b]	0.07	0.00	0.00	0.00	0.03	0.00	0.14	0.13
White[b]	0.11	0.03	0.14	0.00	0.09	0.09	**0.28**	0.00
Other[b]	0.04	0.06	0.04	0.04	0.03	0.14	0.17	0.14
International student status	0.12	0.02	0.06	0.00	0.17	0.00	0.00	0.00
First-generation student status	0.09	0.03	0.06	0.07	0.02	0.17	**0.52**	0.00
Year in school								
Sophomore[c]	0.20	0.02	0.12	0.05	**0.34**	0.11	0.10	0.07
Junior[c]	0.03	0.02	0.03	0.05	0.10	0.08	**0.22**	0.00
Senior[c]	**0.28**	0.14	0.10	0.16	0.18	0.14	**0.58**	0.00
Major								
Social science[d]	0.16	0.02	0.06	0.09	0.15	0.00	**0.41**	0.00
Engineering[d]	0.01	0.00	0.10	0.03	**0.23**	0.11	0.05	0.11
Science[d]	0.02	0.07	0.05	0.00	**0.24**	0.17	**0.31**	0.17
Exploratory[d]	0.13	0.03	0.16	0.02	0.06	0.14	**0.30**	0.19
Age	**0.26**	0.04	**0.35**	0.18	0.01	0.00	**0.25**	0.04
High school GPA	**0.39**	0.01	**0.37**	0.07	**0.30**	0.10	0.17	0.05
ACT composite score	0.01	0.01	0.02	0.04	0.13	0.02	0.08	0.15
Overall SRL score at T1	0.15	0.04	0.10	0.21	0.06	0.16	0.08	0.15
Average covariate balance	0.12	0.03	0.11	0.06	0.13	0.09	**0.23**	0.08
Logit propensity score	**0.65**	0.05	**0.71**	0.06	**0.93**	**0.04**	**1.29**	0.03

Note: d_X = Absolute standardized difference in covariate means before matching; d_{Xm} = Absolute standardized difference in covariate means after matching

Values greater than 0.2 are presented in bold type.

[a]Reference group: Female

[b]Reference group: Hispanic

[c]Reference group: Freshman

[d]Reference group: Art & Humanities

Table F3

Covariate balance before and after matching for each SRL profile (Imputed dataset 4)

	Full sample		Profile 1: competent regulator		Profile 2: self-confident regulator		Profile 3: goal-oriented regulator	
	d_X	d_{Xm}	d_X	d_{Xm}	d_X	d_{Xm}	d_X	d_{Xm}
Gender[a]	0.02	0.03	0.07	0.04	0.12	0.17	0.01	0.00
Race								
Asian[b]	0.10	0.00	0.39	0.14	0.03	0.00	**0.42**	**0.22**
White[b]	0.10	0.00	0.14	0.08	0.17	0.00	0.12	0.00
Other[b]	0.04	0.06	0.02	0.05	0.03	0.00	0.13	0.00
International student status	0.15	0.00	0.14	0.00	0.12	0.00	0.00	0.00
First-generation student status	0.08	0.02	0.05	0.10	0.02	0.05	**0.58**	0.00
Year in school								
Sophomore[c]	**0.21**	0.05	0.09	0.05	**0.38**	0.05	0.02	**0.27**
Junior[c]	0.08	0.03	0.03	0.12	0.10	0.07	**0.28**	0.00
Senior[c]	0.03	0.02	**0.25**	0.06	0.18	0.00	0.12	0.16
Major								
Social science[d]	0.15	0.03	0.06	0.05	0.15	0.05	**0.56**	0.08
Engineering[d]	0.00	0.00	0.12	0.03	**0.23**	0.10	0.20	0.09
Science[d]	0.02	0.03	0.05	0.03	0.20	0.08	0.00	0.05
Exploratory[d]	0.14	0.02	0.16	0.04	0.06	0.09	0.05	0.03
Age	**0.27**	0.01	**0.39**	0.05	0.03	0.04	**0.41**	0.07
High school GPA	**0.41**	0.03	**0.36**	0.03	**0.38**	0.12	0.05	**0.21**
ACT composite score	0.04	0.02	0.08	0.01	0.13	0.06	**0.31**	0.08
Overall SRL score at T1	0.16	0.02	0.10	0.14	0.08	0.09	**0.30**	**0.25**
Average covariate balance	0.15	0.03	0.06	0.05	0.14	0.06	**0.22**	0.09
Logit propensity score	**0.66**	0.04	**0.70**	0.05	**1.03**	0.03	**1.34**	0.03

Note: d_X = Absolute standardized difference in covariate means before matching; d_{Xm} = Absolute standardized difference in covariate means after matching

Values greater than 0.2 are presented in bold type.

[a]Reference group: Female

[b]Reference group: Hispanic

[c]Reference group: Freshman

[d]Reference group: Art & Humanities

Table F4

Covariate balance before and after matching for each SRL profile (Imputed dataset 5)

	Full sample		Profile 1: competent regulator		Profile 2: self-confident regulator		Profile 3: goal-oriented regulator	
	d_X	d_{Xm}	d_X	d_{Xm}	d_X	d_{Xm}	d_X	d_{Xm}
Gender[a]	0.09	0.01	0.06	0.02	0.12	0.00	0.01	0.07
Race								
Asian[b]	0.02	0.00	0.00	0.00	0.03	0.00	**0.42**	0.01
White[b]	0.04	0.02	0.17	0.04	0.17	0.07	0.12	0.13
Other[b]	0.04	0.00	0.08	0.00	0.03	0.13	**0.22**	**0.27**
International student status	0.14	0.00	0.06	0.10	0.17	0.00	0.00	0.00
First-generation student status	0.08	0.04	0.04	0.07	0.02	0.10	**0.29**	0.00
Year in school								
Sophomore[c]	0.18	0.01	0.12	0.02	**0.35**	0.10	0.07	0.00
Junior[c]	0.01	0.05	0.03	0.08	0.10	0.14	**0.30**	0.08
Senior[c]	**0.31**	0.06	0.15	0.04	0.18	0.00	0.12	0.14
Major								
Social science[d]	0.16	0.07	0.06	0.16	0.15	0.16	**0.46**	0.00
Engineering[d]	0.01	0.04	0.10	0.09	**0.23**	0.15	0.15	0.15
Science[d]	0.03	0.06	0.05	0.10	0.20	0.00	0.08	0.03
Exploratory[d]	0.13	0.01	0.16	0.14	0.08	0.04	0.11	0.15
Age	**0.31**	0.04	**0.34**	0.07	0.05	0.07	**0.41**	0.13
High school GPA	**0.37**	0.04	**0.42**	0.06	**0.30**	0.11	0.05	0.00
ACT composite score	0.05	0.04	0.02	0.08	0.13	0.20	**0.31**	0.08
Overall SRL score at T1	0.15	0.00	0.08	0.06	0.03	0.13	**0.30**	0.17
Average covariate balance	0.16	0.07	0.11	0.07	0.14	0.08	**0.21**	0.09
Logit propensity score	**0.64**	0.04	**0.71**	0.05	**0.95**	0.03	**1.19**	0.04

Note: d_X = Absolute standardized difference in covariate means before matching; d_{Xm} = Absolute standardized difference in covariate means after matching

Values greater than 0.2 are presented in bold type.

[a]Reference group: Female

[b]Reference group: Hispanic

[c]Reference group: Freshman

[d]Reference group: Art & Humanities

CURRICULUM VITAE

SOOJEONG JEONG

Instructional Technology and Learning Sciences,
Utah State University
2830 Old Main Hill, Logan, UT 84322
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EDUCATION

2019 **Ph.D., Instructional Technology and Learning Sciences**
Utah State University, Logan, Utah, United States
Dissertation: *The role of a peer-led academic intervention in college students' development of self-regulated learning: A person-centered approach*
(Chair: Dr. David Feldon)

2011 **M.A., Educational Technology**
Korea University, Seoul, South Korea
Thesis: *The use of laptops in university classes: a qualitative study*
(Chair: Dr. Innwoo Park)

2008 **B.A., Education**
B.S., Mathematics Education
Korea University, Seoul, South Korea
Teaching Certificate in Secondary Mathematics Education

PUBLICATIONS

Peer-Reviewed Journal Articles

11. **Jeong, S.**, Litson, K., Blaney, J., & Feldon, D. F. (in press). Shifting Gears: Characteristics and consequences of latent class transitions in doctoral socialization. *Research in Higher Education.* [IF = 1.96]

10. **Jeong, S.**, Blaney, J., & Feldon, D. F. (in press). Identifying faculty-peer interactions among first-year biology doctoral students: A latent class analysis. *CBE—Life Sciences Education.* [IF = 2.38]

9. Feldon, D. F., Litson, K., **Jeong, S.**, Blaney, J., Kang, J., Miller, C., Griffin, K., & Roksa, J. (2019). Postdocs' lab engagement predicts trajectories of Ph.D. Students' skill development. *Proceedings of the National Academy of Sciences of the United States of America*, 1-7. [IF = 9.58]

8. Feldon, D. F., Callan, G., Juth, S., & **Jeong, S.** (2019). Cognitive load as motivational cost. *Educational Psychology Review*, 1-19. [IF = 6.87]

7. Roksa, J., **Jeong, S.**, Feldon, D., & Maher, M. (2018). Socialization experiences and research productivity of Asians and Pacific Islanders: 'Model Minority' stereotype and domestic vs. international comparison. *Research in the Sociology of Education, 20*, 157-181.

6. Feldon, D. F., **Jeong, S.**, Peugh, J., Roksa, J., Maahs-Fladung, C., Shenoy, A., & Oliva, M. (2017). Null effects of boot camps and short-format training for PhD students in life sciences. *Proceedings of the National Academy of Sciences of the United States of America, 114*(37), 9854-9858. [IF = 9.58]

5. Brasiel, S., **Jeong, S.**, Ames, C., Lawanto, K., Yuan, M. & Martin, T. (2016). Effects of educational technology on mathematics achievement for K-12 students in Utah. *Journal of Online Learning Research*, *2*(3), 205-226.

4. **Jeong, S.,** Shin, W. S., & Park, I. (2015). Students' use of notebook computers in the college classroom: benefits and pitfalls. *Educational Technology International, 16*(1), 31-57.

3. Kim, K. Y., Ko, Y., **Jeong, S.,** Lim, K., & Sim, H. (2010). The effect of micro blogging learning activities with smartphones in social presence. *The Korea Educational Review, 16*(3), 205-224.

2. **Jeong, S.,** Lim, K., Ko, Y. Sim, H., & Kim, K. Y. (2010). The analysis of trends in smartphone applications for education and suggestions for improved educational use. *Journal of Digital Contents Society*, *11*, 203-216.

1. Cha, M. J., Kim, C. M., Kwon, H. J., Cho, H. D, Lee, J. Y., **Jeong, S**., … Kim, J., & Park, I. (2010). A development of learner participation scale in instruction. *The Korean Journal of Educational Methodology Studies*, *22*(1), 195-219.

Chapters in Edited Books

2. Feldon, D., **Jeong, S.**, & Franco, J. (2019). Expertise in STEM Disciplines. *Oxford Handbook of Expertise: Research and Application*. DOI: 10.1093/oxfordhb/9780198795872.013.23

1. Brasiel, S., Close, K., **Jeong, S.**, Lawanto, K., Janisiewicz, P., & Martin, T. (2017). Measuring computational thinking development with the FUN! Tool. In P.

Rich and C. Hodges (Eds.), *Emerging Research, Practice, and Policy on Computational Thinking* (pp. 327-347). New York: Springer.

Manuscripts Under Review or In Progress

Jeong, S., Litson, K., Maierhofer, T., Castleberry, J. S., & Feldon, D. F. (revision). Assessment of open-ended problem solving during simulation: Development and evaluation of a wastewater treatment plant training system. *Educational Technology Research and Development.*

Jeong, S. & Feldon, D. F. (in progress). Doctoral satisfaction with faculty advisors: Advisement characteristics and relationship to socialization outcomes.

Jeong, S., Litson, K., & Feldon, D. F. (in progress). Role of doctoral training environments in scholarly productivity: Moderation from sense of belonging and research self-efficacy.

Litson, K., Feldon, D. F., & **Jeong, S.** (in preparation). Demographic factors affecting the missingness mechanism in a national sample of biology Ph.D. students.

CONFERENCE PRESENTATIONS

Peer-Reviewed Conference Papers

20. **Jeong, S.**, Blaney, J., & Feldon, D. F. (2019, August). Identifying faculty and peer interaction patterns in doctoral students: A latent class analysis. Paper to be presented at the American Psychological Association (APA) convention. August 8-11, Chicago, IL.

19. **Jeong, S.**, Litson, K., & Feldon, D. F. (2019, April). Role of doctoral training environments in scholarly productivity: Moderation from sense of belonging and research self-efficacy. Paper to be presented at the annual meeting of the American Educational Research Association (AERA). April 5-9, Toronto, Canada.

18. **Jeong, S.**, Blaney, J., Feldon, D. F., & Litson, K. (2018, November). Profiling students' faculty and peer interactions during the first three years of doctoral study: Associations with student demographics, sense of belonging, and research productivity. Paper to be presented at the 43rd annual meeting of the Association for the Study of Higher Education (ASHE). November 15-17, Tampa, FL.

17. **Jeong, S.**, Feldon, D. F., Maher, M., & Peugh, J. (2018, April). Doctoral satisfaction with faculty advisors: Advisement characteristics and relationship to socialization outcomes. Paper to be presented at the annual meeting of the American Educational Research Association (AERA). April 13-17, New York City, NY.

16. **Jeong, S.**, Maher, M., Feldon, D. F., & Peugh, J. (2018, April). Doctoral students' faculty and peer interaction patterns: Relationships to researcher self-efficacy and skill acquisition. Paper to be presented at the annual meeting of the American Educational Research Association (AERA). April 13-17, New York City, NY.

15. Roksa, J., **Jeong, S.**, Feldon, D. F., & Maher, M. (2017, November). Revisiting the "Model Minority" Stereotype: API Students' Socialization Experiences and Research Productivity. Paper to be presented at the 42nd annual meeting of the Association for the Study of Higher Education (ASHE). November 8-11, Houston, TX.

14. Feldon, D. F., **Jeong, S.**, Roksa, J., & Peugh, J. (2017, April). What I did on summer vacation: Limited impacts of boot camps and summer bridge activities. Paper to be presented at the annual meeting of the American Educational Research Association (AERA). April 27-May 1, San Antonio, TX.

13. Feldon, D. F., **Jeong, S**., & Peugh, J. (2017, January). Progressions of research skill development in the biological sciences. Paper to be presented at the 15th Annual Hawaii International Conference on Education (HICE). January 3-6, Honolulu, HI.

12. Martin, T., Brasiel, S., **Jeong, S.**, & Yuan, M. (2016, March). Mixed methods evaluation of statewide implementation of mathematics education technology for K-12 students. Paper to be presented at the Society for Research on Educational Effectiveness (SREE). March 2-5, Washington, D.C.

11. Martin, T., Brasiel, S., **Jeong, S.**, Close, K., Lawanto, K., & Janisiewicz, P. (2016, March). Macro data for micro learning: developing the FUN! Tool for automated assessment of learning. Paper to be presented at the third (2016) ACM Conference on Learning@ Scale. March 14-15, Vancouver, BC, Canada.

10. Brasiel, S., Martin, T., **Jeong, S.,** Lawanto, K., Ames, C., & Yuan, M. (2016, March). Achievement impacts from a K-12 mathematics technology scale-up statewide. Paper to be presented at the 27th International Conference of the

Society for Information Technology and Teacher Education (SITE). March 21-26, Savannah, GA.

9. Brasiel, S., Smith, S., & **Jeong, S.** (2015, November). An innovative statewide approach to bringing STEM focused education technology to teachers and students. Paper to be presented at the Annual Convention of the Association for Educational Communications and Technology (AECT). November 3-7, Indianapolis, IN.

8. Brasiel, S., Martin, T., & **Jeong, S.** (2015, June). Statewide pilot of digital mathematics technology for secondary Students. Paper to be presented at the annual conference of the International Society for Technology in Education (ISTE). June 28-July 1, Philadelphia, PA.

7. Martin, T., Brasiel, S., Janisiewicz, P., & **Jeong, S**. (2015, April). Capturing changes in children's computer programming ability while playing Scratch. Paper to be presented at the annual international conference of the National Association for Research in Science Teaching (NARST). April 11-14, Chicago, IL.

6. **Jeong, S.**, Martin,T., & Brasiel, S. (2015, April). Do educational technology products improve mathematics outcomes of students in Grade 7 and 8? Paper to be presented at the annual meeting of the American Educational Research Association (AERA). April 16-20, Chicago, IL.

5. **Jeong, S.**, Ames, C., Brasiel, S., & Martin, T. (2015, March). Improving mathematics outcomes with personalized Learning: A pilot for secondary students. Paper to be presented at the 26th international conference of the Society for Information Technology and Teacher Education (SITE). March 2-6, Las Vegas, NV.

4. Park, I., **Jeong, S.**, Shin, H. & Lee, S. (2011, November). The use of laptops in university classes: a qualitative study. Paper to be presented at the Annual Convention of the Association for Educational Communications and Technology (AECT). November 8-12, Jacksonville, FL.

3. Ko, Y., Lim, K., Sim, H., Kim, K., & **Jeong, S.** (2011, April). The effects of learners' microblogging activities with smartphones on the enhancement of social presence. Paper to be presented at the annual meeting of the American Educational Research Association (AERA), April 8–12, New Orleans, LA.

2. Ko, Y., **Jeong, S.**, Lim, K., Sim, H., & Kim, K. (2010, July). Analysis on the types and interactivities of educational applications in smartphones. Paper to be presented at the 8th International Conference for Media in Education (ICoME). July 14-16, Kumamoto, Japan.

1. **Jeong, S.,** Lim, K., Ko, Y. Sim, H., & Kim, K. (2010, May). The analysis of trends in smartphone applications for education and suggestions for improved educational use. Paper to be presented at the spring conference on Korean Association for Educational Information and Media (KAEIM). May 29, Cheongju, South Korea.

Symposiums

2. **Jeong, S.** (2018, April). Doctoral students' faculty and peer interaction patterns: Relationships to researcher self-efficacy and skill acquisition. Paper to be presented at the Utah State University Student Research Symposium (SRS). April 12, 2018. Logan, UT. *Received **Student Research Symposium Awards (Graduate Oral Presentation Winner)**

1. Feldon, D. F., Peugh, J., Maher, M. A., Roksa, J., & **Jeong, S.** (2016, April). Progressions of skill development in biology doctorates—Findings and ongoing analyses. Poster to be presented at the National Institute of General Medical Sciences (NIGMS) Symposium. April 11, 2016. Washington, D.C.

RESEARCH EXPERIENCE

06/2018 - present

Trajectories into early career research (PI: Dr. David Feldon), *National Science Foundation (NSF-1760894)*
My role: Research assistant
- Conducted literature review
- Helped write grant proposal

03/2016 - present

Progressions of skill development in biology doctorates (PI: Dr. David Feldon), *National Science Foundation (NSF-1431234)*
My role: Research assistant
- Conducted literature review on a range of areas, such as cognitive psychology, science education, higher education, and educational psychology
- Analyzed longitudinal and nested quantitative survey data using diverse statistical techniques, including structural equation modeling, mixture modeling, etc.
- Analyzed qualitative interview data using comparative content analysis and text mining tools
- Wrote conference and journal papers

10/2017 - 05/2018 **Effects of in-class quizzes and practices tests on college Algebra and Calculus students' study skills and academic performance**
(PI: Dr. Scott Smith)
My role: Co-investigator
- Conducted literature review on cognitive psychology and mathematics education
- Worked on IRB application
- Created Qualtrics surveys
- Managed data
- Conducted preliminary data analysis

11/2016 - 03/2017 **Cognitive load imposed by CTA-based videos** (PI: Dr. David Feldon)
My role: Research assistant
- Developed instruments assessing intervention (i.e., CTA-based videos) effects
- Conducted experiments with college students
- Conducted preliminary data analysis

06/2014 - 02/2016 **STEM Action Center technology assessment** (PI: Drs. Taylor Martin and Sarah Brasiel), *Utah STEM Action Center*
My role: Research assistant
- Conducted literature review on K-12 mathematics education, educational technology and teacher education
- Analyzed both qualitative and quantitative data using descriptive analyses
- Helped write final report
- Wrote conference and journal papers

06/2014 - 02/2016 **Macro data for micro learning: Developing FUN! for automated assessment of computational thinking in Scratch** (PI: Drs. Taylor Martin and Sarah Brasiel), *National Science Foundation (NSF-1319938)*
My role: Research assistant
- Conducted literature review on science education
- Wrote conference papers and book chapter

02/2011 - 04/2012 **The development of smart media-based content interoperability standards**
(PI: Dr. Keol Lim), *South Korean Ministry of Knowledge Economy (MKE)*
My role: Research assistant
- Helped manage project
- Conducted literature review on educational technology and teacher education
- Analyzed data using content analysis

03/2010 - 08/2010 **A study on the educational usage of micro blog** (PI: Dr. Keol Lim), *Hanbit ENI Corporation*
My role: Research assistant
- Helped manage project
- Wrote conference and journal papers
- Conducted literature review on educational technology
- Analyzed data using content analysis

05/2009 - 06/2010 **A study on technology-based future schools** (PI: Dr. Innwoo Park)
Korea Education and Research Information Service (KERIS)
My role: Research assistant
- Helped manage project
- Wrote final report
- Conducted literature review on educational technology and teacher education

TEACHING EXPERIENCE

01/2016 - 02/2016 **Teaching Assistant**
Course Title: Research and evaluation in instructional technology (Instructor: Dr. Sarah Brasiel), Department of Instructional Technology and Learning Sciences, Utah State University

03/2011 - 11/2012 **Mathematics Teacher**
Sue Private Educational Institute, Seoul, South Korea
Soongmoon High School, Seoul, South Korea
National High School of Traditional Arts, Seoul, South Korea
Miseong Middle School, Seoul, South Korea

03/2010- 08/2010 **Teaching Assistant**
Course Title: Distance education theory (Instructor: Dr. Keol Lim), Department of Education, Korea University, Seoul, South Korea

AWARDS AND HONORS

2018 - 2019 **CEHS Graduate Student Research Award ($2,350 for Dissertation)**
College of Education & Human Services, Utah State University

2018	**ITLS Tuition Scholarship ($1,000)** Department of Instructional Technology and Learning Sciences, Utah State University
2018	**Student Research Symposium Award (Graduate Oral Presentation Winner)** Office of Research and Graduate Studies, Utah State University
2015, 2017, 2018	**RGS Graduate Student Travel Award ($300)** Office of Research and Graduate Studies, Utah State University
2015, 2017, 2018	**ITLS Travel Award ($900)** Department of Instructional Technology and Learning Sciences, Utah State University
2014	**ITLS Academic Excellence Scholarship ($600)** Department of Instructional Technology and Learning Sciences, Utah State University
2010	**Brain Korea Scholarship** The Brain Korea 21 program (BK21), Department of Education, Korea University
2010	**General Scholarship for Graduate Students** Department of Education, Korea University

PROFESSIONAL MEMBERSHIP

American Educational Research Association (AERA)
Association for Education Communications and Technology (AECT)
Society for Information Technology and Teacher Education (SITE)
Association for the Study of Higher Education (ASHE)
American Psychological Association (APA)