EXAMINING LEARNERS' SELF-REGULATION PATTERNS WITHIN A LEARNING MANAGEMENT SYSTEM

by

Richard M. Hess
A Dissertation
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DEDICATION

For Mom, who inspired me from a young age to pursue education and remain steadfast.

For Dad, Robby, and Ryan, all of whom were most instrumental in my life.

For Angie, whose love and unconditional support made this possible, literally.

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They say it takes a village, and what an extraordinary village I am so fortunate to be part of…

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LIST OF ABBREVIATIONS

Self-Regulated Learning .... SRL
Learning Analytics .... LA
Learning Management System .... LMS
Motivated Strategies for Learners Questionnaire .... MSLQ
Course Signals .... CS
Massive Open Online Courses .... MOOC
Social Cognitive Theory .... SCT
Growth Mixture Modeling .... GMM

ABSTRACT

EXAMINING LEARNERS' SELF-REGULATION PATTERNS WITHIN A LEARNING MANAGEMENT SYSTEM

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The purpose of this study was to explore and analyze the utilization of learning analytics data produced by a learning management system as an indicator of learners' self-regulation. In the Spring of 2021, 258 learners at a four-year, mid-Atlantic university provided access to their learning management system data. Of those 258 learners, 86 completed the Motivated Strategies for Learners Questionnaire. Correlational analyses were utilized to examine learners' self-report self-regulation and their self-regulating behaviors within the learning management system. Relationships between learners' self-report self-regulation and learner's planning and regulating behaviors with the learning management system are consistent with Self-Regulation Theory. Additionally, a growth mixture modeling analysis was conducted to examine learners' self-regulated trajectories over the semester. Five trajectories were identified for the planning activities, four trajectories were identified for monitoring activities, and three trajectories were identified

for regulating activities. Lastly, multiple ANOVAs were conducted to compare academic achievement between the trajectories for planning, monitoring, and regulating behaviors. Learners who had higher levels of planning and monitoring activity also had higher levels of academic achievement.

CHAPTER ONE

Over the past several decades, self-regulated learning (SRL) has become one of the most prominent theories in educational psychology (Winne & Hadwin, 1998; Zimmerman, 1990; Zimmerman & Schunk, 2011). Most commonly, SRL refers to ways in which learners optimize their metacognition, motivation, and behavioral processes to complete a task in an educational environment (Zimmerman, 2000). Self-regulated learners are often referred to as active agents in their own learning process as they can control their learning through intentional behaviors and strategies to achieve academic goals (Zimmerman, 1990). Moreover, self-regulation skills can grow and develop over time through practice (Dweck & Master, 2008). The cultivation and growth of self-regulating skills are of great importance to learners to develop the skills necessary to overcome obstacles and succeed in the academic environment. Prior research demonstrates that SRL is a critical factor for learner success (Pintrich, 2000; Winne, 1997; Zimmerman, 2000; Zimmerman & Schunk, 2011). Specifically, learners who self-regulate experience a myriad of benefits such as higher academic achievement (Hakan, 2016; Vrugt & Oort, 2008), increased levels of learning (Young & Fry, 2008), enhanced levels of motivation and self-efficacy (Omrod, 2011), increased problem-solving abilities (Rosenzweig et al., 2011) and higher levels of engagement (Chapman, 2003; Smith et al., 2007).

Researchers and practitioners have expressed interest in SRL beyond the connection between SRL and learner success. One such area of interest is the ways in which SRL is measured (Araka et al., 2020; Winne, 2017). Traditionally, SRL has been viewed as a global ability or aptitude that remains unchanged over time and has been measured as such with a variety of methods such as self-report questionnaires and structured interviews. More recently, scholars have argued that SRL is best viewed as a dynamic construct that occurs during specific events in time within a particular context. As a result, a growing number of methods have emerged to measure SRL as an event such as think-aloud protocols, error-detection tasks, and trace methodology.

Although a multitude of measurement methods have arisen to measure SRL both as an aptitude and event, researchers have identified a need to further examine the data that is produced via the current set of measurement methods (Winne, 2017; Winne & Perry, 2000). Specifically, questions have arisen regarding the objectivity of data that is being produced as most of the current methods are intrusive in nature and may prompt learners to respond in a way that does not truly reflect learners' SRL behaviors and strategies (Roll & Winne, 2015). To fill this gap, researchers have leveraged the rise of technological advances in educational contexts that have the capabilities of producing more objective data that is unimpeded by researchers (Winne, 2017). One such data source, learning analytics (LA) data, has grown in popularity for researchers measuring SRL as it contains several advantages to remedy current measurement concerns as well as enhance data produced for SRL measurement. However, the current set of studies that utilize LA data for SRL measurement contain many limitations. As such, there is a need to conduct further research to fully actualize LA's potential to indicate learners' SRL. Specifically, there is a need to utilize an LA data source that is ubiquitous in the educational environment, tie SRL and LA data more tightly together, and analyze learner behavior at a more granular level.

SRL can also be situated within student development theory found within the higher education and student affairs literature. For this study, the author employed Patton's et al. (2016) framework. Their text presented an overview of student development theory, with specific emphasis on understanding, utilizing, and translating theory to practice. Their framework organized student development theory into social identity; psychosocial, cognitive-structural, and integrative development; and moral and self-authorship.

Whereas there are several possibilities to situate SRL within student development theory, it seems the most relevant is within cognitive structural development, specifically Perry's (1999) framework. Perry emphasized that as learners grow and develop throughout their college experiences, they pass through several different positions of epistemological growth. These positions demonstrate how learners come to know rather than what they know. At the beginning of college, most learners are dualist thinkers in which their acquisition of knowledge comes from an authority figure, such as a professor. As learners proceed through their collegiate journey, their respective academic and co-curricular experiences foster cognitive dissonance, which aids in learners' development towards becoming a relativist thinker. On their way to relativism, learners pass through multiplicity, which states that everyone has a right to their own opinions and arguments have equal value. Relativism is hallmarked by belief in one's own values, respect towards other values, but a desire to learn how some beliefs hold more evidence than others. In commitment, learners understand that uncertainty is part of life. In this stage, learners leverage prior experience and weigh evidence gathered from external sources to arrive at conclusions.

Connections can be made between SRL and Perry's framework. First, self-regulation is a cyclical process whereby learners engage in strategies and behaviors while completing a task and reflect on performance after the task to determine which strategies and behaviors were most effective. This connects to Perry's work in the sense that for learners to transition from dualism towards relativism, they must possess the ability to evaluate the merits of something for themselves. Thus, the reflective and evaluative processes of self-regulation is critical to reach Perry's higher development stages. Second, learners' engagement with SRL could facilitate the cognitive dissonance necessary to aid learners' transition from dualism to relativism. A core tenant of learners' who self-regulate is their engagement with metacognition, which has the potential to foster cognitive dissonance. Learners who experience cognitive dissonance can enhance the cognitive complexity necessary to transition from Perry's lower stages to advanced stages, if they acknowledge internal reasons for the dissonance (i.e., weighing evidence) rather than blaming others (Taylor & Baker, 2019).

Self-Regulated Learning

Self-regulated learning (SRL) occurs when learners engage in a variety of interrelated subprocesses such as goal planning, task engagement, and reflection, to control and monitor their cognition, motivation, and behavior while engaging in a task (Bandura, 1986). Most scholars suggest that SRL is comprised of the interrelated subprocesses that occur in a cyclical manner based on three components: metacognition, motivation, and behavior (Pintrich, 2000; Zimmerman, 2000). The metacognitive component is referred to as the process of a learner thinking about their own thinking (Flavell, 1979). Two key SRL skills within the metacognitive domain are metacognitive monitoring, which is a learner's ability to examine and assess their thought process, and metacognitive control, which is a learner's ability to exert influence over their thought process (Winne, 1995). The motivational component of SRL is frequently defined as the internal drive or initiation that a learner possesses to direct behavior towards goal obtainment (Boekarts, 2010; Cleary, 2011). Lastly, the behavioral process of SRL is defined as a learners' understanding of the environment and their engagement in conduct that is conducive to goal achievement (Henderson, 1986). Learners who are behaviorally engaged in their learning typically try to optimize learning through structuring the learning environment. This is most frequently accomplished by engaging in behaviors such as soliciting feedback from an instructor or peers as well as asking clarifying questions when necessary (Zimmerman, 1990).

The three components of SRL as described above have served as the underpinnings for several SRL models including Winne and Hadwin's Four-stage Model of SRL (1998), Zimmerman's Social-cognitive Model of Self-regulation (1989, 1990, 2000), Boekaerts' Model of Adaptable learning (1996), Efkildes' Metacognitive and Affective Model of SRL (2011), and Pintrich's General Framework for SRL (2000). Each of these models contains, in some form, the three basic components of SRL; however, each model prioritizes each component differently.

As indicated earlier, scholars have maintained an interest in other aspects of SRL aside from the benefits of learners who self-regulate and the various components and models of SRL. Most notably, SRL measurement has garnered much attention in the research literature as a significant amount of empirical research has examined the various methods to measure SRL (Boekaerts et al., 2000; Rovers et al., 2019; Winne & Perry, 2000). Traditionally, a wide array of measurement methods has been employed such as self-report questionnaires (Pintrich, 2000; Weinstein & Palmer, 2002), structured interviews (Zimmerman & Martinez-Pons, 1986), think-aloud protocols (Azevdo et al., 2007; Cleary & Zimmerman, 2001; Kistsantis & Zimmerman, 2002; Perry & Winne, 2006), error detection tasks (Baker & Cerro, 2000), and trace methodology (Winne, 2017; Winne & Perry, 2000). Each measurement method can be categorized into either aptitude measures or event measures (Boekaerts et al., 2000; Winne & Perry, 2000).

Although similar, a great deal of variability exists between aptitude and event measures. Measures that capture SRL as an aptitude consider personality traits and characteristics as static and predictive of future behavior (Winne & Perry, 2000). The measurement methods commonly used to capture SRL as an aptitude include self-report questionnaires and structured interviews. Self-report questionnaires, which ask learners to reflect on their experiences, remain one of the most popular methods to measure SRL (Pintrich & De Groot, 1990). Additionally, structured interviews, which typically employ a series of open-ended questions, are another common method to measure SRL. The benefit of utilizing aptitude measures for SRL is that they are widely accessible and accepted within the research community. However, there are frequently cited criticisms of aptitude measures such as their intrusive nature and that they lack the ability to produce more objective data. Oftentimes, the researcher interjects during a learner's engagement with a task and could prompt learners to report or engage with an SRL behavior or strategy that they may have not otherwise (Winne & Perry, 2000).

In response to the limitations associated with aptitude measures, scholars developed measurement methods to capture SRL as an event. Event measures consider engagement with SRL as a snapshot in time that represents learner behavior within a moment and can evolve over time (Winne & Perry, 2000). Additionally, capturing SRL as an event considers learners' behavior as dynamic and in the context of the specific environment. Measurement methods that have been utilized to capture SRL as an event include think-aloud protocols, error detection tasks, and trace methodology (Puustinen & Pulkkinen, 2001).

Capturing SRL as an event has increased in popularity, particularly over the past decade (Winne & Perry, 2000). A traditional method to measure SRL as an event is via a think-aloud protocol (Baker & Cerro, 2000). During a think-aloud protocol, a learners articulate their thoughts about their own cognition while engaging in a task. The researcher records and analyzes the learner's articulation to examine for evidence of SRL behavior (Azevedo et al., 2007). Contained within think-aloud protocols is microanalysis, which is designed to elicit a specific attitude, behavior, or SRL processes (Cleary, 2011). Another, less common, method to measure SRL as an event is error detection tasks.

During error detection tasks, the researcher incorporates intentional errors in a task that the learner tries to identify and make decisions on how to handle (Baker & Cerro, 2000. More recently, trace methodology has emerged as a popular method to measure SRL as an event (Winne, 2017). Trace methodology examines traces of learner behavior, oftentimes in the form of cognition that learners produce while engaging in a task. As an example, if a learner is reading text and decides to highlight a passage, then the highlighted text would be considered a behavioral trace as the learner has deemed that part of the text to be important. Although event measures aimed to fill the limitations that have arisen from aptitude measures, questions remain about the intrusiveness and objectivity of data (Roll & Winne, 2015).

Recently, there have been calls from scholars to turn to technological advances to address the questions about the intrusiveness and lack of data objectivity that the current set of SRL measurement methods produce (Baker et al., 2020; Winne, 2017). As a result, there has been a growing body of literature that has attempted to utilize learning analytics (LA) data for SRL measurement, as the mechanisms that produce LA data can objectively track learner behavior in a non-intrusive manner (Gasevic et al., 2014; Gewerc et al., 2016; Greene et al., 2011a).

Learning Analytics

Learning analytics (LA) has emerged as one of the most important trends in higher education over the past decade (Lane & Finsel, 2014). Most commonly, LA is defined as the routinized collection, analysis, and utilization of data about learners in their environment to improve learning (Siemens, 2013). As campuses become more infused with technology capabilities, the amount of LA data produced increases as well. Currently, the most common forms of gathering LA data have been through student identification cards and learning management systems (LMS) such as Blackboard or Moodle. Student identification cards have been used to trace learners' behavior and patterns (Ram et al., 2015). For instance, each time a learner swipes their identification card at a location on campus, their activity is logged within the institution, most commonly with information technology services. Locations for learner swipes include residence halls, rooms, libraries, recreational facilities, and other services. Thus, researchers can track learner's activities and understand patterns in terms of involvement on campus that can be used to improve learner outcomes such as retention (Ram et al., 2015).

Additionally, an LMS has been another source of rich LA data. An LMS is most defined as software that serves as an online platform for the instructor to share content with learners such as the course syllabus, lecture notes, and practice assessments (Sclater, 2017). Most often, an LMS is a complement to face-to-face learning, but can serve as the main vehicle for instruction for an online course (Alias & Zainuddin, 2005). Within the LMS environment, the learner interacts with features based on the design of the course. Examples of learner interactions include accessing course content, watching lecture videos, posting on a discussion board, or submitting assignments. A unique feature of the LMS is its capability to log and store learner activity. Every time a learner "clicks," or interacts, within the LMS platform, the action is logged within the software. Thus, researchers can gain the appropriate permissions to access the log files of learners within a course. These log files can be analyzed to gain insight into learner behavior that can potentially enhance learner outcomes on campus (Baker & Inventado, 2014).

Prior research demonstrates that LA has the potential to enhance a variety of practices and outcomes on campus (Sclater, 2017; Siemens & Baker, 2012). Though LA data and practices are still nascent within institutions, previous studies highlight that LA data has the potential to improve teaching and learning (Dietz-Uhler & Hurn, 2013), academic achievement (Arnold & Pistilli, 2012), retention and graduation rates (de Freitas et al., 2014) as well as operational function and business intelligence on campus (Lane & Finsel, 2014). Of relevance to the current study is LA's application to enhance learning, specifically in the utilization of LA data to ascertain learning behavior within the virtual environment.

Utilizing LA Data for SRL Measurement

Due to LA data's focus on gathering learner behavior in the learner environment, there have been several calls for scholars to utilize LA data for SRL measurement (Baker et al., 2020; Winne, 2017). As such, researchers have begun to utilize LA data for SRL measurement as there are many advantages associated with LA data (Gewerc, 2016; Shell & Soh, 2013; Soffer & Cohen, 2019). One such advantage of LA data is that it offers direct access to a learner's behavior or cognition without outside interference from a researcher or instructor, thus limiting intrusiveness from outside influence on learner behavior. Additionally, LA data captures learner activity in real-time while the learner is engaged in a task and most often without the learner's knowledge that their activity is being logged (Lang et al., 2017). Thus, a learner's engagement with SRL measured by

LA data is unimpeded by researchers, which is markedly different from other SRL measurement methods.

Another advantage of LA data is that it contains several beneficial properties such as volume, velocity, and value that make it conducive to SRL measurement (Lane, 2014). Volume commonly refers to the amount of data produced. LA data has the potential to produce a great deal of data. Velocity, or the speed that data is produced, is a strength of LA as oftentimes learners access a course LMS multiple times a single day or week (Sclater, 2017). Lastly, value refers to the utility of data— which LA data possesses— specifically LMS data, as the data schema for wrangling and interpreting data is available for most LMS.

Previous research on employing LA data from SRL measurement reveals three key considerations with each possessing the need for further research. The first consideration is the mechanisms in which LA data is collected. A review of the extant studies that use LA data for SRL measurement reveals the overwhelming majority of studies utilized data from Massive Open Online Courses (MOOCs; Wong et al., 2019). A smaller subset of studies utilized data gleaned from specialty designed LA tools such as nStudy (Winne et al., 2017). Lastly, an even smaller set utilized data from an LMS (Lim 2016; You, 2016). Recently, there have been calls by scholars to move away from the use of LA data for SRL measurement from MOOCs and specialty designed LA tools and instead utilize an LMS, which serves a more functional source of LA data and are ubiquitous on campus (Baker et al., 2020).

The second consideration related to the utilization of LA data for SRL measurement is the previous techniques utilized to analyze LA data. Overwhelmingly, prior studies have utilized some type of clustering or classification to analyze LA data (Bozpolat, 2016; Li et al., 2020; Romero & Ventura, 2010). Clustering studies most oftentimes sought to categorize learner behavior (Peach et al., 2019). Within the classification studies, many utilized multiple regression, which is often used to predict outcomes such as academic achievement or persistence (Bozpolat, 2016; Kuo et al., 2014). Though prior studies demonstrated some success with the current set of techniques being applied to analyze LA data for SRL measurement, there is a need to tie LA data and SRL data more tightly together, specifically in examining the relationship between data collected from traditional SRL methods such as self-report questionnaires and LA data.

The third consideration is the level of granularity that previous studies examine. Most of the previous studies focus on utilizing LA data to understand learner's behavior at either one or two points within the semester, most commonly at the mid and/or endpoint of the semester (Soffer & Cohen, 2018; Zacharis, 2015). Though LA data has been utilized to understand SRL behaviors at one or two points in the semester, part of the promise of LA data is that due to its availability in real-time, there is potential to increase frequency to understand learners' trajectories of self-regulating behavior over time.

Research Problem

Although LA data is becoming increasingly popular as a data source to measure SRL, key gaps exist in the literature that must be addressed to fully actualize the potential of LA data as an indication of learners' self-regulation. First, most studies utilize either MOOC data or data from a specialty LA tool while a small minority of studies utilize data from an LMS. This is problematic because MOOCs and specialty LA tools are limited in their accessibility and functionality. Though there is a myriad of MOOC classes available, the number of MOOCs is significantly less than the number of courses on college campuses that have an LMS component (Sclater, 2017). Similarly, a small fraction of courses use specialty LA tools and those are typically only utilized by researchers who are interested in studying SRL (Winne et al., 2017). In addition, while MOOC data is oftentimes open access, which makes it an attractive option for researchers, the type of LA data that is captured within the MOOC is limited and can be difficult to interpret or understand (Wong et al., 2019). Likewise, specially designed LA tools are often pre-programmed with a specific number of functions which limits the amount or type of data that the tool can produce. In contrast, LMS is used widely across college campuses and is known to produce a rich data set due to the multitude of functions that the learner can perform within the LMS. Additionally, LMS is known to produce and store a vast amount of data on learner behavior that can be analyzed for insight (Sclater, 2017).

Another core issue concerns previous methods of analysis. As indicated earlier, most studies that utilized LA data for SRL measurement employed either clustering or classification for analysis. However, one key issue found within the classification studies is the lack of correlation between traditional methods used to gather SRL data (e.g., self-report questionnaires) and LA data (Cicchinelli et al., 2018; Yamada et al., 2017). This is problematic because previous studies have not demonstrated that data collected from traditional SRL methods can be highly correlated with LA data. Thus, a lack of robust correlation between SRL data and LA data could call into question the applicability of LA data to indicate learners' self-regulation.

Lastly, the level of granularity is a key issue with the current set of studies. As demonstrated earlier, the majority of studies only measure SRL behaviors and strategies at one or two points during the semester (You, 2016). However, one of the benefits of LA data, particularly gathered by an LMS, is the availability of data in real-time. Thus, the utilization of LA enables a researcher to measure SRL multiple times— or even between in each lesson—during the semester as opposed to simply once or twice. Thus, it is important to understand engagement patterns at a more granular level to determine if behavioral patterns change or alter throughout the semester as opposed to simply understand learner behavior at the mid-point and/or end of the semester. Understanding behavioral patterns or trajectories throughout the semester could enable instructors and practitioners to design courses more intentionally that could ultimately enhance learner outcomes.

Purpose

The purpose of this study is to utilize LA data from an LMS to examine relationships between learners' self-report self-regulation and LMS data, understand learners' trajectories within the LMS over the course of the semester and examine the effect that academic achievement had on learners' trajectories. Though this study is exploratory in nature, the aim is to advance understanding of the relationship between LMS data and SRL measurement.

In addition, the study seeks to fill three identified gaps. First, this study considered the utility of LA data from an LMS, which is widely utilized across college campuses and contains the functionality to produce a rich data set. Second, the study aimed to tie data collected through a traditional SRL method (self-report questionnaire) and LA data from and LMS more tightly together. This was accomplished by gathering a myriad of SRL and LA data and conducting statistical tests examining relationships between the data sets. Additionally, the current study sought to examine the granularity of learner behavior of the semester. This was accomplished by understanding learners' trajectories over time through the utilization of LA data from 13 lessons across the semester. Lastly, the study examined if academic achievement had an effect on learner's trajectories across key SRL domains.

CHAPTER TWO

This chapter provides an in-depth review of self-regulated learning (SRL), learning analytics (LA), and how SRL and LA have been previously linked together, empirically and theoretically. First, a detailed review of SRL wherein commonly used definitions and components of SRL are described. Next, prominent models and theories of SRL are overviewed. This section concludes by reviewing common methods for measuring learners' SRL as well as the strengths and limitations of each approach. The second section provides an in-depth review of LA. First, a discussion on commonly used definitions of LA is presented. Next, common data sources that are used to collect LA data and the various uses of LA data are reviewed. Finally, an examination is presented of how SRL and LA have been previously examined in the literature across three considerations: data sources, methods of analysis, and level of granularity. Within each consideration, previous empirical work is reviewed as well as a presentation of gaps that have been uncovered in the review. The chapter concludes with a preview of the current study, with specific emphasis on the gaps that will be addressed.

Self-Regulated Learning

SRL is the theoretical framework of this study. Included in this overview and discussion are the historical underpinnings of SRL, the components of SRL, their associated definitions as well as prior empirical work for each component, the main SRL theories, and the multitude of ways in which learners' SRL has been previously measured.

Historical Underpinnings of SRL

The origins of self-regulatory processes as it relates to learning can be traced back to research on behaviorism from prominent psychologists such as Watson (1919) and Skinner (1974). The foundational works on behaviorism reinforce that human behavior can be learned via conditioning, which is based on a learner's engagement with their environment. Therefore, learner behavior is an acquired response to environmental stimuli. Building on the work of behaviorism, Bandura (1986) developed the Social Cognitive Theory (SCT) based on observing children. SCT proposes a triadic relationship, known as reciprocal determinism, which is the dynamic interplay between person, environment, and behaviors such as cognition and attitudes. In this sense, SCT states that an individual achieves sustainable and goal-oriented behavior by regulating behavior through control and reinforcement. Self-efficacy is another critical element of SCT, which is defined as an individual's concept of their own ability and behaviors to achieve a goal (Bandura, 1986). Thus, Bandura's theory marked a significant development in advancing the theoretical understanding of self-regulatory processes by bringing together behavior and cognitive elements, which in turn, laid the foundation for SRL.

SRL Defined

Building on the foundational elements as described by Bandura (1986, 1991), SRL has emerged as a critical and well-studied concept in the educational psychology literature over the past several decades (Pintrich, 2000; Winne & Perry, 2000; Zimmerman, 1990). The origin of SRL, in its current form, has oftentimes been referred to as one of the most significant and differentiating qualities of humankind (Zimmerman, 2000). SRL can be traced back to the 1980s, when researchers examined the effect of individual utilization of self-regulatory processes such as goal setting, monitoring, or self-instruction (Zimmerman, 2008). Though the earliest work of SRL examined behaviors— cognition, which is commonly defined as the process of acquiring knowledge, was also heavily emphasized. As the field developed, most scholars agreed that the central principles of SRL included the ability of a learner to understand and exert control within the learning environment (Harris & Graham, 1999; Pintrich, 2000; Schunk, 1990). Additionally, scholars agreed that SRL is a self-directive process in which a learner engages in behaviors that convert thoughts and capacities into action (Zimmerman, 2002, 2013). Learners who demonstrate SRL behaviors and strategies can develop a cognitive picture, assess cognitive demands, understand task conditions, leverage prior knowledge and experiences, set goals, adopt relevant strategies, and monitor progress towards goal completion and adjust as necessary (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2008). Though competing definitions of SRL were posited, the most common and prevailing definition of SRL stated that learners who self-regulate are “metacognitively, motivationally, and behaviorally active participants in their own learning process” (Zimmerman, 2013, p. 137). As these are the three most critical components of SRL, they are reviewed in detail below.

Metacognition. The earliest conceptualization of metacognition emerged in the educational psychology literature in the 1970s and was originally termed metacognitive monitoring, which is defined as the learner’s development of their thinking or the monitoring of one's own cognition (Flavell, 1971). In other words, metacognition is the process of a learner thinking about their own thinking. Flavell (1971) suggested that metacognition includes four main components: metacognitive knowledge, metacognitive experience, metacognitive goals, and metacognitive strategies (Flavell, 1979, 1986, 1992). Metacognitive knowledge is the extent to which a learner understands their capabilities and possesses the ability to assess the difficulty of a task as well as the ability to accomplish a task (Flavell, 1979). Metacognitive experience is the process in which a learner accrues knowledge through experiences and applies knowledge from previous experiences to accomplish a task (Flavell, 1979). Metacognitive goals are the outcomes the learner is expected to achieve because of cognitive exertion (Flavell, 1986). Lastly, metacognitive strategies are employed to monitor and evaluate progress towards task achievement (Flavell, 1992). According to Flavell, the interaction of these four components, particularly, metacognitive experiences and metacognitive strategies, determine the growth of a learner's metacognitive skills (Flavell, 1992).

Several other scholars have contributed to the conceptual understanding of metacognition (Baker & Brown, 1984; Moshman, 1982). Most notably, and important to metacognition as it relates to SRL, is Baker and Brown's (1984) work. They focused on monitoring and self-regulation as a function of metacognition. Specifically, they stated that monitoring is comprised of learner knowledge about cognitive processes and that self-regulating entails learners' understanding of the goal as well as planning, implementing, and evaluating metacognitive strategies. Lastly, their work focuses on strategic control, which is defined as a learner's ability to selectively assert cognitive resources, such as recall or retrieval, at times, when necessary, to obtain the desired outcome. Collectively, the works of Flavell (1985, 1992) and Baker and Brown (1984), serve as the foundational elements to the way in which metacognition has been incorporated into SRL.

As the field of SRL developed, the most influential scholars on metacognition were Zimmerman (1989, 1995) and Winne (1995, 1996). Though, most of the early incorporations of metacognition within SRL were based primarily on elements described by Flavell (1992) and Baker and Brown (1984). In Zimmerman's Social Cognitive View of SRL, he referred to metacognition as "decision-making processes that regulate the selection and the use of various forms of knowledge" (Zimmerman, 1989, p. 329). Included in Zimmerman's model are three key phases of metacognition: the forethought phase, the performance phase, and the reflective phase (Zimmerman, 2002). In the forethought phase, metacognitive strategies such as learner planning and organizing are strategically employed by the learner. In this stage, learners try to forecast and envision goal obtainment, which in turn, increases self-motivation. Additionally, engagement with the forethought phase enables learners to develop a positive attitude towards their own learning and goal obtainment.

The performance phase involves learners monitoring and evaluating the progress of their learning and goal obtainment. Invoking monitoring activities enables learners to exert more control over their learning experience, which equips learners with a greater sense of responsibility in their learning. In addition, successful engagement with metacognitive monitoring within the performance phase tends to lead learners to successful goal obtainment. Lastly, the self-reflective phase entails learners analyzing the strategies that were successful and unsuccessful towards goal obtainment. In turn, learners leverage that information for future engagement in similar tasks. According to Zimmerman (2002), widespread engagement in these phases of metacognition promotes learner autonomy and self-efficacy; however, Zimmerman was not the only scholar to contribute to the incorporation and development of metacognition within SRL.

Winne (1995, 1996) is another prominent SRL theorist who influenced the development of metacognition in SRL. Winne (1996) suggested that metacognition combines knowledge objects and cognitive operations to form one construct. Knowledge objects are comprised of two informational levels: the object level and the meta-level. At the object level, information is derived from a person's external world experience and inner cognitive world. At the meta-level, information is derived from the object level. Similarly, cognitive operations are comprised of two kinds of operations: metacognitive monitoring and metacognitive control. Metacognitive monitoring refers to an individual's ability to examine their own thought process and assess one own's existing knowledge. Metacognitive control is the ability of an individual to exert influence over one's thought process and memory retrieval. Thus, Winne's (1996) conceptualization of metacognition is predicated on the learner's ability to employ cognitive operations such as metacognitive monitoring and metacognitive control. In juxtaposition, Zimmerman's (2002) conceptualization of metacognition involves processes, as opposed to operations as described by Winne, that can be understood through the three identified phases: forethought, performance, and reflective phases.

Most current models of SRL (discussed below) contain a component of metacognition as described by the works of Zimmerman (1989, 1995) and Winne (1995, 1996). Additionally, there has been much previous research conducted on metacognition, particularly on the benefits of metacognition and the elements that comprise metacognition, specifically metacognitive monitoring and metacognitive control, which is explored in more depth in the next section.

Prior Research on Metacognition within SRL. Learners who implement metacognitive strategies are shown to experience a myriad of benefits (Fink, 2013; Winston et al., 2010). Prior research highlighted the benefits to learners who engaged in metacognition included obtaining higher levels of academic achievement (Hakan, 2016; Justice & Dornan, 2001; Peverly et al., 2003; Vrugt & Oort, 2008), enhanced learning (Young & Fry, 2008), higher levels of self-regulating behaviors (Narciss et al., 2007; Schunk & Zimmerman, 1997), increased motivation and self-efficacy (Omrod, 2011; Wolters & Pintrich, 1998), engagement (Chapman, 2003; Smith et al., 2007), and enhanced problem-solving abilities (Rosenzwejg, 2011).

Previous research highlighted individuals who engaged in metacognitive strategies and skills are shown to have higher levels of academic achievement (Hakan, 2016; Justice & Dornan, 2001; Peverly et al., 2003; Vrugt & Oort, 2008). In their study, Peverly et al. (2003) examined college learners' metacognitive SRL skills and attempted to improve their metacognitive SRL skills by offering additional study time before test-taking. Their study also examined background knowledge and note-taking strategies. Their sample consisted of 88 undergraduate learners enrolled in an introductory psychology class. Participants were instructed to predict their performance on exam questions. Next, participants were asked to read a passage in which half were asked to take notes and the other half were instructed not to take notes. Afterward, learners were instructed to write a summary of the passage they previously read. Results indicated that participants did not display evidence of metacognitive SRL skills, specifically in estimating their preparedness for test taking or how well they performed on the test. Additionally, learners' prediction of their grades was unrelated to the amount of time spent taking notes as well as the content of notes. Though, their study found that learners who implemented notetaking strategies and possessed background knowledge performed better on tests.

Another common benefit of learners who exhibit metacognition is higher levels of engagement. Although many definitions of engagement exist, engagement, as it relates to metacognition, focuses on the cognitive, behavioral, and affective elements of involvement in learning tasks (Skinner & Belmont, 1993). Smith et al. (2007) investigated the utilization of cognitive, affective, and metacognitive strategies employed by high school learners to increase learner engagement and performance. Their study employed structured journal questions over a 12-week timeframe on a sample of 86 first-year high school learners in a world history class. Results demonstrated that learners who engaged in course content by responding to metacognitive and affective questions on the structured journal questionnaire retained more course material as measured by final grade in juxtaposition to those learners who did not engage in course content.

In addition to the benefits of those who engage in metacognition, prior research has been conducted on specific aspects of metacognition, namely metacognitive monitoring and metacognitive control as described above by Winne (1995, 1996). Butler and Winne (1995) contend that metacognitive monitoring is a key element in the development of learner's SRL skills. Additionally, learners who engage and practice metacognitive monitoring typically demonstrate academic improvement and higher levels of achievement. As an example, Wagener (2016) studied the effects of a metacognitive intervention, where learners in an experimental group completed a metacognitive monitoring worksheet each week. An experimental design was employed on a sample of 118 learners in which 30 learners were the control group, 36 learners were in the first experimental group, and 43 learners were in the second experimental group. The first experimental group was exposed to metacognitive monitoring training from the beginning of the semester; the second experimental group was exposed to metacognitive monitoring training only during the second half of the semester; the control group was not exposed to metacognitive monitoring training. Results demonstrated that learners who were involved in metacognitive monitoring training at either the beginning of the semester or the middle of the semester had higher grades than those learners who did not engage in metacognitive monitoring training at any point in the semester.

Another specific aspect of metacognition that has garnered attention in the research literature is metacognitive control, which is the ability of an individual to exert influence over one's thought process and memory retrieval (Winne, 1995). Learners who practice and implement metacognitive control are shown to have better outcomes in college (Amzil, 2014; Son, 2004; Son & Sethi, 2006). For example, Son (2004) examined metacognitive learner control of spacing strategies during study. Spacing is defined as a study strategy in which a learner studies concepts over an extended timeframe with several repetitions or review of concepts. Spacing is often juxtaposed with cramming, which is defined as a learner studying concepts in a limited timeframe with restricted repetitions. In her study, Son utilized a sample of 32 learners from an introductory psychology course that was presented with a list of word-synonym pairs for a later exam. Next, learners were asked to make a judgment on if they would "study now," study later," in which "study now" represented a cramming strategy and "study later" represented a spacing strategy. Results demonstrated that learners implemented a spacing strategy when concepts seemed easy to grasp. In contrast, learners that judged concepts difficult to grasp employed more cramming strategies. Lastly, learners who engaged in the metacognitive control strategy of spacing earned higher final test scores than their learner counterparts who engaged in a cramming strategy.

In review, the earliest conceptions of metacognition in SRL stemmed mostly from the work of Flavell (1985, 1992). Zimmerman (1989, 1995) and Winne (1995, 1996). They were the earliest SRL theorists to incorporate metacognition within SRL. Prior empirical work demonstrated the benefits to learners who engaged in metacognitive behaviors and strategies. Most notably, these benefits included higher levels of academic achievement (Hakan, 2016; Justice & Dornan, 2001; Peverly et al., 2003; Vrugt & Oort, 2008) and higher levels of learning (Young & Fry, 2008). Much prior empirical work demonstrates metacognition is a central component of SRL. However, another related, central component of SRL, that oftentimes has been studied in unison with metacognition, is motivation, which is addressed in detail in the next section.

Motivation. As described above, motivation is a core tenant of SRL (Zimmerman, 1989). Though variability exists, a common general definition for motivation within the context of SRL is the extent a learner possesses initiation and wherewithal towards goal-directed behavior (Boekaerts, 2010; Cleary, 2011; Pintrich, 2000; Zimmerman & Schunk, 2011). Since SRL involves learner's attentiveness to the learning process, analyzing and evaluating alternatives, and varying levels of effort, it is critical to understand motivation as it relates to SRL (Zimmerman & Schunk, 2011). Most commonly, there are three elements to motivation for a learner (Rheinberg et al., 2000). First is the value component, in which the learner has beliefs regarding the importance and the value of a task. Second is the expectancy component, which is the learner's belief about their own skill and ability to accomplish a task. Third is the affective component which is a learner's feeling about their emotional state regarding their task. Of note, one of the most common aspects of the expectancy component, and most well researched in the SRL literature, is self-efficacy. Bandura (1986) defined self-efficacy as a learner's belief about their own ability. In an SRL context, a learner's self-efficacy most often is related to SRL processes such as goal setting, self-monitoring, and self-reflection (Zimmerman & Kitsantas, 2005).

Prior Research on Motivation within SRL. Most of the prior research on motivation within SRL focuses on motivational constructs such as attributions and achievement goals as well as motivational components. Additionally, Zimmerman and

Schunk (2008) highlighted five key insights based on prior research on the importance of motivation in the SRL process. First, prior research demonstrated that learners who are highly motivated tend to have more favorable outcomes and are more attentive to their own learning in juxtaposition to less motivated learners (Bouffard-Bouchard et al., 1991). Second, learners who possessed a greater degree of motivation when choosing a task tend to complete that task in contrast to unmotivated learners (Zimmerman & Kitsantas, 1999). Third, more highly motivated learners had a higher propensity to mastery difficult tasks (Schunk & Hanson, 1985). Fourth, learners who demonstrated motivation to persist in goal obtainment are more likely than their less motivated counterparts to persist (Schunk, 1984). Lastly, highly motivated learners demonstrated greater satisfaction with the learning process than their less motivated counterparts (Zimmerman & Schunk, 2008).

Prior research has focused on several key motivational constructs as they relate to SRL. Most notably, researchers have examined the relationship between goal orientation and SRL (Ames, 1992; Pintrich, 2000), interests and SRL (Hidi & Renniger, 2006; Pintrich & Schunk, 2002), outcome belief and SRL (Bandura, 1997; Shell et al., 1989), task values and SRL (Eccles et al., 1998; Pintrich & De Groot, 1990), volition and SRL (Corno, 1993; Oettingen et al., 2000), intrinsic motivation and SRL (Vansteenkiste et al., 2004), casual attributions and SRL (Weiner, 1992; Schunk & Gunn, 1986) and goal setting and SRL (Boekaerts & Niemivirta, 2000; Locke & Latham, 2002). As an example, prior research between goal orientation and SRL demonstrated that learners are motivated by their capabilities of goal obtainment (Dweck & Master, 2008). Learners were more likely to be motivated to orient towards a goal if they perceive certain abilities, such as knowledge about the task, to be high as well. Additionally, learners with a learning goal orientation tended to recover from poor performance more quickly than learners who possessed a performance goal orientation (Grant & Dweck, 2003).

Lastly, self-efficacy has been one of the most well-studied concepts as a motivational component of SRL (Zimmerman, 2008). Previous studies on self-efficacy within SRL demonstrated that learners who felt more confident in their ability were more likely to engage in SRL behaviors and strategies in juxtaposition to those learners who did not feel as confident in their ability (Pintrich & De Groot, 1990; Wolters & Pintrich, 1998). Other studies confirm that self-efficacy is a strong predictor of engagement with SRL strategies (Pajares, 2008; Zimmerman, 2000).

Another strand of self-efficacy research is the population and context being studied (Crede & Phillips, 2011; Usher & Pajares, 2006). As an example, Crede and Phillips (2011) found that college learners demonstrated positive association between self-efficacy and memorization mainly because memorization was evidence of deeper SRL strategies. As another example, Usher and Pajares (2006) found that elementary school learners demonstrated a higher level of engagement with self-efficacy for SRL than their middle and high-school counterparts. Though their study emphasized that learner behavior, such as the SRL strategy that the learner engaged with, was a key factor to consider between different populations.

In review, motivation in an SRL context contains three key elements: value, expectancy, and affect. A multitude of previous research has been conducted on a variety of different constructs as they relate to motivation and SRL, though most commonly with self-efficacy. Related to motivation and metacognition are behaviors in which learners engage, which is the third core component of SRL and reviewed in more detail below.

Behavioral Process. The behavioral process involves learners' understanding of their environment. Self-regulated learners who exhibit SRL skills pertaining to behavioral processes optimize learning by selecting, structuring, and creating the ideal learning environment (Henderson, 1986; Wang & Perverly, 1986; Zimmerman, 1990, 2005, 2013). This is achieved by engaging in behaviors that promote learning. Examples of those include soliciting feedback from peers or instructors, understanding the learning modality in which they best learn (i.e., face-to-face, or online), and employing strategies, such as peer review, that foster greater levels of achievement.

Previous Research on Behavioral Process within SRL. Previous research suggested that the behavioral component of SRL is tightly coupled to both the metacognitive and motivational components. Much of the empirical work on the behavioral component examined evidence of behavioral traces of SRL (Hadwin et al., 2001; Jamieson-Noel & Winne, 2003; Perry & Winne, 2006; Zhou & Winne, 2012). Traces are observable or identifiable indicators of a learners' cognitive decisions during engagement with a task (Winne 1982; Winne & Perry, 2000). Winne (2013) stated the importance of examining traces as evidence of engagement in SRL behavior by examining patterns of learner highlighting and annotating of text. When learners decide to highlight text, they are making a conscious choice of the importance of that specific part of the text. As Winne (1982) suggested, highlighting produces behavioral traces of learning that represent cognitive activities that would have otherwise been unobservable. In that, the learner demonstrates cognition based on some internal standard that is set by the learner. Winne (2013) suggested that there are several different reasons for this type of behavioral activity, such as it might be an easy way for the learner to review later or because highlighting represents a critical component for comprehension.

Learning tactics or strategies that learners employ in accomplishing a task is another critical element of the behavioral process of SRL (Nicol & Macfarlane-Dick, 2006; Pintrich 2000; Zimmerman & Campillo, 2003). As described above, learner solicitation of feedback is a common SRL behavior (Butler & Winne, 1995). For learners engaged in SRL, feedback can become a powerful tool and incentive for learning, in that, the learner has the potential to achieve greater levels of learning as well as becoming a more autonomous learner (Fisher & Frey, 2009). There are many types of feedback that a learner can solicit, though the most common comes from the instructor (Hawk & Shah, 2008) or peers (Van den Boom et al., 2007).

In review, this section provided an overview of the three major components of SRL: metacognition, motivation, and behavioral process. Additionally, as demonstrated, there is much empirical work to support each of the components of SRL. These three components of SRL have been the underpinnings for most models of SRL, with each theorist placing different weights and emphasis on each component. The next section presents notable models of SRL that are based on the three identified components of SRL.

Models of SRL

As the field of SRL developed, several theoretical models of SRL emerged including Winne and Hadwin's Four-stage Model of SRL, (Winne & Hadwin, 1998), the Social-Cognitive Model of SRL (Zimmerman, 2000), the process-oriented model of metacognition (Pintrich, 2000), metacognitive and affective model of SRL (Efklides, 2011), and adaptable learning (Boekaerts & Niemivirta, 2000). Although widespread nuances exist between models, there are some commonalities found between models. For example, most models suggest that learners who exhibit self-regulation are active agents in their learning process and engage in a variety of dimensions including thoughts, feelings, and behaviors (Puustinen & Pulkkinen, 2001). Additionally, many of the commonly used models propose SRL as a cyclical process, whereby learners engage in a set of thoughts, feelings, or behaviors, then evaluate performance, and implement adjustments as necessary (Boekaerts & Niemivirta, 2000; Winne & Hadwin, 1998; Zimmerman, 2000).

Lastly, as mentioned in the previous section, each model of SRL contains the three components of SRL: metacognition, motivation, and behavioral processes (Zimmerman, 2008). This section presents an in-depth review of two of the most well-cited models that demonstrate the incorporation of the three components of SRL: Winne and Hadwin's Four-stage Model of SRL (1998) and Zimmerman's Social-Cognitive Model of Self-Regulation (1989). Lastly, this section presents other common models of SRL and concludes by comparing models of SRL.

Winne and Hadwin's Four-stage Model of SRL. One of the key models of SRL is Winne and Hadwin's (1998) Four-stage Model of SRL. Their model contains four unique stages: Task definition, goal setting and planning, goal execution and planning, and metacognition adaption. Each stage contains elements of metacognition, motivation, and behavioral processes as illustrated in the previous section. Winne (2013) noted that if a learner engages with any of the stages at any point during the learning process, then the learner demonstrates the ability to self-regulate. As for the specific stages, task definition includes perceptions that learners have about a task in which they are engaging. In this phase, learners leverage prior memories of past work, thoughts about the current task, self-knowledge, and domain knowledge to create a perception or picture of the current task (Winne, 2013). In this stage, learners assess abilities such as motivation or self-efficacy needed to complete the task. If learners are accurate in their assessment, it could lead to task completion (Winne, 2013). As an example, a learner who is currently taking a math test may recall recently earned good grades on homework assignments leading up to the test. Here, the learner can draw on memories of performing well on homework assignments, which in turn, can foster higher levels of motivation and self-efficacy to perform well on the current test. Once learners develop a picture of the task at hand or define the task, they can determine goals.

Second, learners set relevant goals and make plans on achieving outlined goals (Winne, 2013). Without goal setting, learners would lack a basis for regulating their thoughts, behaviors, or actions as there would be nothing to strive towards or obtain (Winne, 2013). During the goal obtainment processes, self-regulated learners can examine their progress towards goal obtainment as well as successes and/or failures. A unique feature of Winne and Hadwin's (1998) model is the separation of learners' understanding of a task and approach to the task. As an example, if learners have an assignment due, they must develop an understanding of expectations, most commonly, from the instructor. Next, the learners may develop an approach to completing the task at hand based on prior feedback from the instructor. In this example, the learner first develops an understanding of the task from the instructor, then develops an approach to achieve goals based on feedback from the instructor. This process helps reduce task ambiguity and promotes appropriate goals for completing the task by the learner. After learners identify the appropriate goals, then they can turn to goal execution.

The third step involves executing planned goals through specific action (Winne, 2013). In this step, the learner enacts the strategies and/or tactics decided on in the previous step of goal planning. Additionally, learners actively monitor their progress towards goals and reflect to see if their plan is producing desired results. As an example, if a learner sets the goal of passing an exam in the previous stage, then in this stage, it is the responsibility of the learner to successfully pass the exam via the appropriate actions. Engagement with activities leading up to the exam that help facilitate success in passing the exam is evidence of goal execution. More specifically, strategies for passing an exam could be reviewing previous lecture notes, practicing problem sets, reviewing homework, and completing practice exams. While engaging in these review activities, learners monitor their progress towards goal obtainment. For instance, the learner could review the results of practice exams to see if their score is aiding in obtaining the goal of passing the exam. After engaging in the goal execution process, learners can reflect on the success of their strategies.

Lastly, learners exert metacognitive adaption, which involves learners regulating their cognitive resources for the completion of future tasks (Winne & Hadwin, 1998). This stage, as described by Winne (2013), is a critical reflective component of SRL that encompasses two key areas: a) addressing failures or challenges, and b) improving learning. Because SRL involves more than identifying and implementing the appropriate strategy, learners must exhibit SRL practices incessantly to improve their learning strategies and tactics to obtain goals. Thus, it is critical for SRL learners to possess and refine skills for their own learning and can obtain useful SRL information. As an example, when the learner receives feedback from an instructor on an assignment, the learner will alter or adjust learning strategies as necessary to attempt to improve performance. As a result, a learner may choose to develop a study group or visit the instructor during office hours.

Relating to the three key components of SRL, Winne and Hadwin's (1998) Four-stage Model of SRL emphasizes metacognition, particularly in the task definition and metacognitive adaption stages. In contrast, Zimmerman's Social-Cognitive Model of Self-Regulation, which is explored in more detail in the next section, emphasizes behavioral processes more so than metacognition and motivation.

Zimmerman's Social-Cognitive Model of Self-Regulation. Arguably, the most influential model based on utilization in the SRL literature is Zimmerman's Social-Cognitive Model of Self-Regulation (1989, 1990, 2000). Zimmerman's model ties directly to social cognitive theory and contains three interrelated domains: covert personal, behavioral, and environmental, which is based on Bandura's (1986) notion of reciprocal determinism as described earlier. A key tenant of Zimmerman's model is that each domain contains events that can be separated, but they are interdependent, and when taken together, affect the learner process. According to Zimmerman, covert personal involves learners' ability to examine and alter certain states such as cognition. Second, within the behavioral domain, the learner observes behavior and alters as necessary based on performance. Lastly, the environmental domain consists of a learner's ability to examine and alter environmental factors, as necessary.

Another point of emphasis in Zimmerman's (2000) model is that SRL is a cycle. Although there is general agreement among SRL theorists that SRL is cyclical, Zimmerman's model places the highest emphasis on it. The cycle typically starts with the forethought phase wherein the learner leverages (or not) previous experiences and filters through a myriad of helpful strategies in obtaining a goal. As a result, the learner has access to prior knowledge and strategies to inform the current task. Typically, the learner will identify and select a strategy to employ. Next, the learner engages in the performance phase in which the learner employs the selected strategy to complete the task. Lastly, the learner will engage in the reflection phases and evaluate the selected strategy and performance. This cycle repeats each time a learner engages in a task.

Winne and Hadwin's (1998) and Zimmerman's (2000) models remain the more popular models of SRL in terms of application (Panadero, 2017). However, several other influential models in the SRL literature exist that integrate the three key components of

SRL: Metacognition, motivation, and behavior. Yet, each model is unique and is compared across the three key components of SRL in further detail below.

Comparing and Contrasting SRL Models. In addition to Winne and Hadwin's (1998) Four-stage Model of SRL and Zimmerman's (2008) Social-Cognitive Model of Self-Regulation, there are three other prominent models in the SRL literature that contain components of metacognition, motivation, and behavior process. Those models are Boekaerts' Model of Adaptable learning (Boekarts, 1996), Efklides' Metacognitive and Affective Model of SRL (Efklides, 2011), and Pintrich's General Framework for SRL (Pintrich, 2000). Each model contains elements of metacognition, motivation, and behavioral processes; however, each model prioritizes or emphasizes each component to a different degree. Thus, this section juxtaposes each of the five models across each SRL component. In addition, each model contains differing stages and processes, which is necessary to review first when juxtaposing each model to provide the foundation for a discussion on three components of SRL.

Stages and Process. Broadly, each model concurs that SRL is a cyclical process comprised of a variety of phases or stages (Panadero, 2017). Puustinen and Pulkkinen (2001) conducted a comprehensive review of the five identified SRL models and categorized each model's phases into three broader phases. They concluded the three overarching phases were: 1) preparatory, 2) performance, and 3) appraisal. More specifically, in the preparatory phase Boekaerts (1996) model consisted of identification, interpretation, and goal setting. Efkildes's (2011) model included task representation, whereas Pintrich's (2000) model included forethought, planning, activation. Winne and

Hadwin's (1998) model contained a task definition phase and Zimmerman's model contained a forethought phase. Considering the models together, the preparatory phase includes task identification, planning, and goal setting. Similarly, a performance phase is present in each of the five models. In the performance phase, learners are actively engaged in SRL strategies that promote task completion. For instance, Boekaerts (1996) termed this as goal striving, Pintrich (2000) referred to this as monitoring, and Winne and Hadwin (1998) called these applying tactics and strategies.

Lastly, each model contains an appraisal phase, which supports Panadero's (2017) statement that each of these models is cyclical, as the appraisal phase oftentimes contains a reflective component with the potential to alter the approach of a future task. As an example, Winne and Hadwin (1998) termed this adaptive metacognition whereas Zimmerman (2000) called this self-reflection, and Pintrich (2000) called this reaction and reflection. Thus, each of the five identified models contains the same overarching principle that SRL is a cyclical process. Similarly, models also contain the three SRL components; however, the way in which each model incorporates each component is different.

SRL Components. The five models considered in this section each contain the three components of SRL: metacognition, motivation, and behavior processes; however, considerable variability exists on the weight that each model places on each component (Panadero 2017).

As for metacognition, Winne and Hadwin's (1998) model weighs metacognition as the most important in juxtaposition to the other models. Most of the stages in Winne and Hadwin's (1998) model is rooted in metacognition (Panadero 2017). Efklides (2011), Pintrich (2000), and Zimmerman's (2000) model contain many elements of metacognition throughout their various stages. In juxtaposition to Winne and Hadwin's (1998) model, these models incorporate metacognitive strategies, but are not a key focus of the model as is the case with Winne and Hadwin (1998). Lastly, Boekaerts's (1996) model mentions the importance of metacognitive strategies and tactics but does incorporate specific details or strategies for learners to engage.

As for motivation, Panadero (2017) suggested a two-tier classification system to categorize SRL models. The Boekaerts (1996), Pintrich (2000), and Zimmerman (2000) models place the highest emphasis on motivation. For example, Zimmerman's (2000) model is presented as goal-driven based on motivation. More specifically, his forethought phase focuses heavily on self-motivation. Similarly, the self-reflection phase includes self-reactions, which can motivate a learner's propensity to engage in an alike task in the future. Additionally, Pintrich's (2000) model is comparable to Zimmerman's (2000) in explicitly stating the importance of motivation throughout the model; however, Pintrich's (2000) model places a higher value on metacognition in juxtaposition to Zimmerman's model. In contrast, Efklides (2011) and Winne and Hadwin's (1998) models make mention and include motivation in parts of their models, but they are not the main focus of either model. Instead, their models place a greater value on metacognition and a lower value on emotion.

The third key component of SRL activity is the behavioral process (Panadero, 2017). Behavioral processes oftentimes refer to the environment in which the learner has constructed to optimize learning; however, not every model places a great deal of emphasis on the learner's need to structure their environment to engage in SRL. For example, Zimmerman (2000) and Winne and Hadwin (1998) placed the highest degree of emphasis on the learner structuring their environment and suggest that SRL learners are active agents in creating an optimal learning environment. In contrast, Boekaerts' (1996) model emphasized environment less, but rather centered his model around goal processes and the behaviors that a learner engages within to help strive towards goal obtainment. Like Boekaerts, Pintrich's (2000) model does emphasized environment, but sought to also understand motivation, specifically with respect to the behaviors that facilitated different types of goal orientations, such as mastery orientation or performance orientation.

In review, this section compared five different models of SRL along with the three key components of SRL and provided an in-depth analysis of the two most studied SRL models: Winne and Hadwin's (1998) Four-stage Model of SRL and Zimmerman's (2000) Socio-Cognitive Model of Self-regulation. Additionally, this section analyzed differences between the five different models' stages and processes to bread a deeper understanding of the nuances between models. While there is considerable variability between models, most models and their associated scholars agree on the ways to measure SRL, which is the focus of the next section.

SRL Measurement

Over the past several decades, many scholars have sought to measure the key components of SRL as well as the various models of SRL as described above (Winne &

Perry, 2000). Rovers et al. (2019) noted that SRL is complex to measure, which has resulted in a variety of considerations and methods, most notably in the way to capture SRL. The primary ways SRL has been captured is either as an aptitude, which is a personality trait that remains unchanged over time, or an event, which is a snapshot of a point in time. Associated with each way to capture SRL are different measurement methods. For example, aptitude measures include self-report questionnaires (Weinstein & Palmer, 2002; Pintrich et al., 2015) and structured interviews (Zimmerman & Martinez-Pons, 1988). Event measures include think-aloud protocols (Pressley & Afflerbach, 1995), error detection methods (Baker & Cerro, 2000), and trace methodology (Winne & Perry, 2000). As such, the section here first discusses SRL captured as an aptitude then presents the methods employed when SRL was previously captured as an event. Included in the discussion are the advantages and disadvantages of each method.

SRL as an Aptitude. Most traditional researchers in the SRL community captured SRL as an aptitude and have subsequently employed methods to measure as an aptitude (Endedijk et al., 2016). SRL as an aptitude considers personality traits and characteristics as enduring and provides an indicator of future behavior. A key advantage of measuring SRL as an aptitude is that it tends to measure SRL as a global ability by averaging scores across several items on an instrument, such as a self-report questionnaire. This makes understanding SRL, in this context, straightforward as researchers can represent the aspect of SRL that they are interested in measuring with a single value. As an example, if a researcher is interested in the metacognitive monitoring of a learner studying for a quiz, the researcher might employ a single self-report questionnaire that contains 15 items aimed at measuring metacognitive monitoring. To determine how a learner performed on metacognitive monitoring, the researcher will average the responses on these items to create a composite score that reflects the level of metacognitive monitoring. Though aptitude measures are popular, Winne and Perry (2000) noted the difficulty in capturing SRL as an aptitude, in that, most facets of SRL are not readily available, such as thoughts and feelings; however, self-report questionnaires aim to address this issue.

Self-Report Questionnaires. Self-report questionnaires are one of the most popular methods to measure SRL (Roth et al., 2016). On self-report questionnaires, learners are asked to reflect on their previous experiences, particularly on an assignment or homework, and report on the SRL behaviors such as metacognition, motivation, and tactics/strategies that they employed to complete the assignment or homework. Most commonly, self-report questionnaires measure SRL as an aptitude by attempting to ascertain the SRL behaviors that are consistent over time as opposed to a singular event (Winne & Perry, 2000). Typically, the structure of self-report questionnaires includes Likert-scale responses to items of a particular construct of interest (Demetriou et al., 2015). In the context of SRL, the most common constructs that are measured via self-report questionnaires are motivation, self-efficacy, behaviors, and metacognition (Pintrich & De Groot; 1990; Weinstein & Palmer, 2002). A review of the extant literature on self-report questionnaires on SRL reveals the Motivated Strategies for Learning Questionnaire (MSLQ) and the Learning and Study Strategies Inventory (LASSI) are the most widely utilized self-report questionnaires (Winne & Perry, 2000). For the current study, the MSLQ is reviewed in more detail below.

Originally developed by Pintrich et al. (2015), they sought to develop the MSLQ to measure college learner's motivational and learning strategies within a given course. The MSLQ is grounded in a robust cognitive perspective that views learners as active agents in their learning process whose beliefs and understandings are key mediators of instructional participation (Pintrich et al., 2015). The cognitive perspective that the MSLQ employs is a differentiating aspect of the MSLQ from other self-report questionnaires as the MSLQ contains several subsections aimed at understanding learner cognition whereas other instruments do not.

Response items on the MSLQ are comprised of two categories: declarative statements (e.g. — I know that I will be able to learn the material for this class) and conditional relationships (e.g. —When I am studying a topic, I try to make everything fit together). Learners respond to items on a 7-point Likert Scale, ranging from "not at all true of me (1) to very true of me (7). Learners are instructed to respond to questions in the context of the class in which the MSLQ is being administered (Pintrich et al., 2015).

In total, there are 81 items on and 15 subscales on MSLQ and are divided into two categories: motivation and learning strategies. The motivation category is comprised of six subscales: intrinsic goal orientation, extrinsic goal orientation, task value, control of learning beliefs, self-efficacy for learning and performance, and task anxiety. The learning strategies category is comprised of two separate sections. First, the cognitive and metacognitive strategies section includes five subscales: rehearsal, elaboration, organization, critical thinking, and metacognitive self-regulation, which mostly capture the critical SRL components of metacognition and motivation. The second section is on resource management and includes four subscales: time and study environment, effort regulation, peer learning, and help-seeking, which mostly capture the behavioral processes of SRL. To score, the MSLQ, the researcher computes the mean value of responses for each subscale (Pintrich et al., 2015).

The MSLQ has been studied widely and employed in a variety of different settings including face-to-face (Karadeniz et al., 2008; Stark, 2019) and online environments (Ali et al., 2014). Additionally, the MSLQ has been administered across various populations including middle schoolers (Herges et al., 2017), high schoolers (Bonanomi et al., 2018), and most often, college learners (Jackson, 2018; Jacobson & Harris, 2008). Additionally, previous work demonstrated the MSLQ’s internal consistency and predictive validity (Panadero, 2017; Pintrich et al., 2015). As an example, Pintrich et al. (2015) administered the MSLQ to 356 college learners from 37 different classes across 14 subject domains. To determine internal consistency and validity, they employed coefficient alphas and confirmatory factor analysis. Results demonstrated that the coefficient alphas for all motivational scales indicated strong internal consistency values. Coefficient alphas for the learning strategies scales were lower in juxtaposition with the motivational scales; however, they were within acceptable values. Their work also highlighted the predictive validity values of certain scales. Motivational scales found the most significant correlations with final grade except for extrinsic goal orientation. Additionally, learners who reported higher levels of test anxiety were less likely to do well in the course. Lastly, most of the learning strategies subscales strongly correlated with course grade. Thus, internal consistency and predictive validity are key advantages of the MSLQ.

Self-report questionnaires, such as the MSLQ, have arguably advanced the field of SRL further than any other measurement method (Demetriou et al., 2015). As such, there are many advantages to employing a self-report questionnaire which includes monetary cost, administration, data, and scoring. Self-report questionnaires can be administered at a relatively little-to-no monetary cost, depending on the instrument. For example, the MSLQ does not require payment to use the tool (Printrich & DeGroot, 1990). Though, the LASSI has a nominal fee associated with its utilization (Weinstein & Acee, 2018). Thus, this makes self-report questionnaires an attractive option to researchers. In addition, the low monetary cost associated with most self-report questionnaires extends access of this method in comparison to more costly methods.

Second, the administration of self-report questionnaires is a key advantage. Oftentimes, self-report questionnaires are designed to be administered in their current format with no alterations needed. Additionally, researchers can utilize parts or certain scales of the self-report questionnaire as opposed to the entire questionnaire. For example, if researchers are interested in measuring motivation, they may choose to administer the six subscales associated with motivation from the MSLQ rather than the entire MSLQ. Related, the administration of the self-report questionnaire is straightforward and is not too labor intensive.

Third, self-report questionnaires enable researchers to gather a great deal of data, which is mostly quantitative; however, open-ended questions can provide the opportunity to gather qualitative data. As an example, the MSLQ provides a potentially rich data set as it is comprised of 81-items and 15 subscales as described above (Pintrich & DeGroot, 1990). Thus, researchers who are seeking to gather a considerable amount of data from their sample will have the potential to collect a robust data set on a wide array of constructs from their participants through the utilization of the MSLQ. Gathering a large amount of quantitative data could also facilitate one of the critical missions of quantitative research in being able to generalize findings (Demetriou et al., 2015).

Scoring is another key advantage of self-report questionnaires. Most often, self-report questionnaires contain detailed instructions on how to score and interpret the respective instrument. An 80-page manual has been created that addresses each part of the MSLQ with specific emphasis and attention to detail on how to score the MSLQ and interpret its findings (Pintrich et al., 2015). Such materials make it attractive for researchers to utilize self-report questionnaires as the scoring and interpretation of the instrument are provided in a straightforward manner. Lastly, widely used instruments that have robust scoring documentation provide the opportunity to compare findings across different studies as researchers are most likely using the same information for scoring and interpretation comprised for each instrument. This makes comparing results straightforward across different contexts, demographics, and constructs.

In sum, self-report questionnaires, such as the MSLQ, have a myriad of benefits, most notably with their relatively low monetary cost to utilize, straightforward nature of administering, potential to obtain a rich data set, and a shared understanding among researchers how to score and interpret. Though, for all the important advantages of self-report questionnaires and their role in advancing knowledge related to understanding SRL, there are several key limitations, which are reviewed in detail below.

Though self-report questionnaires are the most common approach to assessing SRL, they are subject to much criticism and limitations such as bias, inconsistency between reported behavior and actual behavior, and lack of specificity or context (Demetriou et al., 2015; Roth et al., 2016). First, a key concern with self-report questionnaires is bias. Most commonly, there are two types of bias with respect to self-report questionnaires: response bias and social desirability bias (Demetriou et al., 2015). First, response bias is an individual's inclination to respond similarly to each question even though questions are unrelated. As an example, if a learner responds that they are "unlikely" to read an additional chapter for studying, the next question may be about submitting an assignment on time, and they may be more likely to select "unlikely" based on the previous response. The second type of bias is social desirability bias which is when a respondent may not respond truthfully to a question if their honest response may not be socially acceptable. As an example, a learner may not respond truthfully to submitting work on time because there are negative social and academic connotations associated with turning in work late. In either case, bias presents are a critical issue with data objectivity, in that, bias responses promote data subjectivity, which could interfere with a researcher's ability to truly understand a phenomenon of interest and conduct a study in the appropriate manner.

Second, prior research reveals that learners may not respond to a Likert scale in a manner that matches their behavior, which could lead to difficulty in capturing the true SRL behaviors and strategies employed by the learner (Bernacki et al., 2012; Rovers et al., 2019). This is mainly true because self-report questionnaires are retroactive in nature and ask learners to reflect on experiences that have already occurred some time ago. This is problematic due to memory deficits (Rovers et al., 2019). Learners are likely to have an imperfect memory, which may cause them to incorrectly report the SRL strategy employed on the self-report questionnaire (Perry & Winne, 2006). Additionally, the presence of certain considerations such as different learning strategies on a scale may prompt learners to respond in a manner that they may not have previously considered (Bernacki et al., 2012; Perry & Winne, 2006; Samuelstuen & Bråten, 2007). Lastly, learners may be unfamiliar with certain strategies or terms that are mentioned on the self-report questionnaires, which could lead to respondents avoiding selecting those responses, even though they may have been using those strategies (Roth et al., 2016).

Lastly, another key limitation of self-report questionnaires is that most lack specificity to the individual context or situation in which the learner is responding (Winne & Jamieson-Noel, 2003). Thus, the learner could produce different results depending on their current context. Hadwin et al. (2001) explored the effects of the context on learners' self-report data and found that context significantly influenced respondents' answers as well as their responses and behaviors, which had varied over time. In their study, learners were asked to note the frequency they applied 26 study tactics, 20 textbook features, and 30 goals for studying across three contexts: reading, writing an essay, and studying for a test. Their results suggested that learners displayed and engaged in different SRL behaviors across each context. Thus, this study raises concerns about the applicability of measuring SRL with self-report questionnaires—as well as more broadly as an aptitude— as behaviors changed with context. Still, self-report questionnaires are widely employed as an acceptable measure of SRL and remain popular for measuring SRL. As noted, a core benefit of self-report questionnaires is in their ability to produce a good deal of quantitative data. However, researchers also have desired to obtain qualitative data to capture SRL as an aptitude, most commonly with interviews.

Interviews. Like self-report questionnaires, interviews are another popular method to measure SRL as an aptitude. In the context of SRL, the goal of interviewing is to acquire information from learners regarding their experiences employing SRL techniques either retrospectively or prospectively (Roth et al., 2016). Unlike self-report questionnaires, interviews most often contain open-ended questions, which enable the researcher to develop a deeper understanding of SRL behavior(s) that the learner employed without the prompting that a Likert-scale might provide. One of the most used interview protocols is the Self-Regulated Learning Interview Schedule (SRLIS) developed by Zimmerman and Martinez-Pons (1986). The SRLIS contains several questions aimed at eliciting information from learners about their strategies in response to eight different contexts (Effeney et al., 2013). The eight contexts are revising class work, completing homework tasks, exam preparation, dealing with distractions and difficult issues, structuring an essay, checking work after completion, and arranging a place of choice to study (Zimmerman & Martinez-Pons, 1986, 1988). To score the instrument, participants are asked to indicate the consistency in which they use each strategy. Thus, the instrument relies on the gathering of prospective information from learners about hypothetical situations in which they may find themselves, which is true of many of the interview protocols in the SRL literature (Winne & Perry, 2000).

Interviews as a form of measurement for SRL have several advantages. Most notably, interviews have the potential to produce rich, in-depth data as well as offer a great deal of flexibility in their administration, particularly in an unstructured interview protocol (Opdenakker, 2006). Most often, interviews involve short open-ended questions or scenarios posed by the researcher followed by an elongated response by the participants. Therefore, researchers can obtain rich and in-depth data through participants' responses, which has the potential to shed insight on a phenomenon of interest. In addition, interviewing protocols, particularly unstructured interviews offer more flexibility in gaining insight. As an example, if a participant conveys something of interest to the researcher during the interview, then the researcher can ask follow-up questions to delve deeper or gain more specificity. In this sense, interviews as a method to measure SRL offers advantages that other methods to measure SRL do not.

Though interviewing remains a popular method to understand learners' SRL behaviors, many limitations are present. First, a key issue with interviewing is that learners may not be accurately representing how they engage in SRL, rather they may respond on how they see themselves or how they wished they engaged—either is problematic because the researcher may not get a true sense for the SRL behaviors that the learner employed. Second, participation may be limited due to the amount of information that the learners would have to reveal about themselves as well the potential lack of anonymity of the interview with the researcher (Roth et al., 2016). Related, interview research is time consuming and resource intensive (Opdenakker, 2006). Therefore, transcribing and analyzing interviews could be a cumbersome and time-consuming process.

In review, this section described two common methods to capture SRL as an aptitude, self-report questionnaires and interviews, along with their associated advantages and disadvantages. Although a plethora of measures sought to capture SRL as an aptitude, the most frequently cited criticism is that capturing SRL as an aptitude may not account for the dynamic environment in which learning occurs, which has promoted the rise of capturing SRL as an event (Panadero, 2017).

SRL as an Event. Capturing SRL as an event is considered a snapshot in time that affords the opportunity to understand learner engagement in SRL behaviors at a moment in time (Winne & Perry, 2000). Endedijk et al. (2016) stated that measuring SRL as an event includes a dynamic set of context-dependent activities, which contrasts SRL as an aptitude, which considers behaviors static and unchanging over time. Winne and Perry (2000) stated that measuring SRL as an event has three complex levels: occurrence, contingency, and patterned contingency. Occurrence contains two phases. The first phase involves an observable feature indicating SRL was not present by the learner followed by a second phase indicating SRL was present by the learner. As an example, a learner may state that a test is hard which indicates within the current moment that the learner may not have engaged with SRL behaviors or skills necessary to perform on the test but asks the teacher for clarification on instructions. In asking the teacher for clarification the learner demonstrates engagement with SRL. Thus, this potentially enables learners to feel as though the test is not as challenging as originally thought. Second, SRL as a contingency is oftentimes described as a binary conditional relationship. In the previous example of a learner claiming a test is hard, two measurements exist that can illustrate the aforementioned binary conditional relationship. The first is metacognitive monitoring, which is the ability of the learner to examine the cognitive resources needed to perform a task, and the second is metacognitive control, which is the ability of the learner to adjust the number of resources needed to perform a task. Returning to the above example, the learner has made an assessment about the difficulty of a test and thus judged the cognitive resources needed and then after asking for clarification adjusted the number of resources needed. SRL behaviors demonstrate engagement of a learner in a binary conditional relationship in which metacognitive monitoring must precede metacognitive control to complete the task.

Lastly, patterned contingency arranges several if-then contingencies into a broader group. Returning to the previous example of a learner taking a test, several smaller cognitive tactics, such as recall, can be arranged into a learner's cognitive strategy, such as metacognition (Butler & Winne, 1995; Winne & Perry, 2000). However, not all these various levels of SRL are necessary to capture SRL as an event, rather the research can isolate and study a singular level, depending on the availability of data, which Winne (2000) has described as the most appropriate way to capture SRL as an event, such as think-aloud protocols.

Think-aloud Protocol. One way to capture SRL as an event is a think-aloud protocol (Winne & Perry, 2000). Think-aloud protocols are a learner's articulation of thoughts about cognitive processes while completing a task. Typically, researchers will record the verbalization of the learner's thought process and then analyze it to determine the types of SRL processes or behaviors that the learner employed to the task at hand (Azevedo et al., 2007). Think-aloud protocols can be unstructured or structured depending on the nature of the phenomena that the researcher desires to explore. As a common way to assess think-aloud measures, instructors may ask learners to "show work," particularly in math or reading courses (Winne & Perry, 2000). As an example, in their broad review of studies that employed think-aloud protocols to measure metacognition in reading, Pressley and Afflerbach (1995) noted that learners would verbalize their thoughts as they were reading and that learners were instructed in some cases what to report on, such as elaborations or predictions, and in other cases, they were not asked what to report on, but rather just what came to mind to the learner. Thus, there is considerable variation in the ways in which think-aloud studies are structured and are typically considered a more reliable measure of SRL, in juxtaposition to self-report questionnaires and interviews. Think-aloud protocols have also been applied to study science, particularly in understanding complex topics such as the circulatory system (Azevedo, 2005).

A more recent type of think-aloud protocol is microanalytic assessment or simply, microanalysis (Cleary et al., 2012). Though variability exists in defining microanalytic assessment, it is oftentimes described as an overarching term that aims at measuring a specific element of behavior or cognition as they occur in real-time. Microanalytic assessment has grown as a popular method to measure SRL because microanalytic assessment enables researchers to assess learners in authentic contexts via moment-to-moment behavioral exchanges that minimize response bias (Cleary & Zimmerman, 2001; Cleary et al., 2012).

Think-aloud protocols have several notable advantages as an SRL research method (Greene et al., 2011a). First, think-aloud protocols have the potential to provide in-depth insight into a phenomenon of interest without the learner being prompted to answer specific questions as is the case with interviewing. However, the researcher must take great care to ensure they are not interjecting during a learners' think-aloud process. Thus, this could provide a researcher with more objective SRL data as learners' attention is not drawn to certain aspects as it would be in an interview. In addition, think-aloud protocols offer real-time insight into SRL strategies used as, oftentimes, the participant is talking through their current thought processes whereas self-report questionnaires and interviews typically have learners recall how they have acted previously. Real-time insight into a learner's thought process preserves the integrity of data.

One of the commonly noted criticisms of think-aloud protocols is that they are intrusive in nature. In other words, many think-aloud study designs entail a researcher interjecting during the task. Interjection may cause the learner to lose their thought, which could interfere with the quality of data. Additionally, this could cause the learner to inform the researcher of SRL processes that may not be occurring or employed by the learner, but rather mentioned only since they were prompted (Winne & Perry, 2000). Further, learners may be biased in their think-aloud reporting if the researcher prompts certain thoughts or elicits certain behaviors. As an example, a researcher may ask the learner questions about their metacognitive process, such as "what are your goals for reading this text?", which could promote the learner to think about goals more intentionally in that specific moment than they ordinarily would (Puustinen & Pulkkinen, 2001) Thus, there are concerns about the objectivity of data as prompting due to researcher interjection is often a key component of think-aloud protocols—even though think-aloud protocols have the potential to produce more objective data as noted in the advantages portion of this section. To remedy the intrusiveness that is inherent in think-aloud protocols, error detection tasks seek to eliminate intrusiveness.

Error Detection Tasks. Another, though less common, method to capture SRL as an event is error detection tasks. In this method, researchers intentionally introduce errors into a task or materials that learners utilize (Winne & Perry, 2000). The goal is for learners to detect the error(s) as well as make decisions about how to handle identified errors (Baker & Cerro, 2000). Winne and Perry (2000) suggested that error detection methods are an appropriate way to capture SRL as an event, specifically in understanding metacognitive evaluation and control. When an error is detected, the learner employs metacognitive evaluation to determine that an error has indeed occurred. Next, the learner decides how to proceed knowing that they detected an error such as a grammatically incorrect sentence, which is evidence of metacognitive control. Thus, prior research within error detection focuses on the measurement of metacognitive evaluation and control (Zamora et al., 2018).

Though an important addition to the SRL measurement literature, several limitations for error detection methods exist. First, the method assumes that a learner will, indeed, detect an error. However, if a learner does not detect an error in the materials being reviewed, then the researcher will be unable to examine SRL (Winne & Perry, 2000). Second, some error detection studies contain instructions by the researcher to look for an error in materials. As a result, data produced by the learner may be compromised because the mindset in which the learner approaches the task may shift from completing the task to focusing on uncovering the error in the materials. As a result, a researcher may not be able to ascertain true learner engagement in SRL behaviors via error detection (Winne, 1995). Lastly, error detection methods are limited primarily to understanding various aspects of cognition. Thus, there could be limited applicability of error detection methods to understand other aspects of SRL behaviors and strategies such as motivation. Although key limitations exist, error detection methods are beneficial to provide a snapshot into learner engagement with SRL behavior in a less intrusiveness manner, albeit at a macro-level. In contrast, trace methodology affords the opportunity to examine SRL behavior as an event at the micro-level while offering limited intrusiveness.

Trace Methodology. Trace methodology has emerged as one of the most popular ways to capture SRL as an event (Jamieson-Noel & Winne, 2003) At the center of trace methodology are behavioral expressions of learner beliefs (Winne, 1982). Traces of learner behavior are oftentimes representations of cognition that learners produce while engaging in a task. Thus, trace methodology focuses on the examination and uncovering traces of learner behavior (Winne, 1982). The most frequently cited examples of behavioral traces are a learner's engagement with text, specifically in highlighting and annotating (Winne & Perry, 2000). In each case, the learner is making a cognitive choice as to what is important to either highlight or note in the margins of the text. Thus, these can be interpreted as traces of learner behavior within trace methodology. Additionally, Winne (2013) noted that highlighting is a type of tactic that can be characterized as a product and conforms to the IF-THEN rule: If a certain piece of information seems important, then the learner will highlight it. As such, SRL occurs when learners are engaged in the identification, implementation, and monitoring of tactics. Thus, researchers can examine cognition via traces in understanding what the learner perceives to be important.

As an example, Jamieson-Noel and Winne (2003) highlighted self-report data and trace data of learners studying and achievement. Sixty-nine undergraduate learners were asked to complete a 26-item self-report questionnaire as well as take an exam. Traces of learner behavior, such as the number of times a lecture was viewed, were tracked via *PrepMate*, which is a software study environment. A series of multiple regressions were conducted and revealed that both self-report data from questionnaires and traces did predict achievement; however, tactics, such as goal setting or planning were different for each method. The study revealed that both traces and self-reports are useful measures in predicting achievement. Thus, this study confirmed that trace methodology is an appropriate method to measure SRL as it performs on par with other accepted measurement practices such as self-report questionnaires. In fact, as evidenced by this study, trace methodology has the potential to enhance what is known about SRL behavior as this study uncovered different tactics, such as goal setting and planning, that the learner employed that were not uncovered by the self-report questionnaire.

Trace methodology contains two key advantages. First, it has the potential to produce unobtrusive data. Oftentimes, the researcher provides instructions for the participant at the beginning of the task and does not interact with the participant until the task is completed. Thus, this reduces any type of bias that could be introduced by researchers as evidenced by other methods. Second, it has the potential to be extended via technological advances more so than other methods (Winne, 2017). In the virtual environment, behavioral traces can potentially be tracked via a learning management system (LMS). Thus, trace methodology can grow in its measurement capacity.

In review, common methods to capture SRL as an event include think-aloud protocols, error detection, and trace methodology. Each method contains unique advantages as well as limitations, which were reviewed in detail. Of these measures, trace methodology has the potential to address most limitations that are contained within other methods.

Summary

SRL contains three main components: metacognition, motivation, and behavior processes. These three components have been the basis for a variety of SRL models such as Zimmerman's Social-Cognitive Perspective on Self-Regulation and Winne and

Hadwin's Four-stage Model of SRL. Additionally, a key component within the SRL literature is measurement. Typically, researchers capture SRL as an aptitude via measurement methods such as self-report questionnaires and interviews or as an event via measurement methods such as think-aloud protocols, error detection methods, and trace methodology. As demonstrated, many gaps exist within the current scope of SRL measurement methods. Most notably—and of concern to the current study—is the intrusive nature and lack of objectivity in the data produced by current methods to measure SRL. This presents concerns because the data produced with the current set of SRL measures have the potential to limit the understanding of SRL behaviors and strategies by learners. To address these limitations, scholars have called on the utilization of technological advances (Roll & Winne, 2015; Winne, 2017). Specifically, the production of data that learners produce when engaging with technology on campus has the potential to advance what is currently known about learner behavior. Collecting data from different data sources, such as a student information system (SIS) or learning management system (LMS) on college campuses offers the opportunity to gather and utilize data to understand aspects of SRL. Winne (2017) believed that this type of data or learning analytics (LA) data can produce the most appropriate data to measure SRL, which other methods described above seemingly struggle to do. To fill this gap, researchers have turned to learning analytics (LA).

Learning Analytics

As noted by SRL scholars (Roll & Winne, 2015; Winne, 2017), data produced from LA sources have the potential to advance SRL measurement. Most defined as the “measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” (Siemens, 2013, p. 1382). LA, in this context, emphasizes insights generated on *learning*. LA’s focus on the learner and learner behavior has led scholars to connect LA to SRL (Baker et al., 2020; Durall & Gros, 2014; Kovanovic et al., 2015; Vovides et al., 2007). Though prior to delving into previous work that has utilized LA data for SRL measurement, it is necessary to review the foundational pieces of LA. As such, this section will provide an overview of LA including defining LA, LA data sources, and the uses of LA and other considerations in working with LA data. The last section summarizes LA and presents the argument that LA data can be (and has been) a useful source of data for SRL measurement.

Defining LA

Over the past decade, higher education leaders and scholars realized that analytic practices—that is, the systematic collection and computation of data produced by a variety of institutional systems such as LMS, learner information records, and learner behavior logs via swipes of student IDs—could benefit the academy (Lang et al., 2017). The earliest works of influential higher education analytics scholars, such as Campbell et al. (2007) understood analytics’ potential to improve institutional outcomes and increase transparency. Originally termed as academic analytics within higher education, Campbell et al. (2007) presented case examples of institutions that utilized analytics for enrollment growth, improving learner retention, and the development of an early alert system for learners’ academic success.

Simultaneously, another term for analytics, institutional analytics, coincided with the rise of academic analytics. Institutional analytics focused on improving the operational function of business practices within institutions (Yanosky & Arroway, 2015). At some point, scholars began to pivot from using academic analytics—to learning analytics— for analytic practices that centered on learner and learner outcomes. As a result, the term learning analytics (LA) began to dominate the higher education discourse on analytics related to analytics and learners (Siemens, 2013), while institutional analytics remained for analytics related to analytics and operational business functions.

As LA's capacity grew, scholars still struggled to establish a common definition for LA (Long & Siemens, 2011). Although this concern still exists today, the most widely adopted definition in the LA literature was coined by arguably the most influential LA scholar, George Siemens. As described above, the most widely accepted definition of LA considers it as the "measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens, 2013, p. 1382). LA's emphasis on learning differs from an array of associated terms such as institutional analytics, machine learning, and educational data mining (Lang et al., 2017, Lawson, 2015). Though the terms and definitions of LA have evolved, LA data sources have remained largely unchanged since the inception of LA.

LA Data Sources

As LA has grown precipitously on college campuses over the past decade, so has the amount of LA data (Lane & Finsel, 2014). The most common types of LA data sources are student ID cards and learning management system data (LMS)

Student Identification Cards. A common method to track learner behavior is through their student identification card. Most often on campuses, learners need to swipe their student identification card to access services and facilities on campuses such as residence hall rooms, recreational facilities, classrooms, dining halls, student events, and the student center. Each time a learner logs a swipe, a digital trace is produced that can help understand learner interactions and patterns of movement (Ram et al., 2015).

Most prior research that examined student identification cards use it as a proxy for engagement (Vytasek et al., 2020). As an example, the University of Arizona followed first-year learner behavior via tracking their student ID card utilization to determine which learners may drop out of college (Ram et al., 2015). Their study identified that there were almost 700 locations that accepted the student ID card across campus. They tracked three different first-year classes over a three-year period and examined how learner interactions changed over time by creating networks for learners via two-week increments for a 12-week period. Based on their model, at the end of the 12-week period, they were able to successfully predict which learners would drop off with an 85-90 percent success rate. Though a popular mechanism for tracking learners, a key limitation is that there may not be enough data produced via student identification cards; however, a learning management system can remedy this limitation as it has the capability of producing millions of data points each semester (Sclater, 2017).

Learning Management System. Increasing in popularity within higher education settings, learning management systems (LMS) is software or web-based technology used to aid in the learning process (Alias & Zainuddin, 2005). Oftentimes, the LMS acts as a complementary component to face-to-face instruction or the platform in which online courses are conducted. Most commonly, an instructor or an instructional designer will design the LMS to fit the needs of a specific course or instructor. Whereas there are a multitude of features that can be contained with the LMS, the most used features are posting the course syllabus, the course schedule, lecture slide decks or lecture videos, practice problems, assessments, quizzes, or exams, and creating a discussion board for learners to post and engage peers. Additionally, there is an opportunity for the instructor to post announcements for learners to view, send emails to learners, post grades, and provide feedback to learners who submit assignments within the LMS (Kakasevski et al., 2008). The most common LMS across college campuses include Blackboard, Moodle, and Canvas (Endozo et al., 2019; Kakasevski et al., 2008; Machado & Tao, 2007).

Although LMS is of great benefit to learners, it is also an attractive entity for researchers who desire to understand learner behavior within the LMS environment due to its ability to capture and store data in real-time (Sclater, 2017). Most LMS stores learner activity each time a learner interacts within the platform See Table 1 for a list of potential LMS activities.

Table 1

Types of LMS Activities

Number of times a learner accesses each content area within the LMS
Number of times a learner accesses specific content (i.e.—lecture slides)
Number of times a learner downloads lecture
Number of times a learner downloads practice problems/quizzes/exam
Number of times a learner accesses the discussion board
Number of times a learner posts on the discussion board
Number of times a learner submits an assignment
Number of times a learner checks grade
Number of times a learner interacts with peers within the LMS
Number of times a learner emails with peers within the LMS
Time stamp of each learner activity
Time stamp of assignment submission
Duration of each session with the LMS
Duration of each session with the discussion board
Duration spent on completing an assignment

Additionally, there are many more data points (aside from points listed in Table 1) stored within the LMS that are available to researchers (Macfadyen & Dawson, 2010). Prior research has been conducted with LMS data by applying sophisticated machine learning and data mining techniques to gain insight about learners such as how instructors can optimize learning in the online environment and interventions that can help bolster learner achievement (Baker & Inventado, 2014; Baker & Yacef, 2009; Gasevic et al., 2015; Siemens & Baker, 2012).

The Uses of LA

The research and utilization of LA within higher education have been prioritized by many higher education stakeholders including institutions (Lester et al., 2017; Sclater, 2017), government (Bienkowski et a., 2012), associations (Ekowo & Palmar, 2016; Gagliardi & Turk, 2017), and scholars (Arnold & Pistilli, 2012; Siemens & Baker, 2012). Most commonly, these stakeholders have utilized the insights provided by LA data to improve a variety of outcomes on campus such as teaching and learning (Brooks & Thompson, 2017; Dietz-Uhler & Hurn, 2013), academic achievement (Arnold & Pistilli, 2012; Conijn et al., 2017; Shum & Crick, 2012; Tempelaar et al., 2015), and retention and graduation rates (Dawson et al., 2017; de Freitas et al., 2014). Reviewed in this section are a variety of the most common uses of LA data, starting with teaching and learning.

Teaching and Learning. One of the most common applications of LA data is in teaching and learning contexts (Brooks & Thompson, 2017; Dietz-Uhler & Hurn, 2013). The development of predictive models based on LA data can aid a faculty member in teaching by identifying at-risk learners and identifying the necessary interventions. These aid in learning and transform pedagogical approaches (Dietz-Uhler & Hurn, 2013). As an example, a predictive model could be developed based on LA data aimed to predict learners' GPA in a particular course, which could include variables such as prior grades earned in a similar set of courses, class year, major, and engagement information within the courses' LMS. This model would inform faculty of probable grade earned. Thus, a key benefit of this type of predictive model is that faculty can identify learners who may struggle prior to taking the course, or early in the semester. As a result, a faculty can monitor those learners more carefully in the early stages of the semester. If necessary, faculty members can craft specifically designed interventions aimed at improving learner success. Many institutions have created and implemented an early alert system to identify learners who may be at risk of failing early in the semester (Arnold & Pistilli, 2012; Denley, 2013; Fritz, 2013; McKay et al., 2012).

A well-known example to the LA community, the Course Signals (CS) program at Purdue, identified learners at-risk of failing a course (Arnold & Pistilli, 2012) Though now defunct, CS was an early intervention tool for faculty to provide learners real-time feedback in hopes of grade improvement. CS utilized LA data generated by learners to predict which learners might be at-risk as indicated by their level of engagement within a given course. The CS algorithm mined data from four sources: a) performance, which corresponds to a percentage of points earned in a course at a given time, b) effort, measured by interaction (clicks) within their virtual learning environment (Blackboard), c) previous academic history entailing high school GPA and test scores, and d) learner background features such as credits attempted, residency status, and age. The CS algorithm calculated either a red, yellow, or green color for each learner that was displayed on the learner's (LMS) course homepage and was also accessible to the instructor. Red indicated a high probability of a learner being unsuccessful in the course, yellow meant a potential inhibitor was present for success, and green meant a high probability of success in the course. Once notified, the instructors had the ability to monitor or design an intervention for the learner.

One key feature of the CS program is that its real-time capabilities allowed for the learners' red, yellow, or green color to be updated throughout the term. Results from the CS program suggested that learning increased throughout the semester as well as retention rates for learners who had at least one CS course in comparison to those learners who did not have at least one CS course. CS is a practical comprehensive example and model on how institutions can build or adopt a signaling mechanism for early intervention through LA for those institutions who desire to improve teaching and learning.

LA data also can enhance pedagogical practices. The utilization of LA data in courses could reveal knowledge gaps that occur in learning (Greller & Drachsler, 2012). Once gaps in learning are revealed, faculty can alter or change curriculum or teaching methods to ensure higher levels of learner success. However, a potential issue could arise if faculty do not have the appropriate time to respond to individual learner needs or if knowledge gaps potentially reinforce culture bias or racial/gender stereotypes (Dietz-Uhler & Hurn, 2013).

As another example, adaptive learning, which is the modification of course content based on learner performance, is a pedagogical platform that LA data can enhance. Mavroudi et al. (2018) proposed a framework for adaptive LA in which they blend two previous models by Knutov et al. (2009) and Brusilovsky (1996) to formulate six key adaption dimensions: 1) what to adapt, 2) what to adapt to, 3) why the need for adaption, 4) where to apply adaption, 5) when to apply adaption, and 6) how to adapt. Thus, the incorporation of LA data has the potential to enhance each component of the framework with a particular focus on the "how" as LA modeling has the potential to produce new data sources on campuses that may have not been previously available. As such, the incorporation of the new data can inform and enhance adaptive learning to provide the learner with more tailored course content and curriculum options.

In review, the incorporation of LA data in teaching and learning contexts provides the ability for instructors to develop interventions to enhance learner success, increase learning, as well as enhance pedagogical practices. The next section focuses on LA data's application in enhancing academic achievement.

Academic Achievement. Arguably, the most attention in LA has been applied to academic achievement, mostly commonly operationalized as grades. As Baker (2019) stated at the 2019 Learning Analytics and Knowledge Conference keynote address, over 75% of articles that appear in the *Journal of Learning Analytics,* the leading journal in the LA field, focus on the utilization of LA data to predict learner grades (Baker, 2019). Most commonly, researchers develop predictive models from LA data gathered from the course LMS (Conijn et al., 2017; Tempelaar et al., 2015; Shum & Crick, 2012). The current landscape of studies in this capacity sought to identify a wide array of predictor variables that can be gleaned from LA data. A non-exhaustive list of previously tested LA predictors includes the total number of clicks, number of online sessions, total time online, number of course page views, irregularity of study time, irregularity of study interval, number of quizzes started, number of assignments submitted, number of wiki views, and average assessment grade (Conijin et al., 2017).

As an example, EAB collaborated with George Mason University to test a model on three semesters worth of page views on over 871 undergraduate courses (Venit, 2017). They sought to predict final course grade in the learner's current course grade as well as persistence to the next term. After conducting a regression analysis, findings suggest that more learner page views correlated with higher grade obtainment. However, a frequently cited criticism is that this is an elementary finding as LMS engagement can serve as a proxy for learner engagement and it is well documented in the higher education literature that increased engagement leads to higher grades (Mayhew et al., 2016). Nevertheless, this study provided evidence of the need to further examine LA data and academic achievement.

As another example, Wieling and Hofman (2010) examined the effect of LA data in the form of online video recordings and automated feedback on learner achievement. Their purpose was to determine the extent to which a blended learning configuration of face-to-face lectures, online on-demand video recordings of face-to-face lectures, and the offering of online quizzes incorporated with feedback had a better impact on the performance of online learners compared to face-to-face courses. The participants were learners who were enrolled in a second semester seven-credit course entitled European Law at the University of Groningen. A total of 474 learners participated in the study as the experimental group and 867 were the control group. To examine the effect of viewing online lectures, the researchers entered all variables and scales into a sequential linear regression model to examine effects on final exam grade. The results of the final model suggested that viewing online lectures as well as attending lectures in person had a significant positive effect on final exam grades for learners; however, access to formative assessment and attendance of workshops had no additional benefit on performance.

Though studies pertaining to predicting academic achievement are insightful, a large concern raised by the LA community is that most studies are difficult to test or replicate because most studies use predictors the are unique to the individual study or developed within a specific context (Baker, 2019). As a result, the current scope of models that use LA data to predict grades is limited due to the uniqueness of each context, thus limiting generalizability. Oftentimes, scholars create predictor variables based on the uniqueness of the course they are studying and since most courses contain different content, grade mechanisms, and structure, an identified challenge is developing a model that can be applied to other contexts. Though this limitation exists, models that have incorporated LA data have been influential in enhancing academic achievement; however, LA data can be applied to other contexts as well, such as retention and graduation rates.

Retention and Graduation Rates. Two key institutional metrics that universities are incessantly trying to improve are retention and graduation rates. Utilizing LA data to develop predictive models has been shown to improve retention and graduation rates (Dawson et al., 2017; de Freitas et al., 2014). A common approach in the LA literature is the utilization of early alert systems (as in the CS example) that can provide a basis for intervention. However, the CS example was aimed at equipping learners and faculty with knowledge of performance and potential pitfalls, whereas broader alert systems can help with retention.

Dawson et al. (2017) piloted a LA retention program that sought to improve learner success by a combination of proactive advising and referrals to support services such as counseling, disability services, or tutoring services. The developed program would inform specific support services of potential learner issues in hopes learners' utilization of support services would increase retention. In their study, a predictive model was developed using association rule mining algorithm and integrated classification. Predictor variables included historical learner performance variables, basic learner demographic variables and LMS activity variables. The program was piloted to 17 first-year learner courses that reached 11,160 learners. A subset of 1,868 learners was identified as potentially at-risk of which 1,271 learners were reached out to during the semester. Results suggested that when learners were contacted by support staff, they were 31.24% more likely to be retained than those who were not contacted by support staff; however, the explanatory power of the model was very low. Other logistic regression tests did not reveal any significant findings or differences in retention. This study was an important case study for the instructors and practitioners to understand how to incorporate LA data into a model of retention.

As for graduation rates, one of the most common approaches in the LA literature is utilizing LA data to develop predictive models to individualize curriculum (Nam et al., 2014; Sclater, 2017). LA data has the potential to develop an algorithm based on a variety of data points that recommend courses for learners to select (in conjunction with advising services). Developing tailored course recommendations based on prior learner LA data, performance, and interest can increase graduation rates. For example, Stanford developed and tested a program called CourseRank aimed at aiding learners in deciding courses to select (Bercovitz et al., 2009). The overall goal of the program was to recommend courses taken by similar learners in hopes of leading to greater learner outcomes. The program presents learners with personal recommendations for courses to take along with course descriptions, evaluation, and grade distributions. Though the learners engaged often with the service and garnered good feedback from learners, Sclater (2017) pointed out that the system missed an opportunity to connect more closely to courses needed for graduation. Though a missed opportunity, this presents an important case study for the possibility of LA data's application in higher education to increase graduation rates.

In review, LA has shown much potential as described above even though LA practices on campus remain nascent. LA data, mostly collected from student ID cards or LMS, have been shown to enhance teaching and learning, academic achievement, and retention and graduation rates. In its myriad of capabilities and benefits, scholars have started to use LA data for SRL measurement. Thus, the next section addresses how the field of SRL has previously engaged utilized LA data as an indication of learners' self-regulation.

Utilizing LA Data for SRL Measurement

As noted by a variety of scholars and explored earlier, there is much room for improvement with respect to SRL measurement, specifically in the data that is being collected and utilized (Roll & Winne, 2015; Siadaty et al., 2016; Winne, 2017). One promising option is the utilization of LA data produced by learners in a variety of contexts, specifically LMS. A growing body of literature has emerged that focuses on utilizing LA data for SRL measurement (Gasevic et al., 2014; Gerwerc et al., 2016; Greene et al., 2011a; Jarvela et al., 2016; Shell & Soh, 2013; Soffer & Cohen, 2019). Thus, this section reviews considerations and prior research on utilizing LA data for SRL measurement. First, the advantages of LA data and how it fills the current gaps of data produced with traditional SRL methods are presented. Second, a review of empirical studies utilizing LA data for SRL measurement is reviewed. Contained within this section is a review of studies by data type, method, and granularity as well as the shortcomings of the current set of studies. Lastly, the section concludes by addressing how the present study seeks to fill identified gaps.

Advantages of Utilizing LA Data for SRL Measurement

The literature highlights that LA has several advantages related to the utilization of data derived from LA for SRL measurement. As established earlier, key concerns regarding most of the current set of SRL measurement methods is that they may not produce more objective data and are intrusive in nature (Panadero, 2017; Rovers et al., 2019; Winne & Jameison-Noel, 2003; Winne & Perry, 2000). Thus, there have been calls by the SRL community to utilize LA data for SRL measurement (Baker et al., 2020; Durall & Gros, 2014; Kovanovic et al., 2015; Vovides et al., 2007; Winne, 2017). Winne (2017) suggested that LA data has the potential to remedy current data issues of SRL measurement in that LA data offers direct insight into learner behavior and cognition without prompting or interference from outside influences such as researchers or instructors. Most LA data is captured in real-time as the learner is engaging within a task and oftentimes without a learner's knowledge that data is being collected (Lang et al., 2017). As a result, the learner's engagement with SRL behaviors or strategies is unimpeded, which differs starkly from other methods such as interviews or think-aloud protocols. In essence, LA data enables the researcher to observe learners in their natural state of performing a task. In turn, this has the potential to create more objective data that is not influenced by an external source. Oftentimes, other methods of SRL, such as self-report questionnaires or interviews, may promote SRL strategies or behaviors that the learner may not have otherwise considered. Thus, LA has the potential to preserve objectivity with data being collected.

Another key advantage of the utilization of LA data is the properties it contains, such as volume, velocity, and value that make it an attractive option for researchers (Lane & Finsel, 2014). Volume refers to the amount of data that is available, which in the case of LA is vast. Velocity refers to the speed of accumulation of data, which is at high speed with LA. Lastly, value is the utility or usefulness of data, which LA has been demonstrated (as illustrated in the previous section) to have many uses. These properties work well when using LA data from a learning management system (LMS). For instance, the volume of data that an LMS produces is significant over the course of a semester, several semesters, or even several years. As described earlier, the LMS logs and stores all learner activity for the entire course. Thus, the researcher can sort through the LMS data to identify relevant data.

Second, LMS data possesses much velocity. In comparison to other methods such as think-aloud measures or self-report questionnaires, a researcher may only be able to capture SRL behaviors at one point in time. As for the LMS, learner behavior is captured every time the learner logs into the LMS system, which enables researchers to track learners' behavior over time as opposed to one or a few points in time that other methods offer. Lastly, LMS provides many valuable data points. As illustrated previously, LMS data can be organized and analyzed to improve many learner outcomes such as improving academic achievement, and graduation and retention rates. Thus, the volume, velocity, and value of LA data is an attractive option for researchers that also can extend current measurement methods, such as trace methodology.

Winne (2017) and Baker et al. (2020) have laid a robust foundation for utilizing LA data to extend current SRL measurement methods. Winne (1982, 2017) suggested that LA data could enhance SRL measurement, specifically, trace methodology, by examining trace data in the virtual environment. As established previously, trace data can be used as evidence of learner cognition or engagement of SRL behaviors and/or strategies (Winne, 2017). Additionally, Baker et al. (2020) added that LA data can be a better measure of SRL than the traditional methods of SRL measurement such as self-report questionnaires and think-aloud protocols because LA data can provide both timely and more objective measures of SRL. For instance, LA data provides real-time traces of learner thought processes by recording all learner interactions in the LMS environment.

Winne (2017) expanded on his notion of LA data as evidence of trace data. As an example, if a learner clicks on a certain link, the data produced can demonstrate the learner's cognition and motivation. The click is a trace that provides the opportunity to make strong inferences about cognitive processes, metacognition, and motivation. Additionally, Winne (2017) described four features that need to be present to utilize LA data for SRL measurement. First, nearly all operations that the learner performs throughout the episode are traced. In other words, each time a learner logs onto the LMS, all interaction activity is tracked by the LMS until the session is ended (or timed-out due to inactivity). Second, information is identifiable in that researchers can identify specific student data and interpret the data housed in the LMS. Third, timestamps are available. With each interaction that a learner performs within the LMS, a subsequent timestamp is produced. Lastly, the product of the operations is recorded. This 4-tuple trace data framework enables researchers to generate rich LA data for SRL measurement. Thus, since the conditions outlined by Winne (2017) can be met by LA data, specifically an LMS, it is appropriate for LA data to be used for SRL measurement.

In review, the utilization of LA data for SRL measurement has several key advantages including increased objectivity, non-intrusiveness, and has the attractive properties of volume, velocity, and value as outlined above. Lastly, key SRL scholars, such as Winne (2017) have outlined conditions necessary that have been met by LA data for it to serve as an indication of learners' self-regulation. Understanding its utility and applicability, both SRL scholars and LA scholars have started to conduct studies using LA data for SRL measurement.

Previous Empirical Work Utilizing LA Data for SRL Measurement

For the purposes of this study, there are three key areas of prior research that utilized LA data for SRL measurement. First, the type of LA data that has been used for SRL measurement with particular emphasis on Massive Open Online Courses (MOOCs) is reviewed. Other, though less utilized, sources reviewed are specialty analytics tools and LMS data. Next, the previous methods of analysis and their associated shortcomings are analyzed. Lastly, the level of granularity of previous studies is reviewed.

Previous Studies Utilizing LA Data for SRL Measurement: Data Sources. In this section, the types of LA data that have previously been used for SRL measurement are reviewed. Most previous studies that employed LA data for SRL measurement utilized MOOC data. The second most common is specifically designed LA tools such as nStudy (Winne et al., 2019). The least common, yet most advantageous, is LMS data, which is discussed in detail.

MOOC Data. Over the past decade, MOOCs have altered the landscape of higher education (de Freitas, 2015). Due to their openness, scholars have also been able to glean LA data from learners in the MOOC environment. Wong et al. (2019) conducted a comprehensive literature review of studies that linked SRL and LA data produced by MOOCs. Their review identified several SRL strategies that were measured via LA data generated by MOOCs including prompting and feedback.

First, prompting was a key SRL strategy studied via LA data generated by MOOCs. Prompting involves the instructor asking the learner guided questions such as "do you understand the key points" or suggestions such as "take time to read" to promote SRL behaviors (Wong et a., 2019). This type of prompting can lead to learner's engagement with SRL strategies and ultimately enhance outcomes. As an example, Bannert and Reimann (2012) used an experimental design to examine prompting vs non-prompting behaviors. Their study found that the group of learners that were prompted demonstrated engagement with significantly more SRL strategies such as goal orientation, goal specification, evaluation, and monitoring in juxtaposition to the control group of learners that did not have such prompting. In a follow-up experiment, Bannert and Riemann (2012) added a training session before prompts. Like the earlier study, those who received the training session demonstrated higher levels of engagement in SRL strategies such as goal orientation and monitoring in juxtaposition to those learners who did not receive prompting or training.

Other examples of successful prompting studies include evidence of prompting on planning, goal specification, evaluating (Bannert & Reimann, 2012), metacognition (Bannert et al., 2015, Kaufmann et al., 2008), self-monitoring (Kauffman et al., 2011), and reflection (Ifenthaler, 2012). Additionally, some studies demonstrated that prompting could have positive effects on academic success (Crippen & Earl, 2007; Moos & Azevedo, 2008). Though prompting in a MOOC environment has had success, there have been challenges and limitations identified as well. First, prompting involves interfering with learner behavior or promotes certain learner behavior, which could encourage SRL behaviors that otherwise would not be present. Thus, a critical point that is not yet well understood is if learners are engaged in SRL behavior because they are truly self-regulating or if they were prompted before measurement occurred, therefore presenting an illusion of self-regulation. Another key limitation is that oftentimes prompting is difficult to carry out in a MOOC setting. MOOCs are often asynchronous, which limits the opportunity for instructors to prompt learners to engage in SRL behaviors as it relies on learners reading a prompt.

Feedback is another type of SRL strategy that has been measured using LA data within the MOOC context. Feedback is most defined as the information received from an instructor or peer that the learner receives after engaging in an activity (Wong et al., 2019). Feedback is a critical mechanism for learners because feedback raises awareness of prior learner behavior and offers the opportunity for learners to reflect on their performance, which could lead to enhanced performance going forward. Prior data from MOOCs demonstrates the role of feedback in SRL processes. As an example, Biesinger and Crippen (2010) examined differences between norm-referenced and self-referenced (forms of feedback) and the perception of the learning environment. However, this study did not reveal any significant findings as a major limitation was the failure to measure learners' awareness of feedback. Another study conducted by Wäschle et al. (2014) examined visual feedback as a tool to inform learners of their behaviors, such as procrastination, in hopes that it would deter them from further procrastination. Results demonstrated that learners who were exposed to visual feedback had much lower levels of procrastination than learners who were not exposed to visual feedback.

Similarly, there is another strand of research that combined feedback and prompts. Adhering to Zimmerman's (2000) notion that SRL is a cyclical process, several studies combined prompts with feedback to support a cyclical process. A study conducted by Van den Boom et al. (2007) examined factors within an online environment: reflection prompts with tutor feedback; reflection prompts with peer feedback; and a control group with no support. Utilizing the Motivated Strategies for Learning Questionnaire (MSLQ), results suggested that learners who received prompts and feedback scored higher on the

MSLQ than those who were not supported. Though much prior empirical work was conducted on feedback as well as feedback and prompts, a key limitation is that there is a significant reliance on the learner to utilize feedback from the instructor.

Though LA data generated by MOOCs have been widely utilized, there are several limitations that categorized MOOCs as a less than ideal data source for LA data to measure SRL. First, not all MOOCs can track learner engagement in the online platform, so data could not be collected and analyzed. Thus, the set of courses available for research is contingent upon the researcher's ability to track learner engagement in MOOCs. Second, there are many issues with MOOC data due to the dropout or incomplete rates of MOOCs. Thus, very little could be known about learners who do not finish a MOOC whereas dropout or incomplete rates among learners at most Universities remain low. Third, the LA data that is produced by MOOCs is limited. MOOC platforms are often restrictive in their functionality and do not offer as many tools as other LA platforms such as LMS. Lastly, MOOC data is oftentimes difficult to interpret due to the data schema. Therefore, analysis may be cumbersome. In contrast, other types of LA platforms, such as an LMS, have analytic components for purchase or can be obtained through an institution's information technology services.

In sum, LA data generated by MOOCs to measure SRL have been successful in measuring and conveying the benefits of prompting and feedback to promote SRL strategies. However, there are key limitations to using LA data produced by MOOCs to measure SRL as MOOC platforms do not always track learner behavior. Additionally, MOOCs tend to have very high dropout rates which can compromise data. Lastly, data produced by MOOCs can be limited and difficult to interpret due to its data schema. As an improvement to a few of these key issues, some researchers have developed specialty analytics tools, which are reviewed in detail below.

Specialty LA Tools. A review of the extant literature on LA and SRL reveals that there are specifically designed LA tools found in the literature aimed at measuring a learner's SRL strategies or behaviors. Most commonly, the nStudy tool has been used to generate LA data to measure SRL (Beheshitha et al., 2015; Bernacki et al., 2011; Jarvela et al., 2016; Winne et al., 2019). The nStudy tool is a web browser extension and designed for learners to engage with peers, information, and chatbots as they perform tasks related to learning. There are two key components associated with the nStudy: artifacts and trace data. Artifacts are observable formations created by a learner when they are engaged with the text. An example of an artifact within the nStudy is when a learner highlights text, like traces generated in trace methodology, as discussed earlier. Other types of artifacts that learners can engage within nStudy are bookmarking, creating notes, writing essays, posting messages, annotating text, organizing information, and viewing text. Every time a learner creates an artifact, it is a form of trace data.

As previously discussed, trace data is a representation of learning, namely cognition or behavior, that a researcher can make inferences about the learner's cognitive operations in a specific context. Thus, highlighting a word or passage in the nStudy tool, could be a representation of metacognitive monitoring as the learner has deemed this part of the text important. Winne et al. (2017) stated that it is reasonable to infer that highlighting represents metacognitive monitoring in the sense that the learner most likely highlighted the text because that portion of text is important to review later.

The nStudy builds on traditional trace methodology with more advanced capabilities. Within traditional trace methodology, learners would simply highlight or annotate text without any additional information being ascertained by the researcher. Within the nStudy software, when a learner highlights text, the software can automatically have a secondary popup window displayed, in which a learner can select certain tags or phrases that further emphasizes engagement in SRL behaviors or activities (Winne et al., 2017). For example, Beheshitha et al. (2015) compared learners' self-reported aptitudes via the R-SPQ-2F instrument used to evaluate learner study approaches to SRL behaviors present in the nStudy tool. Their sample included 22 third-year undergraduate learners in an interdisciplinary interactive arts and technology program. Participants responded to the R-SPQ-2F instrument, which is composed of 20 items divided into four subscales aimed at understanding study approaches. Additionally, learners were asked to utilize the nStudy tool within their research project for a variety of different activities that the nStudy tool captures such as bookmarking, taking notes, and organizing resources.

To analyze the data, the researchers clustered survey responses using agglomerative hierarchal clustering. In addition, trace data were analyzed by learning strategy and learning activity using Fuzzy miner algorithm for processing. Their results suggest that two clusters were identified from the survey data: deep learners and surface learners, in which deep learners orient themselves towards a richer understanding of concepts, whereas surface learners are more apt to memorize facts. Apply processing mining to the nStudy activities that learners performed demonstrated that deep learners applied more elaboration strategies, which demand the most cognitive resources, such as critical thinking. In contrast, surface learners employed more organizational strategies, such as arranging information.

Though the previous study clarifies examples of learner profiles, this study contains limitations that are common across specialty-designed LA tools. First, specifically designed LA tools have the potential to limit processes that can be observed within the environment. For example, within nStudy there are only a select number of actions that can be performed by the learner. Thus, these types of tools could limit the SRL behaviors or strategies that are able to be observed, which in turn, limits the amount of data available to the researcher. Second, specifically designed LA tools may have limited accessibility and understandability (Gelan et al., 2018). Even though the nStudy tool is available as a web browser add-on, most specifically designed tools do not have such accessibility. Moreover, these tools tend not to have much content available to instruct how to operationalize them. As a result, they could be cumbersome for researchers to implement and interpret. Lastly, most of these tools lack widespread utilization in contrast to MOOC or LMS data. Lack of widespread adoption could limit the generalizability or the applicability of findings to other contexts. This could also make studies that employ these tools challenging to replicate.

In sum, specialty-designed LA tools have been previously employed and can provide unique, tailored insight into a particular aspect of SRL. However, several limitations exist with specialty-designed LA tools including limited functionality, accessibility, and widespread utilization. The next section presents LMS data, which is an alternative in gathering LA data from MOOCs and specialty-designed LA tools. Additionally, LMS data addresses the aforementioned limitations.

LMS Data. As described earlier, LMS has become increasingly popular on campus (Sclater, 2017). Previous research reveals not many studies employ LA data collected from an LMS for SRL measurement. This fact represents a missed opportunity to gain a deeper understanding of learners' self-regulation. Learners engage in a variety of activities in the LMS environment, which makes it a prime opportunity to examine learners' SRL behavior. Examples of these activities include clicking on course content, downloading course material, posting on discussion boards, completing assignments, engaging in practice exams, etc. (Lane & Finsel, 2014; Sclater, 2017). As Winne (2017) suggested these interactions or traces could be understood as displays of learner's engagement with SRL. Despite its promise, only a few studies have utilized LMS data to measure SRL. Those studies focused primarily on time management as an SRL skill (Baker et al., 2019; Cicchinelli et al., 2018; Lim, 2016; You, 2016).

As an example, Baker et al. (2019) conducted a randomized control trial of learners in an online course at a 4-year public university. Their study originally utilized 157 learners enrolled in the online course. Of those 157 learners, 145 completed the pre-course, which was used to understand the heterogeneity of treatment effects across groups. This enabled the researchers to categorize learners into groups based on their self-reported time management skills (i.e., high time management skills). Within the

LMS, the course was designed to provide learners the opportunity to engage in time management related items. These included tracking learner clicks on lecture videos. They used the time in which learners accessed the lectures as well as learner procrastination and cramming behaviors as variables.

As for their design, learners were randomly assigned (split evenly) into either the experimental group or the control group. Learners in the experimental group were asked to sign up for the day and time they would watch each of the lecture videos. In contrast, the control group was not asked to sign up for a specific day and time in which they watched each lecture video. A multiple regression analysis was conducted to examine the effects of the treatment on several outcomes such as quiz performance and final course grade. Results suggested that the intervention had a positive impact on achievement scores. In addition, learners who scheduled their lecture watching had better results in the first quiz than their counterparts who did not have the opportunity to schedule. Lastly however, they did not find that the intervention influenced learners' propensity to procrastinate, cram, or complete their work. Indeed, this study provided evidence that LMS data gathered from an LMS can serve as an appropriate measure for learners' SRL with respect to time management.

In another study, Montgomery et al. (2019) explored SRL as measured by LA data in a flipped blending learning environment. The study employed a sample size of 157 fourth-year undergraduate learners enrolled in a music teacher education course. The researchers captured metacognitive SRL behaviors via an LMS and categorized the behaviors across three domains: 1) activating, which was comprised of online access location, day of week, and time of day, 2) sustaining, which included online frequency, and 3) structuring, which was comprised of online regulating and exam review. The researchers employed Cramer's V coefficient to test association between categorical variables and the categories of academic performance and Spearman correlation coefficient to test the relationship between noncategorical variables and course grade. Their results suggested that day-of-the-week and access frequency were the strongest predictors of learner success, namely course grade. The impact of the study demonstrated that, when combined with previous SRL and LA research, access regularity is an important SRL behavior for learners within the blended learning environments (Montgomery et al., 2019). Thus, like the study conducted by Baker et al. (2019), LA data collected by an LMS has the potential to extend current SRL measurement methods.

A review of the previous empirical studies reveals the paucity of work the utilizes LMS data for SRL measurement despite many advantages that differentiate LMS data as a superior LA data source in juxtaposition to LA data generated by MOOCs and specialty LA tools. First, LMS is ubiquitous on campus with nearly every institution having an LMS, which in turn, creates more LA data (Sclater, 2017). Thus, this creates the possibility of accessing a large amount of rich data on every college campus. In addition, similarities in LMS (i.e.— Blackboard, Moodle) create common data points that researchers can obtain and compare across different campuses' LMS. Next, there is much more functionality within an LMS in juxtaposition to MOOCs or the nStudy. Due to the diversity of activities that a learner can perform within the LMS environment, there are many different opportunities to examine different aspects of SRL. Third, LMS has the potential to produce a rich data set. Unlike MOOCs, most of the learners complete the course in which they are currently enrolled, which has the potential to track learner behaviors over the duration of the semester. In addition, LMS data is conducive to understanding how learner engagement patterns can change throughout the semester, which is a key limitation of specialty- designed LA tools as they are typically administered at one point during the semester.

In review, this section discussed three common LA sources of LA data for SRL measurement, MOOCs, specialty-designed LA tools such as the nStudy tool, and LMS. Each source possesses advantages as well as limitations; however, LA data produced by an LMS offers the most advantages with the least number of limitations for SRL measurement. Yet, studies that utilized data produced from an LMS are significantly underrepresented in the research literature. The next section seeks to build on the source of LA data by examining the most common methods for analyzing LA data for SRL measurement.

Previous Studies Utilizing LA Data for SRL Measurement: Methods for Analysis. ElSayed et al. (2019) conducted a comprehensive analysis examining the common approaches and methods to analyze LA data for SRL. Their review included an eight-year time frame from 2011-2019 and included 109 studies. Their inclusion criteria were any study that focused on SRL and related terms such as SRL skills, strategies, and behaviors as well as LA keywords such as process mining, data mining, neural networks, and data analytics. Utilizing their analysis as well as additional studies located since this study, the following section reviews the most common types of LA techniques and analysis applied when using LA data for SRL measurement as well as the advantages of each. The most common types are cluster analysis (approximately 50 studies) and classification studies (approximately 30 studies). Other techniques that have been applied less frequently include temporal data mining techniques, social network analysis, and principal component analysis. For this paper, clustering and classification are reviewed in detail.

Clustering. Overwhelming, the most common technique utilized was clustering techniques. The most common clustering techniques were agglomerative hierarchical, k-means, and latent profile analysis (LPA). Clustering is an appropriate method in understanding LA data for SRL measurement as the purpose of clustering is to categorize or create learner behavior profiles (Kim et al., 2018; Romero & Ventura, 2010; Segedy et al., 2015). Additionally, clustering is a popular technique because it affords the opportunity for adaptive scaffolding as the learner progresses in their learning (Bouchet et al., 2013).

Because it is closely aligned with the purpose of this dissertation, a study utilizing LPA is reviewed in detail. Ning and Downing (2015) conducted a study on 828 final-year learners from a university in Hong Kong. They administered the Learning and Study Strategies Inventory (LASSI) to learners to measure self-regulated learning, motivation, attitude, and test anxiety. Additionally, they measured academic self-concept utilizing five items from the Janis-Field Feelings Inadequacy Scale as well as students' learning experience via a 23-item Course Experience Questionnaire, and academic performance via learner's cumulative GPA. The three questionnaires were administered within a common course and learner's cumulative GPA was obtained from their institutional records. As for the analysis, the researchers ran descriptive statistics before conducting an LPA. Results from the LPA demonstrated four types of learners with distinguished SRL orientations, competent, cognitive oriented, behavior oriented, and minimal self-regulated learners. Other findings demonstrated that competent learners had the highest levels of motivation and attitude, the lowest level of test anxiety, and the best academic performance. This study, in addition to other studies (Broadbent & Fuller-Tyszkiewicz, 2018; Greene et al., 2011b) demonstrated the potential for LPA to be applied as an appropriate method to enhance understanding of SRL processes that learners' employ.

Clustering as a method has several advantages when utilizing LA data. First, clustering is a powerful tool for data mining that can handle the vast amount of LA data an LMS can produce. Additionally, clustering is a useful method in understanding learner profiles or groups based on similar engagement patterns within the LMS. This enables researchers to understand groupings of learner behaviors and strategies. Next, a review of classification studies is presented.

Classification. Following clustering, classification techniques are the second most common method utilizing LA data for SRL measurement. Overwhelmingly, the most common type of classification technique is regression analysis, which is an appropriate method as oftentimes previous studies seek to predict outcomes such as academic achievement or persistence, based on collected SRL and LA data (Bozpolat, 2016; Kuo et al., 2014; Li et al., 2020; Lim, 2016; Umbleja & Ichino, 2017; You, 2016). As an example, Li et al. (2020) examined LA data and learner's SRL behaviors in an online course. Their sample included 220 undergraduate learners in a 10-week fully online Chemistry course. They conducted a correlation analysis to determine the extent that LA data of time management and effort regulation corresponded with self-reported data from learners. In addition, they conducted a regression analysis to determine if LA data measuring time management and effort regulation complemented self-reported data from learners in predicting learner performance. Results suggested that LA data of time management and effort regulation were significantly associated with learners' self-reported time management and effort regulation. Addition results demonstrated that LA measures better predicted learners' academic achievement than self-reported data from learners. Though an insightful study, other studies that have attempted to determine the relationship between LA data and SRL self-reported data have been less successful (Cicchinelli et al., 2018; Yamada et al., 2015).

As an example, a study conducted by Cicchinelli et al. (2018) examined learners' LA data to find traces of SRL behavior and strategies in activities streams of LMS data. A sample of 170 first-year learners completed the Motivational Beliefs and Self-Regulating Strategies (MBSRS) questionnaire, which is a variant of the MSLQ. The 44-item questionnaire contains five subscales: self-efficacy, intrinsic value, text anxiety, cognitive strategy use, and self-regulation. Additionally, they collected learner engagement data within the course LMS and categorized based on SRL theory: planning, monitoring, and regulating. The researchers conducted a correlation analysis between each subscale on the MBSRS and indicators of SRL behavior in the LMS. The researchers created nine factors based on LMS data on the categories of planning, monitoring, and regulating (total planning, total monitoring, total, regulating, average planning per session, average monitoring per session, average regulating per session, average time planning, average time monitoring, average time regulating). Of the five subscales and nine LMS factors, there were only three that correlated out of 45 total possibilities. Thus, a key limitation of this study, and general issue with using LA data for SRL measurement, is the lack of correlation between LA data and SRL behavior as compared to other sources such as self-report questionnaires. This is one of the key gaps that the current study seeks to fill by developing a robust set of correlations between LMS data points and learners' self-report SRL behaviors and strategies.

In review, clustering and classification techniques are the most common methods in analyzing LA data for SRL measurement. Most commonly, agglomerative hierarchal clustering and multiple regressions are the most common clustering and classification techniques, respectively. However, a startling trend that was uncovered in the classification section is that most researchers did not establish convincing evidence of the relationship between SRL data collected from traditional SRL methods and LA data. In the next section, another key aspect of utilizing LA data for SRL analysis, which is the level of analysis, is explored.

Previous Studies Utilizing LA Data for SRL Measurement: Granularity of Analysis. The granularity of analysis has been an important consideration in previous work. Each study presented in this section has been intentional about the granularity of analysis. Previous research oftentimes presented the time of data collection (i.e., over the course of the semester, during a week of class) followed by the point within the course that SRL behaviors were measured (i.e., prior to an exam). A review of the extant literature utilizing LA data for SRL measurement reveals most studies focused on aggregating LA data across the semester (or several weeks) to measure SRL behaviors and strategies employed by learners at one point during the semester, most commonly prior to the final exam or midterm exam (Vaessen et al., 2014; Wise & Cui, 2018; Zhou & Winne, 2012). A fewer set of studies sought to aggregate LA data across the semester (or several weeks) to measure SRL behaviors and strategies at more than one point during the semester (You, 2016).

As an example, You (2016) conducted a study that identified factors using LMS data that predicted course achievement. The researcher gathered LMS data for the entire semester on a sample of 530 learners. LMS data was utilized to create six factors based on SRL concepts: regular study, total viewing time, sessions, late submissions, proof of reading course information packets, and messages. First, the researcher conducted a multiple regression to uncover which LMS factors were predictors of course achievement. Results demonstrated that regular study, late submissions, number of sessions, and proof of reading course information packets were significant in predicting final grade. The second part of the study examined which of the significant predictors were found to predict course achievement could also predict performance in the middle of the semester. Findings demonstrated that regular study, the number of sessions, and late submissions were significant predictors for midterm performance. This study illustrated an effort to aggregate LA data that was collected over the course of the entire semester and examine specific SRL behaviors during two points in the semester, the midpoint and endpoint, which is a common approach in previous work that has used LA data to measure SRL.

The current set of available studies demonstrate that researchers have sought to measure SRL behaviors once, or in some instances twice, in a semester via data that is collected across the whole semester. In contrast, there were no studies uncovered at the time of the present study that considered learner LMS behavioral patterns on a week-to-week basis. This is a large gap in the literature as measuring SRL only once or twice in the semester significantly limits the ability of instructors and practitioners to craft interventions during the semester to improve learner success.

In review, this section addressed prior efforts by researchers in utilizing LA data for SRL measurement. As noted, utilizing LA data for SRL measurement has several key advantages. First, LA data has the potential to produce unintrusive data, which is a key limitation for most of the current measurement methods. Additionally, LA data contains properties such as volume, velocity, and value that have the potential to extend SRL measurement methods. Next, previous work was reviewed that utilized LA data for SRL measurement with three domains: data sources, methods for analysis, and granularity of analysis. As for data sources, most of the current studies employed MOOC data or a specialty LA tool, such as nStudy. A smaller subset utilized LMS data; however, LMS data is a promising data source due to its ubiquitous nature on campus and functionality. Second, the most common methods for analysis were clustering and classification; however, there is a significant gap in the lack of establishment of the relationship between SRL data collected from traditional SRL data sources and LA data. Lastly, the level of granularity for analysis of previous studies demonstrated that LA data has been gathered most frequently across the whole semester, but SRL measurement points have only occurred one or two times during the semester.

Present Study

Self-regulated learning (SRL) has become an increasingly popular and well-studied educational psychology concept over the past several decades. Most commonly, SRL is comprised of three main components: metacognition, motivation, and behavior. One of the key considerations within the SRL literature is the ways in which SRL is measured. Though a myriad of benefits exists with the current scope of SRL measurement methods, two frequently cited criticisms are that the existing methods contain concerns with data objectivity and that they are intrusive in nature, which could compromise the quality of data collected. To fill these gaps, there have been recent calls by scholars to examine the utility of learning analytics (LA) data to extend the quality of data produced to measure SRL.

Over the past decade, the utilization of LA data has risen dramatically on college campuses. As such, demonstrable benefits have been noted to improve university and learner outcomes including enhancing operational function, student learning, academic achievement, and retention and graduation rates. Additionally, a growing body of literature has examined the utility of LA data in measuring SRL, specifically metacognition and motivation. However, many limitations exist with respect to the previous studies that utilized LA data for SRL measurement. First, most studies employ LA data from a data source that is limited in accessibility or functionality, such as a specifically designed LA tool (i.e., nStudy) or Massive Open Online Education (MOOC) data. Such data may not provide a robust data set. Thus, the present study utilizes data from an LMS. Second, prior work has failed to establish a robust link between SRL data collected from traditional SRL methods and LA data. The present study seeks to address this gap by utilizing data collected from the MSLQ and a plethora of data collected from an LMS and establish relationships between the two sources via correlational analyses. Lastly, most previous studies measure SRL behaviors via aggregated LA data at one or two points during the semester. Instead, the current study seeks to uncover learner's trajectories over the course of the semester through LA data that was gathered at the lesson level.

CHAPTER THREE

Measuring SRL with LA data has been previously attempted in various studies; however, there are many areas in which further research is needed. For example, most of the current studies utilized a data source such as MOOC or a specialty designed LA tool, which possesses limited functionality and accessibility (Beheshitha et al., 2015; Bernacki et al., 2011; Kuo et al., 2013) To address this gap, the current study utilized data produced by an LMS, which is known to produce a comprehensive set of data for SRL measurement as well as act as a more accessible and widespread data source on campus (Sclater, 2017). Additionally, the current set of studies are limited in the tie between data produced from traditional SRL methods and LA data (Cicchinelli et al., 2018). Thus, the current study sought to tie LA data and SRL data gathered from a traditional SRL method, specifically a self-report questionnaire, more tightly than previous work. Lastly, previous studies are limited in the level of granularity in their analysis as most studies seek to measure SRL behaviors with LA data at one or two points during the semester as opposed to across the semester (Li et al., 2020; You, 2016). To fill this gap, this study considered if learner activity within the LMS changes across the semester via examining behavior at the lesson level. Lastly, this study sought to determine if there were significant differences in academic achievement among clusters identified from the previous step. This chapter reviews the methodological procedures used in this study, including research design, research questions, procedure and data collection, data sources, data preparation and cleaning, and the analysis plan.

Research Design

This exploratory study employed a correlational design that included cross-sectional survey and longitudinal LMS data to examine relationships between learners' self-reported SRL data and LMS data, patterns in LMS data across lessons, and the relationship between LMS data and achievement in the course. Learners in the study completed a survey, which included demographic questions as well as the Motivational Strategies for Learning Questionnaire (MSLQ), an instrument designed to measure types of learning strategies and academic motivation of college learners (Pintrich & de Groot, 1990). Additionally, LMS data was gathered from consenting learners that tracked learner behavior in the virtual learning environment. Lastly, grade earned from the course was obtained as well from consenting learners.

Research Questions

This study was conducted at a large, research-intensive, public, suburban institution. The purpose of this study was threefold. First, the study sought to determine if correlation exists between participants' self-reported SRL behaviors and their behavior within the LMS. Second, the study examined patterns of activity within the LMS across multiple lessons via the identification of clusters from a trajectory analysis. Lastly, the study aimed to determine if there were academic achievement differences from trajectories identified in the second part of the study. Thus, the research questions of this study are as followed:

RQ1: Is there a relationship between learners' self-reported SRL and their behavioral data in the LMS?

RQ2a: Are there distinguishable behavioral patterns in LMS usage at the lesson level?

RQ2b: Are there differences among the clusters with regard to their academic achievement?

Participants, Procedures, and Data Collection

Participants in this study were degree-seeking undergraduate learners enrolled in a financial management course required for every learner who graduated with an undergraduate degree from the School of Business at the institution of study. The financial management course, which is housed in the School of Business within the institution of study, was utilized for several reasons. First, the financial management course is part of the core curriculum for every business school learner. Each learner who graduates from the School of Business must pass the course with at least a “C” or higher. Second, the course setup, which is discussed in more detail below, is conducive to an LMS study as the course relies heavily on learners’ utilization of the LMS, which was Blackboard for this course. Third, the financial management course is the most failed course at the institution of study. Learners only have three attempts to earn at least a “C”. Failure to do so after three attempts results in dismissal from the School of Business. Lastly, this course is known internally within the School of Business as a potential “weed-out” course wherein the course is intentionally designed for learners who perform well in the course to pursue a finance or accounting major and learners who do not perform well tend to pursue another major offered in the School of Business. Although “weed-out” courses have been documented in the literature, oftentimes talk of “weed-out" courses is internal and unique to the school or respective department and typically not publicized (Weston et al., 2019).

The sampling frame for the study was all learners enrolled in the financial management course in the Spring 2021 semester. All learners enrolled in the financial management for the Spring 2021 semester were sent an email from the financial management course coordinator, inviting them to participate in a survey. Several subsequent reminder emails were sent inviting learners to participate in the survey. Learners accessed the survey by clicking the link at the end of the invitation email. Learners who clicked the link were directed to a Qualtrics survey, which contained several components. First, learners viewed an Informed Consent Form which required them to type in their name and date to consent to participating in the study. If learners consented, they proceeded to the survey, if they did not consent then the survey ended for them. After consenting, learners began the survey which included all questions from the Motivated Strategies for Learning Questionnaire (MSLQ), which is an 81-item survey. The questions were randomized for each participant. The last section of the survey was six demographic questions. To ensure data integrity, three randomized attention checks were included in the survey. Responses were gathered and collected from the Qualtrics platform after the last day of the semester.

As for the second part of data collection, Blackboard data for each learner was collected at the end of the semester. A unique capability of an LMS, such as Blackboard, is that it stores, or logs, each interaction with a timestamp that a learner performs within the LMS environment (Sclater, 2017). As an example, if a learner logs onto the LMS, then accessed the syllabus tab, then downloaded the syllabus, and proceed to check grade, each one of these interactions, was stored within the LMS with a corresponding timestamp. Each learner enrolled in the financial management course had access to Blackboard.

There were several features designed within Blackboard to aid in learning as well as provide the opportunity to examine learner's self-regulation. For example, the instructor provided learners with content for ten lessons spread across 13 weeks, (a) time value of money, part one, (b) time value of money, part two, (c), time value of money, part three, (d) bonds and stocks, (e) capital budgeting criteria, (f) relevant cash flows and net present value analysis, (g) risk and return, (h) cost of capital, (i) annuity and annuity due, and (j) corporate financial management. A lesson was a topic that contained a lesson overview, lesson material, a lesson problem set, and lesson problem solutions, that was provided by the instructor to every learner. A new lesson was introduced approximately every week. Other resources available to learners via Blackboard were the course syllabus, weekly quizzes of knowledge, and discussion board for both instructor interaction and peer interaction.

After the completion of the semester, a list of all the financial management course learners was provided to the University's Information Technology Services (ITS) unit, which downloaded all blackboard data and final grade information for all learners enrolled in the financial management course. The University's ITS sent downloaded blackboard data and final grade information to the author of this study.

As for the sample of this study, the census date for enrollment was used to determine total learner enrollment in the financial management course, which was 824 learners. Next, the final enrollment in the course was determined by utilizing the number of learners enrolled at the conclusion of the semester, which was 812. Thus, 12 learners dropped or withdrew from the course during the semester and were subsequently removed from consideration for the study. Of the 812 potential participants, 258 learners provided consent to utilize their LMS and final grade data. Thus, included in the analysis of LMS data were 258 participants.

Of the 258 learners who provided consent, 134 responded to the survey. Of all survey participants, 19 respondents' survey data were removed because they missed at least two attention checks, which the author determined compromised data quality. Two respondents missed at least one attention check, but their data remained as the author determined the quality of data was sufficient to remain in the study. Additionally, 18 respondents' survey data was removed because they did not complete the minimum 25% of the survey, which is consistent with the previous handling of MSLQ data (Karadeniz et al., 2008; Jackson, 2018). Lastly, 11 participants completed the survey more than once. All 11 participants completed the survey completely on their first attempt and partially on their second attempt. Therefore, data from their second partial attempt was removed for all 11 learners. Thus, there were 86 useable participant surveys that were included in the analysis. Since RQ1 considered learners' survey responses and LMS data, the 86 learners who completed the survey were included in the analysis. Since RQ2a and RQ2b only considered LMS data, all 258 consenting participants were included in this portion of the analysis. The researcher was unsure if the 86 learners who responded to the survey and provided demographic data were representative of the 258 included in the LMS data. Though the researcher did have academic achievement, in the form of final grade, for all 258 learners. The mean final grade for the 86 learners who responded to the survey was 74.88, whereas the mean final grade for all 258 learners was 71.33. Thus, learners who completed the survey had a higher final grade than learners who did not complete the survey. The author knows the demographics of the business school, which includes approximately 70% White learners, 15% Asian learners, 5% African American learners, 5% Latino learners, and 5% other and approximately 60% male and 40% female. Though, the author is unsure if these trends hold for the remaining 172 who did not fill out the demographic on the survey.

Data and Measures

The current study employed the following measures: demographics, learners' self-reported self-regulation, academic achievement, and LMS data. Full descriptions of each measure are presented below.

Demographic Data*.* Included in the survey that learners completed were demographic questions. Participants were asked to provide their race, gender, major, age, transfer status, and generation in college status. For the race questions, the survey followed how the institution of study recorded race. Thus, the options for race were African American, Asian American, Hispanic American, Native American, Pacific Islander, White American, Two or more, International student, or prefer not to respond. Consistent with practices of inclusivity, response options for gender were woman, man, transgender, non-binary/non-conforming, or prefer not to respond. As for majors, the major selections were majors that were offered in the School of Business at the time this study was conducted, which were accounting, business analytics, finance, financial planning and wealth management, management information systems, management, marketing, and supply chain management. Participants were able to select more than one major for learners who were double majoring. Additionally, the School of Business did not offer an "undecided" option. Rather, students must declare their intended major upon entry to the School of Business. The response option for age was open-ended. Additionally, learners were asked to respond to their transfer status. Options were either that the learner started their collegiate career at the current institution or started their collegiate career elsewhere and transferred into the current institution. Lastly, learners were asked to identify if they were first- generation in college.

Self-reported Self-regulation. In order to ascertain learner's self-report self-regulation, participants completed the Motivational Strategies for Learning Questionnaire (MSLQ). Pintrich and De Groot (1990) developed the MSLQ to "assess college students' motivational orientations and their use of different learning strategies for a college course" (Pintrich et al., 2015, p. 5). The theoretical framework of the MSLQ is based on a belief that the self-regulation of learners includes elements of behavior and cognition (Pintrich & De Groot, 1990). The MSLQ is comprised of 81 items and contains two sections: motivation and learning strategies. The motivation section is comprised of 31 items and six subscales: Intrinsic Goal Orientation, Extrinsic Goal Orientation, Task Value, Control of Learning Beliefs, Self-Efficacy for Learning and Performance, and

Test Anxiety. The learning strategies section is comprised of 50 items and nine subscales: Rehearsal, Elaboration, Organization, Critical Thinking, Metacognitive Self-Regulation, Time and Study Environment, Effort Regulation, Peer Learning, and Help Seeking. Learners were asked to complete the entire assessment. Learner responses were scored on a seven-point Likert scale ranging from “not at all true of me” (1) to “very true of me” (7), which is the conventional scoring scale for the MSLQ (Pintrich et al., 2015). Several items noted in the MSLQ manual needed to be reversed coded and subsequently reversed coded prior to analysis (Pintrich et al., 2015).

The MSLQ was selected for several reasons. First, whereas there are many tools to measure SRL, the MSLQ is one of the most common instruments to measure self-regulation (Gonzalez-Torres & Terrano, 2008). Second, it has been previously utilized as an appropriate tool to gather learners’ self-reported data regarding their self-regulation and compare those data to LMS data (Cicchinelli et al., 2018). Lastly, the research questions that sought to be answered in this study are conducive to adopting the original version of the MSLQ.

Academic Achievement Data. Previous literature suggests that academic achievement has been measured in a multitude of ways, though most commonly as GPA or an exam score (Wibrowski et al., 2017). Additionally, some studies have used final course grade (You, 2016). This study used final course grade in the form of final points earned in the course, as the measure for academic achievement. Academic achievement data was included in the dataset obtained with the LMS data. In the course, the final grade was computed based on various graded components, all of which total to 100 percent (Table 2).

Table 2

Weight Distribution for Graded Components

Course Component	Weight of Numeric Grade
Lowest Test Score	10%
Second Lowest Test Score	15%
Second Highest Test Score	15%
Highest Test Score	20%
Final Exam	25%
Scantron Form and Exam Information	2%
Maple TA Registration Information	1%
Graded Assignments	12%

Letter grades in the course were determined by numeric grades for the course and ranges described below in Table 3.

Table 3

Numeric and Letter Grade

Grade	Range
A+	97.2 or Greater
A	93.0 – 97.1
A-	90.0 – 92.9
B+	87.0 – 89.9
B	83.0 – 86.9
B-	79.0 – 82.9
C+	74.0 – 78.9
C	69.0 – 73.9
D	60.0 – 68.9
F	59.9 or less

LMS Data. Previous researchers have tied SRL to LMS data via frequencies and duration (Beheshitha et al., 2015; Lim, 2016; Soffer & Cohen, 2019). Frequencies, or counts, are the number of instances that learners click on a specific item within the LMS (Green et al., 2011). Duration refers to time spent within the LMS, most operationalized as either session duration, or the amount of time a learner logged into the LMS to the time a learner ends their session, or duration within a task, such as the amount of time a learner spent on completing an assignment or watching a lecture video (Gasevic et al., 2015). For this study, frequencies were gathered from learners and utilized in the analysis.

An in-depth review of the previous studies that employed LMS (or more broadly, LA data) and SRL data revealed the lack of consistency in the utilization of a data schema to study LMS and SRL data. The data schema employed by Cicchinelli et al. (2018) is the most appropriate for this study because they categorized LMS activity within three domains from SRL theory: planning, monitoring, and regulating. Planning activities include self-regulating learner behavior in the LMS environment that helps organize efforts such as accessing the course syllabus. Monitoring includes self-regulating learner behavior within the LMS environment that tests learner knowledge such as completing test bank problems, completing lecture problems, or completing practice exams. Lastly, regulating includes self-regulating learner behaviors that were taken to acquire or reinforce knowledge such as viewing content, viewing lectures, viewing discussion board, posting on discussion board.

Data Preparation

This section contains the processes and procedures that were conducted to prepare the data for analysis. Reviewed in this section were scales that were calculated as well as data cleaning procedures for both survey data and LMS data.

Scale Calculation

For this study, there were scales and related units that were computed. First, the study used data from the MSLQ. Scores for the individual subscales were computed by calculating the mean of the items within each subscale. As an example, the intrinsic goal orientation subscale was composed of four items. A learners' score was computed by summing these four items together and calculating the mean. Thus, each learner had a unique value for each subscale.

Although not a scale, another unit that had to be calculated was a lesson. A lesson was a topic with corresponding content that included lesson overview, lesson material, which was a slide deck, a lesson problem set, and lesson problem solutions, that were provided by the instructor to every learner. LMS data for each learner was collected and collated for each lesson. A new lesson was available almost every week. To determine learner LMS activity for each lesson, the timeframe spanned from the moment after a specific lesson became available on Blackboard to when the next lesson became available on Blackboard. For each lesson, each learner had their frequencies computed for each aforementioned lesson variable. Lessons did remain available after the following lesson became available on the LMS. However, learner access and interaction with a lesson outside of the one-week period as described above was not factored into the calculation of a lesson for a given learner or included in lesson analyses.

Additionally, following the method of Cicchinelli et al. (2018), total frequencies and average frequencies were computed for planning, monitoring, and regulating categories. The frequencies for each category were computed for the entire semester by summing all learner activity for each of the respective categories for each learner. Average frequencies were computed by summing all activity within a specific category and dividing that by the number of elements in each category for each learner. Thus, there were six additional variables computed: Total learner planning activity, average learner planning activity, total learner monitoring activity, average learner monitoring activity, total learner regulating activity, and average learner regulating activity.

Data Cleaning

This section presents the steps that were taken to clean data for the analysis. First, steps taken to clean and prepare the survey data are reviewed. Next, LMS data cleaning and preparation are presented.

Survey Data. For the survey data, two main processes occurred for survey data cleaning, missing values and checking for outliers. Afterward, reliabilities for each MSLQ subscale were calculated. First, missing values from any participant were not replaced. Instead, scale means were calculated so that the scale value was the mean of items that participants did answer on that scale.

As for outliers, z-scores were calculated for all continuous variables to identify any univariate outliers. Consistent with best practices, any z-score value larger than +/- 3 was examined for possible removal (Johnson & Christensen, 2017). While there were four values that exceeded the +/- 3 threshold after computing z-scores, none of the outliers were removed as the z-score was just above the +/- 3 threshold. Additionally, for each identified outlier, the next closest value was within 0.2. Thus, based on the distribution of z-scores, it did not seem that these four values were true outliers and subsequently remained in the dataset.

After handling missing values and checking for outliers, reliabilities utilizing Cronbach's Alpha for each MSLQ subscale were computed. To compute reliabilities, the following steps were completed. First, data were reviewed to ensure that all items were scored appropriately. Several items needed to be reverse coded as per the MSLQ guidelines (Pintrich et al., 2015). Those included two items in the Cognitive and Metacognitive Strategies: Metacognitive Self-Regulation scale, three items in the

Resource Management Strategies: Time and Study Environment scale, two items in the Resource Management Strategies: Effort Regulation scale, and one item in the Resource Management: Helping Seeking scale. After accuracy was ensured with all coded items, a composite variable was created for each scale. This was conducted by grouping all items on each scale. Once composite variables were created, reliability was computed for each scale.

The reliabilities for each subscale were computed as follows: Intrinsic Goal Orientation (α = .747), Extrinsic Goal Orientation (α = .724), Task Value (α = .922), Control of Learning Beliefs (α = .854), Self-Efficacy for Learning and Performance (α = .951), Test Anxiety (α = .851), Rehearsal (α = .792), Elaboration (α = .818), Organization (α = .805), Critical Thinking (α = .774), Metacognitive Self-Regulation (α = .803), Time and Study Environment (α = .738), Effort Regulation (α = .705), Peer Learning (α = .759), and Help Seeking (α = .585).

All reliabilities computed were greater than the widely acknowledged 0.7 threshold (Johnson & Christensen, 2017) except for the Resource Management: Help Seeking scale (α = .585). Though the author is unsure why this might have occurred, it is worth noting that the reliability for the Resource Management: Help Seeking scale found within the MSLQ manual was reported as α = .52. Thus, results found in this study exceeded that of results reported in the MSLQ manual (Pintrich et al., 2015). Additionally, a few scales' reliability could have improved marginally by dropping an item; however, the author decided to leave in all items for each scale as the author did not think the difference would have been large enough to merit dropping an item. For example, The Resource Management: Peer Learning could have improved from α = .759 to α = .888 if an item was dropped; however, the author decided to keep the item in as this scale only contained three total items.

LMS Data. As for the preparation and cleaning of the LMS data, not much literature has been written on how to wrangle and clean LMS data appropriately. Though, basic data cleaning principles were followed. The first step was understanding the data. After receiving the raw data, the first step was interpreting and understanding the data utilizing information provided by Blackboard to understand its data schema. The data, in its raw form, contained the following columns: pk1, event_type, internal_handle, title, data, timestamp, session_id, student_id. Pk1 was the primary key or the column that tied all activity to a specific learner. The event_type was the type of event that occurred (either course access or content access). Internal_handle, title, and data each informed of the type of activity that the learner performed. Timestamp was the date and time that each activity a learner performed occurred. Session_id was a number assigned by Blackboard to each session in case issues came about that required troubleshooting. Lastly, student_id was the learner identification number assigned by the institution of study.

After developing an understanding of the raw data columns and rows, it was necessary to filter out any learners who did not provide consent. As such, data were sorted based on student ID number and matched those with the learners who provided consent from the survey. LMS Data from any learner who did not consent was removed immediately and discarded. Additionally, final grade data was added to the data file. Final grade information was obtained from the institution of study's information technology services center as well. The final grade for the 258 learners was in the grade file and the remaining grades for the rest of the non-consenting learners were removed and discarded.

Once the appropriate learners were identified, the next step was to determine the appropriate data elements to be included in the analysis. First, raw data was reviewed from the internal_handle, title, and data to determine the type of activity that occurred. As an example, the following raw data entry: Quiz 3 – TVM3, /webapps/assessment/take/submitted.jsp was interpreted as Quiz3, time value of money was submitted by learner. After ascertaining the type of activity that occurred for every interaction, several data rows were removed due to low frequency. Those activities included "study group," "accounts and billing," "alumni association," "Blackboard tutorials," "bookstore," "career services," "financial calculator," "grade estimator," "health services," "Laptop requirements," "IT support," and "everything you need to know about Blackboard." Each of these activities had a frequency of fewer than ten interactions across all learners in the sample. Additionally, as denoted in the "data" column, a learner may have performed an activity on their mobile device or laptop. Thus, activity that occurred on a different modality was treated as the same. Thus, modality was removed.

After removing the aforementioned data elements, the remaining elements were grouped into seven categories: discussion board, tests, quizzes, syllabus, announcements, grades, and lessons. Each element within the categories was checked to ensure that variability existed between learners. After variability within each element was ensured, all elements were kept in the analysis. Next, an in-depth review of the elements within each category is presented.

Within the discussion board category, the following two data elements were utilized: the number of discussion board posts, which was the number of times a learner posted on the discussion board, and the number of times viewed the discussion board, which was the number of times a learner viewed the discussion board. As for the test category, there were five identified elements, the number of times accessed final exam review video, the number of times downloaded formula sheet, the number of times took a practice test, the number of times accessed test solutions, and the number of this accessed test preparation material. The number of times accessed a final exam review video was the number of times a learner accessed the final exam review video prior to the respective test. The number of times downloaded the formula sheet was the number of times that a learner downloaded a formula sheet that was associated with a test. The number of times took a practice test was the number of times a learner took a practice test prior to taking the submitted test. The number of times accessed test solutions was the number of times a learner accessed test solutions after they had received feedback on a submitted test. Lastly, the number of times accessed test preparation material was the number of times a learner accessed test preparation material that included test date and test time.

As for quizzes, there were four LMS elements included in the analysis: the number of times a quiz was taken, the number of times a quiz was submitted, the number of times a quiz was reviewed, and the number of times quiz solutions were accessed. As for the specifics, the number of times a quiz was taken was the number of times a learner attempted a quiz. A maximum of two attempts was allowed per quiz. The number of times a quiz was submitted was the number of times a learner submitted a quiz attempt. A maximum of two submissions was allowed per quiz. The number of times a quiz was reviewed was the number of times that a learner reviewed a quiz that was submitted. In the review of a quiz, the learner was able to see the results of a quiz as well as the correct answer for each question. Lastly, the number of times quiz solutions were accessed was the number of times a learner accessed quiz solutions after a quiz was submitted. This differentiated from a quiz reviewed as these were detailed explanations of the correct answers to quiz questions.

The syllabus category contained three elements. First, the number of times accessed syllabus was the number of times a learner accessed the course syllabus. Second, the number of times accessed syllabus supplements was the number of times a learner accessed supplemental syllabus information such as updated office hours. Third, the number of times accessed weekly schedule was the number of times a learner checked the weekly schedule which informed the learner of each week's lesson as well as due dates for quizzes.

Announcements and grades each contained one LMS element. As for announcements, the number of times accessed course announcements was the number of times that a learner accessed the announcements page. As for grades, the number of times grades were checked was the number of times the learner checked their grade on the grades tab within Blackboard.

Lastly, the lesson category contained four elements. First, the number of times a lesson overview was accessed was the number of times a learner accessed a lesson overview page, which contained information about each lesson, such as goals and objectives as well as links to subsequent lesson material. Second, the number of times learning materials were accessed was the number of times a learner accessed learning material for each lesson, which included a slide deck for each lesson. Third, the number of times accessed test bank problems were the number of times that a learner accessed practice problems that corresponded to each lesson. Lastly, the number of times accessed test bank solutions was the number of times a learner accessed solutions related to practice problems.

Thus, a total of 20 LMS elements were included in the study that was divided by seven different LMS types (Table 4). Additionally, there were six more LMS elements that were created based on the work of Cicchinelli et al. (2018) and as described earlier, which included, total learner planning activity, average learner planning activity, total learner monitoring activity, average learner monitoring activity, total learner regulating activity, and average learner regulating activity.

Table 4

LMS Data Elements by Element Type

Discussion Board:
1. Number of discussion board posts
2. Number of times viewed the discussion board

Tests:
1. Number of times accessed final exam review video
2. Number of times downloaded formula sheet
3. Number of times took a practice test
4. Number of times accessed test solutions
5. Number of times accessed test preparation material

Quizzes:
1. Number of times a quiz was taken
2. Number of times a quiz was submitted
3. Number of times a quiz was reviewed
4. Number of times quiz solutions were accessed

Syllabus:
1. Number of times accessed syllabus
2. Number of times accessed syllabus supplements
3. Number of times accessed weekly schedule

Announcements:
1. Number of times accessed course announcements

Grades:
1. Number of times grades were checked

Lesson:
1. Number of times a lesson overview was accessed
2. Number of times learning materials were accessed
3. Number of times accessed lesson problem set
4. Number of times accessed lesson solution set

After it was determined which LMS variables were to be included in the study, it was necessary to categorize each as either planning, monitoring, or regulating activity.

This study followed how Cicchinelli et al. (2018) categorized LMS variables to study self-regulation for their study; however, they were not explicit in presenting every LMS element included in their analysis. Thus, the current study utilized the definitions of each type of category in order to categorize LMS data. As a reminder, LMS activities that helped organize or direct learner effort were categorized as planning activities. LMS activities that helped facilitate learners' knowledge acquisition were categorized as monitoring activities. Lastly, LMS activities that helped reinforce learners' knowledge were categorized as regulating activities (Table 5).

Table 5

LMS Elements & Activity Types

LMS Element	LMS Activity Type
Number of times a learner accessed syllabus	Planning Element
Number of times a learner accessed syllabus supplements	Planning Element
Number of times a learner accessed weekly schedule	Planning Element
Number of times a learner accessed grade	Planning Element
Number of times a learner accessed lesson overview	Planning Element
Number of times a learner accessed test prep	Planning Element
Number of times a learner accessed announcements	Planning Element
Number of times a learner accessed lesson materials	Monitoring Element
Number of times a learner accessed lesson problem sets	Monitoring Element
Number of times a learner took a practice test	Monitoring Element
Number of times a learner took a quiz	Monitoring Element
Number of times a learner submitted a quiz	Monitoring Element
Number of times a learner accessed discussion board	Regulating Element
Number of times a learner posted on discussion board	Regulating Element
Number of times a learner accessed lesson problem solutions	Regulating Element
Number of times a learner accessed final review	Regulating Element
Number of times a learner accessed formulas	Regulating Element
Number of times a learner accessed test solutions	Regulating Element
Number of times a learner accessed quiz review	Regulating Element
Number of times a learner accessed quiz solutions	Regulating Element

Once sense was made of the data and the LMS indicators were determined, the data was ready for cleaning. Like survey data cleaning, two main processes occurred for data cleaning, missing values and outliers. However, missing values were not an issue because if a learner did not engage in an LMS activity, it would not be considered missing, rather it was considered absence of performance of activity. Distributions were examined for skewness or kurtosis; however, none was observed.

As for outliers, z-scores were calculated for all continuous variables to identify any univariate outliers. Consistent with best practices, any z-score value larger than +/- 3 was examined for possible removal (Johnson & Christensen, 2017). After calculating z-scores, there were six instances where z-scores were over +/- 3. Each potential outlier was examined; however, all remained in the data set. This was because each potential outlier was a true data point that was reflective of a learner's LMS behavior with that specific LMS element. As an example, one learner checked their grade 234 times over the course of the semester, which was almost 80 more times than the next learner. Reviewing the data in more detail, this learner, in fact, did check the grade page 234 unique times during the semester. If the learner's timestamp activity confirmed that the learner had trouble accessing this page and simply hit "refresh" repeatedly until the page loaded, then instances with similar timestamps would have been treated as an outlier and subsequently removed from the data set. All other potential outliers followed a similar pattern and thus remained in the data set.

Analysis Plan

This section reviews the process and procedures that were followed for data analysis. The section is organized by each research question from the present study. Within each research question, the method for analysis and assumptions of statistical testing are reviewed.

Research Question One (RQ1): Is there a relationship between learners' self-reported SRL and their behavioral data in the LMS?

To answer this question, a correlation test using Pearson's correlation coefficient was conducted to examine the relationship between learner's self-reported information on the MSLQ subscales as well as all LMS elements and LMS element categories. Though prior to conducting the Pearson's correlation coefficient test, assumptions were checked for and met. Assumptions for Pearson's correlation include the level of measurement, related pairs, absence of outliers, and linearity (Johnson & Christensen, 2017). The first assumption was met as all variables derived from the MSLQ subscales and the LMS data were continuous. Additionally, data cleaning processes listed above for the MSLQ subscales and the LMS data elements ensured that the related pairs assumption was met in the sense that each participant had a unique score for each MSLQ subscale and each LMS data element. As noted above, z-scores were computed for each MSLQ subscale and each LMS category to check for outliers. Lastly, a scatterplot was created to check for linearity between variables. After all assumptions were met, the correlation test using Pearson's correlation was conducted.

Research Question Two (RQ2a): Are there distinguishable behavioral patterns in LMS usage at the lesson level?

The second research question is exploratory in nature, in that, different patterns across time of LMS usage were sought to be discovered. Thus, the most appropriate type of statistical analysis was a longitudinal exploratory trajectory analysis, specifically growth mixture modeling (GMM). The data was conducive to employing GMM analysis because the current dataset utilized data from 13 different time points over the course of a semester and the researcher was interested in understanding how patterns of learner activity changed over time. Additionally, GMM was appropriate because it blends mixture modeling and latent growth modeling. In essence, GMM uses mixture modeling to identify classes, but membership to each class is identified by a latent growth model (McDermott et al., 2018; Ram & Grimm, 2009). In the context of the current study, mixture modeling identified the appropriate number of classes and utilized latent growth modeling techniques to understand how learners' behavior or trajectories changed across time and place those learners in the appropriate class.

Moreover, GMM assumes that the population is heterogeneous, but the subpopulations of the are homogenous (Herle et al., 2020). This is true of the data set that was utilized for this study because all learners in the study had a variety of activity patterns within the LMS; however, there were groups of learners that had similar patterns of activity within the LMS, which were grouped together by similarities with the GMM.

Since this research question considered data from the lesson variable, only lesson data were considered for analysis. Moreover, to connect more deeply to SRL, a separate GMM was conducted of SRL category of LMS data, planning, monitoring, and regulating. Thus, there were three GMMs conducted. First, a GMM was conducted for the planning element, which included the lesson overview variable. Second, a GMM was conducted for monitoring elements which included the lesson materials and lesson problem set variables. Lastly, a GMM was conducted for the regulating element, which included the lesson solutions variable.

As for assumptions of GMM, there are not many assumptions to GMM. However, all variables that were included in the analysis were checked to ensure they were continuous, and that independence was met.

Research Question Two (RQ2b): Are there differences among the clusters with regard to their academic achievement?

Once trajectories were identified from RQ2a, a one-way ANOVA was conducted to determine if there were significant differences for mean grades between the different learner trajectories that were produced from RQ2. Thus, a separate ANOVA was conducted for each GMM. In total, three ANOVAs were conducted, one each for planning, monitoring, and regulating.

As for ANOVA, there were several assumptions that were examined and tested. First, the dependent variable must be a continuous variable. In the current study, the dependent variable is grade, which was measured as points earned in the course. Thus, the assumption of a continuous dependent variable was met. Second, the independent variable must consist of three or more categorical, independent groups. Since each GMM produced at least three trajectories, this assumption was met as well. Third, observations must be independent, which was met as each learner was included in only one trajectory for each category. Fourth, outliers must be examined, which was addressed in data cleaning and met. Lastly, homogeneity of variance must be tested using Levene's Test for Equal Variance, which was tested for each ANOVA. Once all assumptions were met, then statistical analyses proceeded, which are discussed in the following chapter.

CHAPTER FOUR

Chapter four contains several sections regarding data analysis and results. Descriptive statistics are presented for both survey data and LMS data to describe learners in the sample. Next, correlational analyses using Pearson's correlation coefficient are presented to examine the relationship between learner's self-reported self-regulated behaviors and LMS data. Next, procedures and results of the growth mixture model are presented that determined different patterns of LMS usage (e.g., trajectories) across time. Lastly, ANOVA procedures and results are presented that examined differences in trajectories on learners' academic achievement.

Descriptive Statistics

Descriptive statistics were computed for survey data and LMS data to understand general learner response patterns through the examination of means and standard deviations. Correlations were also computed to examine the relationship between the continuous variables from survey data and LMS data.

Survey Data

Descriptive statistics were computed for all survey data. First, frequencies were computed for each categorical variable. Next, means and standard deviations were calculated for all subscales to determine typical response patterns (Table 6). Additionally, correlation analysis was conducted to understand the relationship between continuous variables included in the survey data (Table 7).

Frequencies were computed for several categorical variables to garner an understanding of the sample. Those variables included gender, race, transfer status, first-generation status, and major. As for participants, 48, or 55% were women, 35, or 41% were men, and three, or four percent preferred not to respond. For race, 28, or 33% were Asian Americans, 20, or 29% were White Americans, eight, or nine percent were Hispanic Americans, five, or five percent were two or more races, four, or four percent were African Americans, three, or three percent were International Students, and 18, or 21% preferred not to respond. For transfer status, 45, or 53% transferred into the current institution, 36, or 42% started at the current institution, and five, or six percent did not respond. The mean age of learners was 21.7 years, with the minimum age of 19 and the maximum age of 29 out of 85 respondents. As for first-generation status, 51, or 59% were not first-generation, 30, or 35% were first-generation, and 5, or five percent did not respond. Lastly, for major, 31, or 36% were management information systems, 17, or 20 percent were accounting, 13, or 15% were finance, 10, or 12% were marketing, eight, or eight percent were management, one, or one percent was business analytics, and six, or six percent preferred not to respond.

As for the means and standard deviations of scales, the highest mean for motivation scales was Extrinsic Goal Orientation. This suggests that learners in the sample are motivated by reasons such as grades, evaluation of others, and competition (Pintrich et al., 2015). The results make sense for this sample as grade earned in this course is an important factor for learners in determining their viability to pursue finance or accounting as a major. Additionally, Test Anxiety had the second highest mean value, which also makes sense for the given sample as testing comprises 85% of the total grade in the course (Table 2). Taken together, these results make sense for business learners as learners who have higher levels of intrinsic motivation are oftentimes found in majors or colleges outside of business (Lin et al., 2003).

The highest learning strategy scale mean was Effort Regulation, which suggests that learners in this sample possessed the ability to control their effort and minimize distractions. This makes sense as this course is online and requires more effort to direct attention than the traditional face-to-face environment. The second highest learning strategy scale was Time and Study Environment, which suggests learners in the sample were able to manage their time effectively and set realistic goals. It makes sense given that together Effort Regulation and Time and Study Environment were both high as previous research confirms this (Pintrich et al., 1993). In contrast, the lowest learning strategy scale was Peer Learning, which suggests that the current sample did not collaborate with each other often. This finding makes sense for this sample since this was an online course and there were no group assignments.

Table 6

Survey Scale Mean and Standard Deviation

Scale	N	Mean	Standard Deviation
Intrinsic Goal Orientation (IGO)	83	4.25	1.33
Task Value (TV)	84	4.77	1.63
Extrinsic Goal Orientation (EGO)	84	5.65	1.22
Control of Learning Beliefs (CLB)	82	4.83	1.51
Self-Efficacy for Learning & Performance (SEL)	84	4.43	1.52
Test Anxiety (TA)	83	5.24	1.52
Rehearsal (R)	85	4.84	1.44
Elaboration (E)	83	4.78	1.21
Organization (O)	83	3.99	1.30
Critical Thinking (CT)	85	4.79	1.29
Metacognitive Self-regulation (MSR)	84	4.81	.907
Time & Study Environment (TSE)	84	5.10	1.03
Effort Regulation (ER)	83	5.35	1.15
Peer Learning (PL)	84	2.90	1.60
Help Seeking (HS)	84	3.54	1.26

Correlation coefficients for all pairs of continuous variables were examined for statistical significance. A review of results revealed the presence of several correlations with moderate relationships. Those included Intrinsic Goal Orientation and Task Value, Elaboration and Critical Thinking, Effort Regulation and Time and Study Environment. Of these variables that had a moderate relationship, all were in the expected direction. As an example, it made sense that elaboration and critical thinking had a moderate relationship because elaboration strategies are typically employed to build long-term memories and connections between study strategies, which could enhance a learner's ability to think critically.

There were several variables that were statistically significant but had a weak relationship. Those included Intrinsic Goal Orientation and Self-Efficacy for Learning and Performance, Elaboration, Organization. Additionally, Task Value was significant, albeit a weak relationship, with Extrinsic Goal Orientation, Self-Efficacy for Learning and Performance, Elaboration, and Effort Regulation. All the pairs that had weak correlation made sense. Elaboration was statistically significant with weak relationships for the highest number of variables, which suggests that learners in this sample who possessed a high degree of elaboration also possessed a high degree of Organization, Metacognitive Self-regulation, and Effort Regulation. This finding suggested that learners employed strategies, such as paraphrasing or summarizing, to commit information to long-term memory, which would require a higher degree of organization and effort from the learner, as well as metacognition (Table 7).

Table 7

Correlation Coefficients of MSLQ Scales

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. IGO	--													
2. TV	.60**	--												
3. EGO	.29**	.43**	--											
4. CLB	.37**	.39**	.21	--										
5. SEL	.42**	.46**	.19	.53**	--									
6. TA	-.22*	-.15	.13	-.15	-.48**	--								
7. R	.07	.13	.38**	-.03	-.23*	.30**	--							
8. E	.42**	.49**	.43**	.28*	.08	-.05	.32**	--						
9. O	.46**	.24*	.08	.11	.04	-.25*	.15	.43**	--					
10. CT	.29**	.28*	.29**	.13	.07	-.07	.39**	.63**	.36**	--				
11. MSR	.29**	.28*	.32**	.24*	.19	-.09	.36**	.58**	.35**	.58**	--			
12. TSE	.08	.18	.35**	-.08	.09	-.15	.29**	.27*	.14	.32**	.53**	--		
13. ER	.32**	.41**	.53**	.12	.18	-.13	.21	.43**	.18	.37**	.59*	.61**	--	
14. PL	.18	-.13	.20	-.01	.03	.05	.06	.13	.26*	.08	.10	.00	-.04	--
15. HS	-.11	-.13	.17	-.13	-.17	.13	.00	.01	.12	.01	-.13	.00	-.08	.38**

Note: Two asterisks indicate the correlation is significant at the .05 level (2-tailed). One asterisk indicates the correlation is significant at the .01 level (2-tailed).

LMS Data

Descriptive statistics were computed for all LMS data elements. Means and standard deviations were calculated for all LMS elements to summarize typical response patterns (Table 8). Additionally, correlation analysis was conducted to understand the relationship between LMS data elements (Table 9).

As for the means and standard deviations of individual LMS elements, a wide range of learner activity was evident. The most common minimum value was zero for several LMS elements, whereas the highest maximum value was 234, which was the number of times that grades were checked (Table 8). The LMS elements with the highest mean value included the number of times a learner viewed the discussion board (M = 53.42, SD = 45.79) and the number of times a learner checked his or her grade (M = 37.62, SD = 37.17). Other LMS elements that contained relatively high mean values included the number of times a learner accessed the syllabus (M = 25.1, SD = 16.32), the number of times a learner accessed a lesson overview (M = 18.94, SD = 11.04), the number of times a learner accessed learning materials (M = 27.01, SD = 16.01), the number of times a learner accessed test bank problems (M = 25.91, SD = 11.59), and the number of times a learner accessed test bank solutions (M = 23.91, SD = 16.29).

As for interpretation, it makes sense that learners would engage in high numbers of activities around lessons as a new lesson was released approximately once per week. Additionally, as evidenced in the results of the survey descriptives, it makes sense that learners would check their grade frequently as learners in this course were highly motivated by extrinsic rewards such as grades. However, it was surprising that the mean for the number of times a learner viewed the discussion board was very high. This number could have been skewed by a few learners accessing the discussion board with very high frequency across the semester. The median value (*Mdn* = 19) may be a better indicator of the typical number of times a learner accessed the discussion board. However, the instructor oftentimes posted responses on the discussion board, which could have promoted the author of a discussion post to visit the discussion board more frequently.

In contrast, the lowest mean value was for the number of times that learners access syllabus supplements (*M* = 0.86, *SD = 1.7*). Additionally, the number of times a learner accessed the final exam review video had a low mean value (*M* = 3.51, *SD* = 3.48), which makes sense since there was only one final exam. Another low average value was the number of times a learner took a practice test (*M* = 3.63, *SD* = 3.96) even though there were four tests in the course, which suggests that not all learners in the sample accessed a practice test prior to each test.

Table 8

LMS Variables Mean, Standard Deviation, Min, and Max

Scale	N	Mean	Standard Deviation	Min	Max
Number of discussion board posts (DBP)	258	2.23	5.78	0	27
Number of times viewed discussion board (DB)	258	53.42	45.79	0	221
Number of times accessed final exam review video (FER)	258	3.51	3.48	0	19
Number of times downloaded formula sheet (FS)	258	5.06	5.69	0	26
Number of times took a practice test (PT)	258	3.63	3.96	0	18
Number of times accessed test solutions (TS)	258	4.22	4.15	0	23
Number of times accessed test preparation material (TPM)	258	4.69	4.99	0	35
Number of times a quiz was taken (QT)	258	14.51	5.08	6	28
Number of times a quiz was submitted (QSUB)	258	10.94	2.46	5	17
Number of times a quiz was reviewed (QR)	258	10.3	2.58	1	17
Number of times quiz solutions were accessed (QSOL)	258	7.72	6.46	0	30
Number of times accessed syllabus (SYL)	258	25.1	16.32	2	78
Number of times accessed syllabus supplements (SYLS)	258	0.86	1.7	0	6
Number of times accessed weekly schedule (WS)	258	5.97	8.38	0	35
Number of times accessed course announcements (ANN)	258	10	12.04	0	68
Number of times grades were checked (GRC)	258	37.76	37.17	0	234
Number of times accessed lesson overview (LO)	258	18.94	11.04	5	64
Number of times lesson materials were accessed (LM)	258	27.01	16.01	6	87
Number of times accessed lesson problem sets (LP)	258	25.91	11.59	2	65
Number of times accessed lesson problem solutions (LS)	258	23.91	16.29	2	65
Total Planning (TP)	258	103.28	57.74	n/a	n/a
Average Planning (AVP)	258	14.75	8.25	n/a	n/a
Total Monitoring (TM)	258	82	25.23	n/a	n/a
Average Monitoring (AVM)	258	16.4	5.05	n/a	n/a
Total Regulating (TR)	258	110.37	61.82	n/a	n/a

Average Regulating (AVR)	258	13.8	7.28	n/a	n/a

Additionally, correlation coefficients were examined for all pairs of continuous variables for statistical significance. Results suggest that there was statistical significance between many pairs. Pairs that had strong relationships included the number of times a quiz taken and the number of times a quiz submitted ($r = .95$, $p < .01$), the number of times a quiz taken and the number of times a quiz reviewed ($r = .83$, $p < .01$), the number of times a quiz submitted and the number of times a quiz reviewed ($r = .88$, $p < .01$). The pairs that had a strong relationship made sense with respect to direction and magnitude as all of these are related to quizzes and related behaviors. Thus, it is logical that learners who took a quiz also submitted the quiz. Additionally, it makes sense that learners who took a quiz also reviewed the answers to the quiz.

There were several other pairs that were statistically significant and had a moderate relationship. Of interest, there was a moderate relationship between the number of times a learner accessed the lesson overview page and the number of times a learner accessed lesson materials ($r = .26$, $p < .01$). Additionally, there was a moderate relationship between the number of times a learner accessed lesson materials and the number of times a learner accessed lesson problems ($r = .25$, $p < .01$). Lastly, there was a moderate relationship between the number of times a learner accessed the lesson problems and the number of times a learner accessed lesson solutions ($r = .38$, $p < .01$). The correlation, albeit moderate, between these lesson variables made sense with respect to expected direction. It made sense that learners who accessed the lesson overview page would also access the lesson material page. Similarly, it made sense that learners who accessed the lesson problem sets would also access the lesson solutions.

Table 9

Correlation Coefficients of LMS Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. DBP	--												
2. DB	.18	--											
3. FER	-.98	-.06	--										
4. FS	.06	.06	.13	--									
5. PT	.14	0.1	.21	-.02	--								
6. TS	-.19	.41**	.09	.06	.05	--							
7. TPM	.21*	.21	.09	.22*	0.2	0.1	--						
8. QT	-.23*	0.1	.09	-.05	.06	.18	-.02	--					
9. QSUB	-.19	.16	.08	.00	.13	.19	.01	.95**	--				
10. QR	-.14	.05	.05	.03	.16	.14	.05	.83*	.88**	--			
11. QSOL	-.12	.39**	0.2	0.1	.25*	.54**	.29*	.28*	.31**	.26*	--		
12. SYL	-.05	.00	.25*	.08	.28**	.32*	.32**	.13	.14	.16	.29**	--	
13. SYLS	-.11	-.08	0.3	-.05	.22*	0.2	.19	.15	.17	0.1	.22*	.50**	--

Note. Two asterisks indicate the correlation is significant at the .05 level (2-tailed). One asterisk indicates the correlation is significant at the .01 level (2-tailed).

Table 9 (cont)

Correlation Coefficients of LMS Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13
14. WS	.07	.30**	.08	.09	.06	.47**	.33**	.05	.08	.01	.53**	.31**	.21
15. ANN	.25*	.27*	.13	.04	-.03	.23*	.39**	-.16	-.13	-.04	.3**	.07	-.18
16. GRC	.08	.56**	.02	.01	.25*	0.3**	.27*	.18	.26*	.23*	.49**	.15	-.04
17. LO	.33**	.25*	-.14	0.2	.33**	.04	.31**	.02	.07	.06	.12	.06	.11
18. LM	.00	.137	.02	.23*	.24*	.24*	-.06	.21	.24*	.21	.27*	.17	.07
19. LP	.03	.37**	.19	.07	.12	.36*	.03	-.12	-.09	-0.2	.07	.17	.05
20. LS	.04	.37**	.08	.41**	.06	.41*	.43**	-.08	-.02	-.02	.34**	.28**	.07
21. TP	.17	.52**	.10	.11	.33**	.42**	.55**	.13	0.2	.21	.58**	.49**	.17
22. AVP	.17	.52**	.10	.11	.33**	.42**	.55**	.13	0.2	.21	.58**	.49**	.17
23. TM	-.03	.31**	.16	.14	0.4**	.37**	.00	.38**	.42**	.36**	.33**	.26*	.13
24. AVM	-.03	.31**	.16	.14	-0.4**	.37**	.00	.38**	.42**	.36**	.33**	.26*	.13
25. TR	.21	.93**	.07	.27*	.15	.54**	.34**	.12	.18	.01	.53**	.14	-.02
26. AVR	.21	.93**	.07	.27*	.15	.54**	.34**	.12	.18	.01	.53**	.14	-.02

Note. Two asterisks indicate the correlation is significant at the .05 level (2-tailed). One asterisk indicates the correlation is significant at the .01 level (2-tailed).

Table 9 (cont)

Correlation Coefficients of LMS Variables

	14	15	16	17	18	19	20	21	22	23	24	25
14. WS	--											
15. ANN	.35**	--										
16. GRC	.35**	.33**	--									
17. LO	.00	.03	.15									
18. LM	-.03	.05	.14	.26*	--							
19. LP	.20	.07	.17	-.05	.25*	--						
20. LS	.33**	.33**	.27*	.12	.21	.38**	--					
21. TP	.56**	.53**	.86**	.34**	.20	0.2	.43**	--				
22. AVP	.56**	.53**	.86**	.34**	.20	0.2	.43**	1.0**	--			
23. TM	0.1	.01	.28**	.22*	.85**	.61**	0.3**	.37**	.32**	--		
24. AVM	0.1	.01	.28**	.22*	.85**	.61**	.03**	.37**	.32**	1.0**	--	
25. TR	.41**	.37**	.57**	.28*	.23*	.41**	.64**	.62**	.62**	0.4**	0.4**	--
26. AVR	.41**	.37**	.57**	.28*	.23*	.41**	.64**	.62**	.62**	0.4**	0.4**	1.0**

Note. Two asterisks indicate the correlation is significant at the .05 level (2-tailed). One asterisk indicates the correlation is significant at the .01 level (2-tailed).

Research Question 1

The first research question examined if learner's behavior in the LMS correlated with their self-reported self-regulation data. To answer the first research question, a correlation analysis using Pearson's r was conducted. Due to the large nature of the one correlation table for all MSLQ subscales and LMS variables, several things were done for readability. First, correlation tables were broken into three different tables. The first table (Table 10) presents correlation coefficients between MSLQ subscales and LMS planning elements. The second table (Table 11) presents correlation coefficients between MSLQ subscales and LMS monitoring elements. The third table (Table 12) presents correlation coefficients for MSLQ subscales and LMS regulating elements. For each table, all rows contained LMS variables, and all columns contained MSLQ subscales.

Table 10

Correlation Coefficients of MSLQ Subscales and LMS Planning Variables

	IGO	TV	EGO	CLB	SEL	TA	R	E	O	CT	MSR	TSE	ER	PL	HS
TPM					.15		$-.3^{**}$	.18			.15			.19	
SYL		-.12	.10							.14				.19	.18
SYLS		.10	.19		-.11			.15	.16	$.28^{**}$		.10			.10
WS		.13		-.13		.16		.12			.21	.16	.17	.10	.13
ANN	.11		-.15		.15		-.12				$.23^{*}$	.14	.18	-.15	$-.24^{*}$
GRC	.15	.20			$.24^{*}$		.10	.20	-.11	.14	$.35^{**}$	$.27^{*}$	$.28^{*}$	-.19	$-.3^{**}$
LO		.14	.16		$.27^{*}$	-.19			-.12			.12	.12	.13	-.14
TP	.14	.14			$.23^{*}$			.20		.16	$.36^{**}$	$.26^{*}$	$.29^{**}$		-.21
AVP	.14	.14			$.23^{*}$			.20		.16	$.36^{**}$	$.26^{*}$	$.29^{**}$		-.21

Note. Two asterisks indicate the correlation is significant at the .05 level (2-tailed). One asterisk indicates the correlation is significant at the .01 level (2-tailed); All correlations below .10 were removed for readability.

Abbreviations. IGO, intrinsic goal orientation; TV, task value; EGO, extrinsic goal orientation; CLB, control of learning beliefs; SEL, self-efficacy for learning and performance; TA, test anxiety; R, rehearsal; E, elaboration; O, organization; CT, critical thinking; MSR, metacognitive self-regulation; TSE, time and study environment; ER: effort regulation; PL, peer learning; HS, help seeking; TPM, test prep materials; SYL, syllabus; SYLS, syllabus supplements; WS, weekly schedule; ANN, announcements; GRC, grade checked; LO, lesson overview; TP, total planning; AVP, average planning.

Table 11

Correlation Coefficients of MSLQ Subscales and LMS Monitoring Variables

	IGO	TV	EGO	CLB	SEL	TA	R	E	O	CT	MSR	TSE	ER	PL	HS
PT						.19	.16		-.14					-.17	-.12
QT					.10				.10	.11	.20				-.13
QSUB					.12		.11		.15	.18	$.25^{*}$				-.10
LM	.13		-.11	.12	.11	-.17		-.11		-.10					-.13
LP			-.18				.18			.13		-.10	-.20	-.14	-.12
TM	.12		-.14				.16						-.10	-.10	-.19
AVM	.12		-.14				.16						-.10	-.10	-.19

Note. Two asterisks indicate the correlation is significant at the .05 level (2-tailed). One asterisk indicates the correlation is significant at the .01 level (2-tailed); All correlations below .10 were removed for readability.

Abbreviations. IGO, intrinsic goal orientation; TV, task value; EGO, extrinsic goal orientation; CLB, control of learning beliefs; SEL, self-efficacy for learning and performance; TA, test anxiety; R, rehearsal; E, elaboration; O, organization; CT, critical thinking; MSR, metacognitive self-regulation; TSE, time and study environment; ER, effort regulation; PL, peer learning; HS, help seeking; PT, practice test; QT, quiz taken; QSUB, quiz submitted; LM, lesson materials; LP lesson problems; TM, total monitoring; AVM, average monitoring.

Table 12

Correlation Coefficients of MSLQ Subscales and LMS Regulating Variables

	IGO	TV	EGO	CLB	SEL	TA	R	E	O	CT	MSR	TSE	ER	PL	HS
DBP					.22*	-.14	-.20		-.13			-.14			-.15
DB					.12		.25*	.15			.16	.11			-.11
FER		-.13	-.17		-.10			-.20		-.14		-	-.23*		
FS		-.10			-.15		-.18				-.13	-.24*		.12	.15
TS			.12	-.20	-.11		.18				.22*	0.3**	.22*		.10
QR	.16	.12	.11	.10			.13	.11	.17	.21	.32**	.10	.12	.12	-.12
QSOL				-.13			.16				.19	.14	.13		
LS							-.13							.11	
TR					.10		.15	.10			.15	.10			
AVR					.10		.15	.10			.15	.10			

Note. Two asterisks indicate the correlation is significant at the .05 level (2-tailed). One asterisk indicates the correlation is significant at the .01 level (2-tailed); All correlations below .10 were removed for readability.

Abbreviations. IGO, intrinsic goal orientation; TV, task value; EGO, extrinsic goal orientation; CLB, control of learning beliefs; SEL, self-efficacy for learning and performance; TA, test anxiety; R, rehearsal; E, elaboration; O, organization; CT, critical thinking; MSR, metacognitive self-regulation; TSE, time and study environment; ER, effort regulation; PL, peer learning; HS, help seeking; DBP, discussion board post; DB, discussion board accessed, FER, final exam review; FS, formula sheet; TS, test solutions; QR, quiz review, QSOL, quiz solutions; QR, quiz review; QSOL, quiz solutions; LS, lesson solutions; TR, total regulating; AVR, average regulating

A review of the correlation tables reveals that there is a moderate amount of correlation between LMS variables and MSLQ subscales. Specifically, a fair amount of correlation existed between LMS planning variables and MSLQ subscales. In total, 18 pairs were correlated. Self-Efficacy for Learning and Performance as well as Metacognitive self-regulation were each positively correlated with four LMS variables. Upon review, the pairs that correlated made sense with respect to the expected direction or the relationship. For example, it made sense that metacognitive self-regulation was positively correlated with many LMS variables, particularly those that involved a learner's ability to reflect on their performance such as reviewing a quiz that was submitted or accessing test solutions.

Unlike the moderate amount of correlation between LMS planning variables and MSLQ subscales, there was not much correlation between LMS monitoring variables and MSLQ subscales. The only pair that was statistically significant was a positive correlation between Metacognitive Self-regulation and Quiz Submitted ($r = .25$, $p < .01$). The fact that there was a lack of correlation between LMS monitoring variables and MSLQ subscales demonstrates the lack of relationship that learners' monitoring activities had with their self-reported self-regulation.

As for the correlation between MSLQ subscales and LMS regulating variables, there was more correlation than between MSLQ subscales and LMS monitoring variables, but less correlation than between MSLQ subscales and LMS planning variables. Specifically, there were eight pairs that were statistically significant. Out of the eight pairs, Metacognitive Self-regulation, Time and Study Environment, and Effort

Regulation all correlated with two LMS regulating variables. None of the pairs that correlated seemed surprising. For instance, it made sense that effort regulation (*M* = 5.35, *SD* = 1.15) was positively correlated with the number of times a learner accessed test solutions (*M* = 4.22, *SD* = 4.15) and the number of times a learner accessed the final exam review (M = 3.51, *SD* = 3.48) as it seems likely that learners who accessed test solutions as well as final exam review more frequently were likely to exhibit higher levels of effort in the course.

Research Question 2a

The purpose of this question was to determine patterns of LMS usage at the lesson level via the identification of clusters across lessons. To answer research question 2a, growth mixture modeling (GMM) was conducted utilizing R (R Core Team, 2020). This analysis utilized the "lcmm" package within R (Proust-Lima et al., 2017). A separate GMM was conducted for each category utilized to arrange LMS data: planning, monitoring, and regulating, as it related to learner lesson usage across 13 lessons. Thus, there were three GMMs conducted. First, a GMM was conducted for planning, which included the lesson overview variable. Second, a GMM was conducted for monitoring which included the lesson materials and lesson problems variables. Lastly, a GMM was conducted for regulating, which included the lesson solutions variable.

For each GMM, several model iterations were conducted to determine the optimal number of clusters. A separate GMM was conducted on each category for a potential two- through six-cluster solution. To determine the appropriate cluster solution for each category, several goodness-of-fit statistics were examined including maximum loglikelihood, the Bayesian Information Criterion (BIC), the Akaike Information Criterion (AIC), as well as plots utilizing the plot feature within the "lcmm" package (Proust-Lima et al., 2017). Lastly, the number of members in each class was examined. In review, the optimal cluster solution was determined by examining all available goodness-of-fit statistics which included the maximum log-likelihood, BIC, AIC, plots, and the number of learners in each class.

The first variable that was analyzed via GMM on planning, which included lesson overview. After conducting a separate GMM for two through six clusters, the optimal solution was a five-cluster solution (Table 13). The fit statistics, loglik, BIC, and AIC, were similar for all models that were conducted for two through six clusters. Although the BIC and AIC fit statistics were slightly better for the four-cluster solution, there was a significant imbalance in learner distribution within the clusters as one cluster would have 186 individuals and another cluster contained only nine learners. Thus, the decision was made based on fit statistics as well as the number of learners per class and plots. Like the four-cluster solution, the two-cluster solution contained a very low number of learners for at least one class. Additionally, for a three-cluster solution, there was a significant number of learners in one cluster and a much smaller number of learners in the remaining clusters. Although the six-cluster solution contained a relatively equal number of learners, their patterns of activity based on plots did not make theoretical sense. Thus, the five-cluster solution is the optimal solution as the fit statistics were robust, it contained an appropriate number of learners in each cluster, and the plot made theoretical sense.

Table 13

Planning: Lesson Overview GMM Results

Model Type	*Loglik*	*BIC*	*AIC*	# *class1*	# *class2*	# *class3*	# *class4*	# *class5*	# *class6*
4-Cluster	-3,724.698	7,549.35	7,485.40	17	46	186	9		
5-Cluster	-3,720.756	7,563.68	7,485.51	16	53	88	68	33	
6-Cluster	-3,719.158	7,582.69	7,490.32	31	82	43	23	54	25

As for the pattern of each cluster within the five-cluster solution, there are five distinct trajectories (Figure 1). For the first class, learners' utilization of planning within the LMS was relatively consistent over time with a slight decrease in activity as the semester progressed (Very high activity). In the second class, learners' utilization of planning was very low throughout the semester (Very low activity). As for the third class, learners' utilization of planning was moderate at beginning of the semester and remained moderate throughout the semester (Consistently moderate activity). For the fourth class, learner utilization of planning within the LMS started at a moderate level and increased throughout the semester (Moderate increasing to high activity). Within the fifth class, learner utilization of planning started very high in the semester and decreased significantly over the course of the semester (High decreasing to low activity).

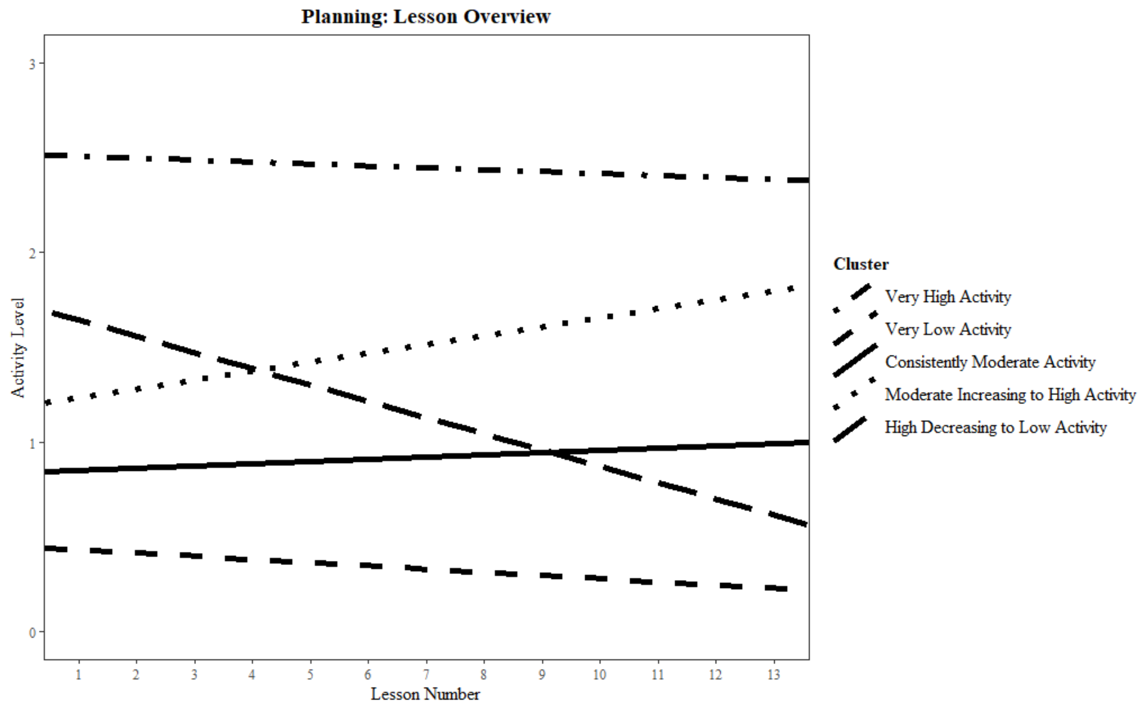

Figure 1

Best Fit Chart Cluster Solutions for Planning: Lesson Overview

The second GMM was conducted on monitoring variables, which grouped together lesson problems and lesson materials. Like lesson overview, a separate GMM was conducted based on a potential two- through six-cluster solution (Table 14). After a review of the available fit statistics, the number of learners in each cluster as well as the plots, the appropriate cluster solution for the monitoring variables was a four-cluster solution. A two- and six-cluster solution was eliminated due to an imbalance of learners in each cluster. Thus, the three-, four-, and five-cluster solution remained as the potential solution and was ultimately determined through fit statistics. Although the loglikelihood and AIC were similar for the remaining cluster solutions, the BIC increased by 15 points between the four- and five-cluster solution whereas it was only a 12-point increase between the three- and four-cluster solution. Additionally, the plot for a four-cluster solution made theoretical sense. Therefore, based on the lower point increase and the plot making theoretical sense, the four-cluster solution model was ultimately picked as the appropriate cluster solution.

Table 14

Monitoring: Lesson Materials and Lesson Problems GMM Results

Model Type	*loglik*	*BIC*	*AIC*	# *class1*	# *class2*	# *class3*	# *class4*	# *class5*
3-Cluster Model	-5,760.24	11,598.22	11,548.48	158	89	11		
4-Cluster Model	-5,755.33	11,610.60	11,546.65	34	66	126	32	
5-Cluster Model	-5,751.66	11,625.49	11,547.33	30	29	92	70	37

The plot was examined for the four-cluster solution for the monitoring variables to understand the trajectory of each class (Figure 2). Each class had a distinct pattern. Learners in the first trajectory started the semester with low monitoring activity and their monitoring activity slightly declined as the semester progressed (Very low activity). Learners in the second cluster started the semester with a very high amount of monitoring activity within the LMS but experienced a decline in monitoring activity as the semester progressed and ultimately ended with a moderate amount of monitoring activity as the semester concluded (High decreasing to moderate activity). As for the third class, learners' monitoring activity in the LMS started at a moderate level and increased slightly as the semester progressed (Consistently moderate activity) Lastly, learners in the fourth class started the semester with a high amount of monitoring activity, but experience significantly increased in their monitoring activity throughout the semester, which resulted in very high monitoring activity as the semester ended (High increasing to very high activity).

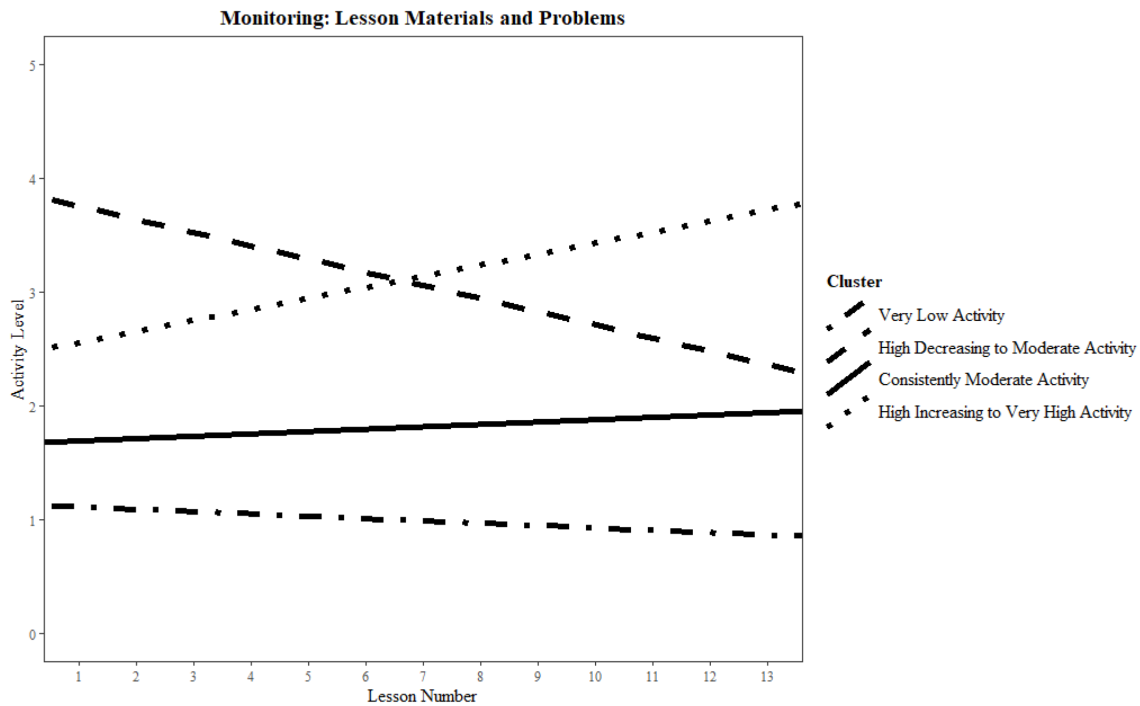

Figure 2

Best Fit Chart Cluster Solution for Monitoring: Lesson Materials and Problems

The third GMM was conducted on the regulating variable, which was the lesson solution set. A separate GMM was conducted for a potential two- through six-cluster solution (Table 15). After examining all available fit statistics, plots, and class membership, it was determined that a three-cluster solution was the most optimal solution. Whereas the fit statistics for each cluster solution were close, the class membership was imbalanced for all cluster solutions except for a three-cluster solution. Additionally, the plot for the three-cluster solution made theoretical sense

Table 15

Regulating: Lesson Solutions GMM Results

Model Type	*loglik*	*BIC*	*AIC*	*# class1*	*# class2*	*# class3*	*# class4*
2-Cluster Model	-4,133.68	8,322.90	8,287.37	144	114		
3-Cluster Model	-4,123.02	8,323.79	8,274.05	60	117	81	
4-Cluster Model	-4,119.43	8,338.81	8,274.86	13	54	88	103

To confirm that the three-cluster solution made sense, the plot was examined to determine trajectories (Figure 3). Learners in the first trajectory started with a moderate amount of regulating activity and increased to a high amount of regulating activity as the semester progressed (Moderate increasing to high activity). Learner activity in the second trajectory was consistently low during the semester with a slight downward trajectory as the semester progressed (Very low activity). Lastly, learners in the third cluster started with a moderate amount of regulating activity within the LMS and experienced a steep downward trajectory as the semester progressed (Moderate decreasing to low activity).

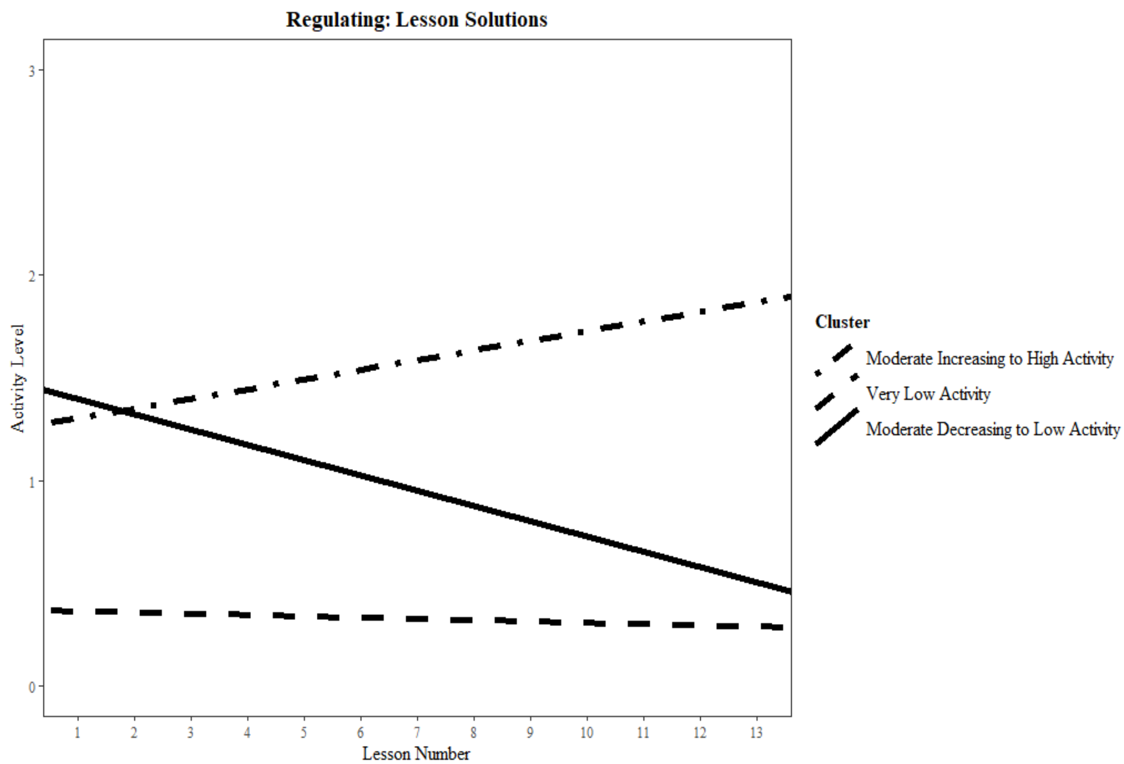

Figure 3

Best Fit Chart Cluster Solution for Regulating: Lesson Solutions

Research Question 2b

The purpose of this research question was to determine if there were academic achievement differences between the identified trajectories from each GMM. A separate one-way ANOVA was conducted for planning, monitoring, and regulating. Thus, this section presents the results of the Levene's Test for Homogeneity of Variance, ANOVA, Games-Howell post hoc, and a table with means for each ANOVA.

A one-way between subjects ANOVA was conducted to compare the effect of planning activity on academic achievement in the five trajectories that were identified from the planning GMM. Results from the ANOVA demonstrated there was a significant effect of academic achievement on planning for the five clusters identified from the GMM that utilized the planning element, $F(4,253) = 83.30$, $p < 0.01$.

Post hoc comparisons using the Games-Howell test was conducted to examine where differences occurred. The Games-Howell test was the most appropriate post hoc test to utilize for planning because Levene's test for equal variances was violated, $F(4, 253) = 24.47$, $p < 0.01$. Post hoc comparisons using the Games-Howell test indicated that the mean grade for the very high planning activity trajectory ($M = 93.88$, $SD = 3.88$) was significantly different than the mean grade for the very low planning activity trajectory ($M = 41.02$, $SD = 5.98$), the mean grade for the consistently low planning activity trajectory ($M = 65.\ 96$, $SD = 2.88$), and the mean grade for the high decreasing to low planning activity trajectory ($M = 67.70$, $SD = 2.44$). Additionally, the mean grade for the very low planning activity trajectory ($M = 41.02$, $SD = 5.98$) was significantly different than the mean grade for the moderate to increasingly high planning activity trajectory ($M = 82.88$, $SD = 2.19$) and the mean grade for the high decreasing to low planning activity trajectory ($M = 67.70$, $SD = 2.44$).

Moreover, the mean grade for the consistently low planning activity trajectory ($M = 65.96$, $SD = 2.88$) was significantly different than the mean grade for the moderate to increasingly high planning activity trajectory ($M = 82.88$, $SD = 2.19$). Lastly, the mean grade for the moderate to increasingly high planning activity trajectory ($M = 82.88$, $SD = 2.19$) was significantly different from the mean grade for the high decreasing to low planning activity trajectory ($M = 67.70$, $SD = 2.44$). Taken together, these results suggest that sustained high levels of learner planning activity or learners who increased their planning to high levels during the semester also had higher grades. In contrast, sustained low levels of planning activity or decreasingly low levels of planning activity are associated with lower grades earned in the course (Table 16).

Table 16

Mean Grade & Activity Level for Planning: Lesson Overview

Class	Mean Grade	Standard Deviation	Mean Starting Activity Level	Mean Ending Activity Level
Very High Activity (1)	93.88 [a]	3.88	2.52	2.39
Very Low Activity (2)	41.02 [b]	5.98	0.45	0.22
Consistently Moderate Activity (3)	65.96 [bc]	2.88	0.84	0.99
Moderate Increasing to High Activity (4)	82.88 [a]	2.19	1.18	1.79
High Decreasing to Low Activity (5)	67.70 [c]	2.44	1.73	0.61

Note. Means sharing a letter in their superscript are not significantly different at the $p < .05$ level according to a Games-Homes post hoc test.

Another one-way between subjects ANOVA was conducted to compare the effect of monitoring activity on academic achievement in the four trajectories that were identified from the GMM that utilized monitoring elements. Results from the ANOVA demonstrated that there was a significant effect of academic achievement on monitoring for the four trajectories that were identified from the GMM that utilized planning elements, $F(3, 254) = 84.87$, $p < 0.01$.

Post hoc comparisons using the Games-Howell test was conducted to examine where differences occurred. The Games-Howell test was the most appropriate post hoc test to utilize for monitoring because Levene's test for equal variances was violated, $F(3,254) = 20.04$, $p < 0.01$. Post hoc comparisons using the Games-Howell test indicated that the mean grade for the very low monitoring activity trajectory ($M = 43.58$, $SD = 3.33$) was significantly different than the mean grade for the high decreasing to moderate monitoring activity trajectory ($M = 82.48$, $SD = 3.29$), and the mean grade for the consistently moderate monitoring activity trajectory ($M = 73.39$, $SD = 1.23$), and the mean grade for the high increasing to very high monitoring activity trajectory ($M = 86.15$, $SD = 2.35$). Additionally, the mean grade of the high decreasing to moderate monitoring activity trajectory ($M = 82.48$, $SD = 3.29$) was significantly different than the mean grade for the consistently moderate monitoring activity trajectory ($M = 73.39$, $SD = 1.23$). Lastly, the mean grade for the consistently moderate monitoring activity trajectory ($M = 73.39$, $SD = 1.23$) was significantly different than the mean grade for the high increasing to very high monitoring activity trajectory ($M = 86.15$, $SD = 2.35$).

Taken together, these results suggest that learners who had a high degree of monitoring activity also had higher grades. Moreover, learners who had lower levels of monitoring activity had lower grades. Importantly, learners who had very high monitoring activity did not significantly differ in their academic achievement than learners who had initially started with a high level of monitoring activity but ended the semester with a moderate level of monitoring activity as one may expect that learners with higher levels of monitoring activity would be the only set of learners that would have high grades (Table 17).

Table 17

Mean Grade & Activity Level for Monitoring: Lesson Problems and Lesson Materials

Class	Mean Grade	Standard Deviation	Mean Starting Activity Level	Mean Ending Activity Level
Very Low Activity (1)	43.58 [a]	3.33	1.13	0.86
High Decreasing to Moderate (2)	82.48 [b]	3.29	3.87	2.36
Consistently Moderate (3)	73.39 [c]	1.23	1.67	1.94
High Increasing to Very High (4)	86.15 [b]	2.35	2.46	3.72

Note. Means sharing a letter in their superscript are not significantly different at the p <.05 level according to a Games-Homes post hoc test.

Lastly, a one-way between subjects ANOVA was conducted to compare the effect of regulating activity on academic achievement in the three trajectories that were identified from the regulating GMM. Results from the ANOVA demonstrated that there was a significant effect of academic achievement on regulating for the three trajectories identified from the GMM that utilized the regulating element, $F(2,255) = 92.38$, $p < 0.01$.

Post hoc comparisons using the Games-Howell test was conducted to examine where differences occurred. The Games-Howell test was the most appropriate post hoc test to utilize for regulating because Levene's test for equal variances was violated, $F(2, 255) = 18.02$, $p < 0.01$. Post hoc comparisons using the Games-Howell test indicated that the mean grade for the moderate increasing to high regulating activity trajectory (*M* = 72.35, *SD* = 3.22) was significantly different than the mean grade for the moderate decreasing to low regulating activity trajectory (*M* = 56.8, *SD* = 2.18). Additionally, the mean grade for the very low regulating activity trajectory (*M* = 71.18, *SD* = 9.19) was significantly different than the mean grade for the moderate decreasing to low regulating activity trajectory (*M* = 56.8, *SD* = 2.18). Taken together, the results for regulating activity and grades are very different than the results of the monitoring and planning ANOVAs. Like the monitoring and planning results, higher levels of activity were associated with higher grades. However, there were no significant differences between low regulating activity and high regulating activity and grade earned. In fact, learners who had low levels of regulating activity almost obtained the same grades as learners who had high activity (Table 18).

Table 18

Mean Grade & Activity Level for Regulating: Lesson Solutions

Class	Mean Grade	Standard Deviation	Mean Starting Activity Level	Mean Ending Activity Level
Moderate Increasing to High Activity (1)	72.35 [a]	3.22	1.26	1.87
Very Low Activity (2)	71.18 [a]	9.19	0.37	0.29
Moderate Decreasing to Low Activity (3)	56.80 [b]	2.18	1.47	0.51

Note. Means sharing a letter in their superscript are not significantly different at the p <.05 level according to a Games-Homes post hoc test.

Learner Tracking Across SRL Category

Lastly, it is necessary to understand how learners tracked across the planning, monitoring, and regulating categories. It is important to know if learners were consistent in the SRL behaviors across the planning, monitoring, and regulating domains. Figure 4 was created as a visual representation to understand learners' trajectories across each domain. As Figure 4 represents, each SRL domain contains the number of trajectories from each cluster solution as well as the corresponding trajectory title. Additionally, the arrows with corresponding numbers represent the movement and number of learners that moved from any given planning trajectory to the monitoring trajectory and then from their monitoring trajectory to their regulating trajectory. As an example, 13 learners in the "very high" planning category were found to have "moderate to high" monitoring activity. Based on Figure 4, high activity learners typically sustained high activity levels regardless of the planning, monitoring, regulating activities. Similarly, low activity learners sustained low levels of activity throughout the semester, whereas learners who possessed a moderate amount of activity sustained a moderate amount of activity throughout the semester but had more movement to higher or lower trajectories depending on the type of activity.

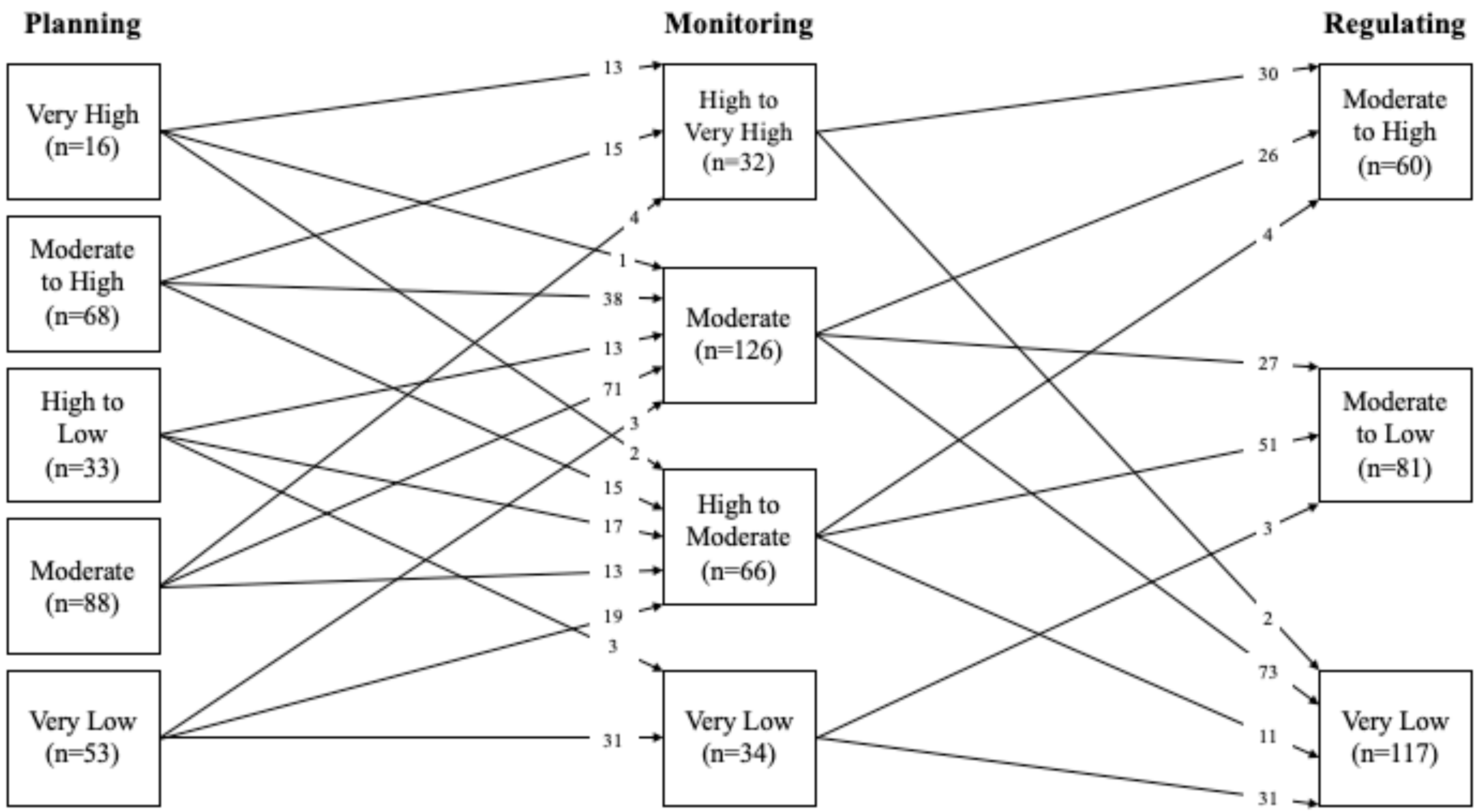

Figure 4

Classification Based on LMS Activity Type between LMS Activity Type

CHAPTER FIVE

Despite previous calls from scholars to utilize LA data to measure SRL (Roll & Winne, 2015; Winne, 2017), relatively little empirical research has been conducted to examine the feasibility in utilizing learners' data produced within a virtual environment, specifically an LMS in a college undergraduate population, to understand learners' use of self-regulation. This study addressed the identified gaps in the literature by examining the utility of LA data as an indicator of learner's self-regulation as compared to learners' self-reported self-regulation from the MSLQ. Additionally, this study examined patterns of learner self-regulation across a multitude of lessons over the course of the semester to determine trajectories of learners' planning, monitoring, and regulating activity within the LMS. Lastly, this study examined achievement differences between identified trajectories for learner's planning, monitoring, and regulating activity within the LMS. Thus, this study has provided several exploratory findings to inform future work that is examined in-depth in this chapter. Additionally, this chapter situates the findings of the current study within SRL theory, which is interwoven throughout this chapter, as well as student development theory. Previous research is drawn upon to complement the findings of the current study to formulate suggestions for practice. Lastly, limitations of the study are presented as well as directions for future research.

Summary of Findings

This study presents several significant findings that extends what is known about utilizing LMS data as an indicator of learners' self-regulation, particularly within the planning, monitoring, and regulating domains. First, the findings extend how LA data from an LMS can serve as an indicator of learners' self-regulation as demonstrated by a broad set of correlations that were found between learners' self-reported self-regulation and their LA data, specifically when it comes to learners' planning and regulating activities. This finding also provides evidence that an LMS is an appropriate mechanism to gather LA data as compared to data gathered from a traditional SRL measurement method that was employed by this study (MSLQ). Additionally, this study builds on previous work that has utilized cluster analysis (Kim et al., 2018; Romero & Ventura, 2010; Segedy et al., 2015) by demonstrating that learner's trajectories with the planning, monitoring, and regulating domains can be identified while utilizing LMS data collected at the lesson level (e.g., 13 time points) across the semester. Lastly, this study demonstrates that trajectories identified from learners' patterns of LMS usage at the lesson level are related to academic achievement as represented by final course grades. Specifically, learners with higher levels of planning and monitoring activity also had higher levels of academic achievement.

LMS as a Data Source for SRL Indication

One of the key takeaways from the study is that an LMS is a good source of LA data that is conducive to understanding learners' self-regulation. As previously mentioned, most of the studies that attempted to utilize LA data to indicate learner's SRL used either a highly specialized tool such as the nStudy (Winne et al., 2017) or LA data from MOOCs (Wong et al., 2019) —both of which contain limitations as outlined previously (Beheshitha et al., 2015; Bernacki et al., 2011; Jarvela et al., 2016; Winne et al., 2019). The current study was able to glean several different LA variables from an LMS and organize them within three domains based on SRL theory: planning, monitoring, and regulating. Included in this study were seven planning variables, five monitoring variables, and eight regulating variables for the correlational analyses. Moreover, the results from the first research question demonstrated correlation was found between LMS data and learners' self-reported self-regulation, particularly with learners' planning and regulating activities. Thus, the results of this study should implore future researchers to consider utilizing LMS data as a source of LA data to examine learners' self-regulation as opposed to the need to have a specialty designed LA tool as the nStudy or a tool that may not be structured for collection of LA data, such as a MOOC.

Additionally, as noted earlier in this paper, two common criticisms of the current set of existing LA methods to collect data to examine learners' SRL is that they are intrusive in nature and lack objectivity (Roll & Winne, 2015). Thus, scholars in both the SRL and LA communities have stated the need to integrate these two fields further to examine if objectivity can be achieved (Gasevic et al., 2014; Gewerc et al., 2016; Greene et al., 2011a; Winne, 2017). As evidenced from this study, the collection of LA data via an LMS as an indicator of learners' self-regulation has proven to be non-intrusive as well as a more objective data source. Learners were not prompted throughout the semester to utilize or engage in any of the tools that were available on the LMS, thus limiting intrusion into the learners' experience. This is different from other LA tools, such as the nStudy, which often directs learner's attention and prompts certain behaviors such as highlight or annotating. Additionally, learners were not told when to access or what to access within LMS, thus objectivity of the data was preserved for analysis. As a result, a rich LA data source that the LMS produced coupled with the lack of intrusion as demonstrated in this study provides robust evidence for the need for future researchers to prioritize LMS as the most appropriate source of LA data for an indication of learners' self-regulation.

LA Data and SRL Correlation

The results from this study demonstrate that there was correlation between the LA data produced by learners within the LMS and learners' self-reported self-regulation, specifically with learners' planning activities and regulating activities. Though much fewer relationships were found between learners' monitoring activities and learners' self-reported self-regulation.

There were several planning behaviors that learners performed in the LMS environment, such as the number of times a learner posted on the discussion board and the number of times a learner checked grades that correlated positively with MSLQ subscales such as Self-Efficacy for Learning and Performance. This finding suggests that learners who posted on the discussion board more frequently and checked their grades more often had higher levels of self-efficacy for learning and performance than learners who did not post on the discussion board frequently or checked grades often. In other words, learners who had a higher sense of belief in themselves also posted on the discussion board and checked their grades more often. This is an important finding as it suggests that instructors can potentially bolster learners' belief in themselves by encouraging or requiring learners to post on the discussion board more frequently or perhaps posting grades earlier or more frequently for learners to check.

Other studies that found correlation between LA and SRL data did not report a relationship between learner's self-efficacy and their planning activities (Cicchinelli et al., 2018; Yamada et al., 2017). Though, previous literature has established a relationship between self-efficacy and academic achievement (Brown et al., 2016; Cicchinelli et al., 2018; Schunk, 1994; Zimmerman & Schunk, 1994). As an example, Cicchinelli et al. (2018) found positive correlation between self-efficacy and academic achievement by learners as well as self-regulation activities— broadly defined— and academic achievement by learners. Thus, the findings of the current study builds upon previous studies that have found correlation between self-efficacy and academic achievement to add that self-efficacy has a positive relationship with learner's planning activities or activities that aid in organizing learners' effort such as posting on the discussion board or checking grades.

Another significant finding is that multiple LMS data elements contained within the regulating category were correlated with learner's self-reported self-regulation. Regulating activities, or activities that reinforce knowledge, such as the number of times a learner accessed test solutions and the number of times that a learner reviewed a quiz were positively correlated with the MSLQ subscale of metacognitive self-regulation. As explored earlier, learners' metacognition is a key aspect of self-regulation (Winne, 1995; Zimmerman, 1989). Additionally, metacognition is a fundamental aspect of SRL whereby learners who engage in metacognition tend to have higher levels of self-regulating behaviors (Narciss et al., 2007; Schunk & Zimmerman, 1997). Thus, as confirmed in this study and within the SRL literature, learners who had higher levels of regulating activities also had higher levels of metacognitive self-regulation. However, this study provides evidence that specific regulating activities such as reviewing quizzes or accessing test solutions also had higher levels of metacognitive self-regulation, which had previously not been found from previous studies.

Lastly, an additional significant finding from the current study is that several LMS variables positively correlated with effort regulation, including the number of times a learner accessed test solutions, the number of times a learner accessed the final exam review, the number of times a learner checked grades as well as learners' total planning and learners' average planning. In essence, effort regulation is the ability of learners to direct control over their actions (Pintrich et al., 2015). Other studies that utilized LMS data to measure SRL have also found correlation between effort regulation and LMS variables. For instance, Li (2019) found that effort regulation was significantly correlated with time management variables such as change in time on task. Thus, these findings confirm previous work within SRL that effort regulation has a relationship with activities that learners need to exert control over. However, this study extends what is known between effort-regulation and LMS variables by demonstrating correlation between effort-regulation and the number of times a learner accessed several different items within the LMS included test solutions, final exam review, and checked grades.

In review, this study builds upon what is known about the relationships between the LA data produced by learners within the LMS and learners' self-reported self-regulation, specifically across the domains of planning and regulating categories. An analysis of the concomitant SRL and LA literature reveals that the present study found more relationships than other studies that have considered LA data produced by an LMS as an indicator of SRL (Cicchinelli et al., 2018; Yamada et al., 2017). One reason that the current study found more correlation could be due to the number of LMS planning, monitoring, and regulating variables that were available to the researcher and included in the study. Previous studies (Cicchinelli et al., 2018; Yamada et al., 2017) were not clear if the course utilized to gather data in their studies were designed intentionally to obtain a wide array of LMS variables as was the case with the current study.

Another possible reason is that perhaps the LMS in previous studies was not as integrated within the course as much as the course was with the current study. Therefore, there may not have been as much learner activity available to the researcher as there was with the current course. Other work that utilized specialty LA tools such as the nStudy or MOOC data (Winne et al., 2017; Wong et al., 2019) demonstrated that there was a predefined set of LMS variables that they were able to glean from their LA tool. Thus, the current study had more LA data elements available through intentional course design, learners' heavy utilization of the LMS within the course, and the fact that the course platform for data collection was an LMS as opposed to another tool such as the nStudy or a MOOC.

Learner's Patterns of LMS Usage and Academic Achievement

Another central aim of this study was to determine if trajectories of learners' LMS usage could be ascertained across the semester as well as if trajectories identified could be tied to academic achievement. Though, unlike the correlational analyses, which included a wide array of LMS variables, only lesson variables were included in this portion of the analysis. To answer this question, a GMM analysis was conducted for each a different type of category based on SRL theory: planning, monitoring, and regulating. As a reminder, planning activity included the number of times a learner accessed the lesson page overview, monitoring activities included the number of times a learner accessed the lesson material and lesson problem set, and regulating activity included the number of times a learner accessed the lesson solutions. Results demonstrated that each SRL domain contained different patterns as well as the number of trajectories. Reviewed below are the findings and pattern for each trajectory with each SRL domain as well as the relation of each trajectory to academic achievement. The last section reviews how the findings across the three domains tie to SRL theory as well as how the findings extend what is known about the utilization of LMS data to indicate learners' self-regulation.

Planning Trajectories and Academic Achievement

Planning activities are those that help organize learner effort. The current study utilized the lesson overview variable for the planning analysis. Using the lesson overview variable from the LMS, five trajectories were identified. The first trajectory contained learners who possessed a consistently high amount of planning activity throughout the semester. These learners accessed the lesson overview page on average of 2.52 times at the beginning of the semester and 2.39 times at the end of the semester and had a mean grade of 93.88. Although only 16 learners were included in this grouping, it is evident that learners who had sustained levels of high planning activities also had higher grades.

Learners in the second trajectory possessed a consistently low amount of planning activity throughout the semester. These learners started the semester accessing the lesson overview page less than once per week ($M = 0.45$) and ended the semester accessing the lesson overview page at an even lower rate than at the start of the semester ($M = 0.22$). There were 53 learners in this trajectory and their mean grade was 41.02, which is a failing grade in the course. Thus, learners in this sample that had a low amount of planning activity also had lower grades.

The third trajectory demonstrated learners who had a moderately amount of activity, though slightly increasing, throughout the semester. These learners accessed the lesson overview page almost once per week ($M = 0.84$) at the beginning of the semester but closer to once per week at the end of the semester ($M = 0.99$). A high number of learners, 88, followed this pattern and had a corresponding mean grade of 65.96, which was a non-passing grade in the course. Thus, learners who did not access the lesson overview page once per semester did not pass the course.

Learners in the fourth trajectory started the semester with a moderate amount of planning activity but ended with a high amount of planning activity. These learners consistently accessed the lesson overview page at least once at the beginning of the semester ($M = 1.18$) but increased their access to the lesson overview page to almost twice as the semester progressed ($M = 1.79$). There were 68 learners in this trajectory and had a mean final grade of 82.88. Thus, like the first trajectory, learners who had a higher amount of planning activity had at the end of the semester also had higher final grades;

however, a key difference with this trajectory is that learners increased their activity as the semester progressed.

Lastly, the fifth trajectory demonstrated learners who started with a high amount of planning activity but ended with a low amount of planning activity. These learners accessed the lesson overview page almost twice at the beginning of the semester (M = 1.73) but dropped off significantly as the semester progressed to the point where these learners did not typically check the lesson overview page with each new lesson (M = 0.61). This group contained 33 learners who finished with a mean grade of 67.70. Thus, learners within this trajectory, who had a decreasing amount of planning activity as the semester progressed, did not earn a passing grade in the course.

Thus, when it comes to overall patterns with learners' planning activity, learners who ended the semester with a high amount of planning activity earned higher grades in the course as evidenced by the first and fourth trajectories. In juxtaposition, learners who ended the semester with a low amount of planning activity earned worse grades in the course as evidenced by second, third, and fifth trajectories. Other patterns that were evident were those learners who increased their planning activity over the course of the semester had higher grades whereas learners who decreased their planning activity over the semester had lower grades.

Monitoring Activities and Learners' Academic Achievement

Monitoring activities are those that help learners acquire knowledge. In the context of the current study, the monitoring variables included in the GMM were the number of times a learner accessed lesson material and the number of times a learner accessed the lesson problem set. Using the monitoring elements from the LMS, four trajectories were identified. The first trajectory showed learners that started with a low amount of monitoring activity ($M = 1.13$) that decreased as the semester progressed and resulted in a lower amount of monitoring activity as the semester ended ($M = 0.86$). These learners accessed the lesson material and lesson problem set more than once at the beginning of the semester, but less than once at the end of the semester. There was a total of 34 learners in this trajectory that had an average grade of 43.58, which was a failing grade in the course. Thus, learners in this trajectory had low monitoring activity and very low academic achievement in the course.

Learners in the second trajectory started with high monitoring activity at the beginning of the semester ($M = 3.87$), experienced a slight decrease during the semester, but ultimately ended with a moderately amount of monitoring activity as the semester ended ($M = 2.36$). These learners accessed the lesson material and lesson problem sets almost four times at the beginning of the semester and slightly over two times at the end of the semester. This trajectory contained 66 learners who had an average grade of 82.48. Thus, this trajectory demonstrated that learners that had high monitoring activity and ended with moderate activity also earned a passing grade in the course.

The third trajectory contained learners who performed monitoring activities at a consistently moderate level throughout the semester. These learners accessed the lesson material and the lesson problem set more than once ($M = 1.67$) with each new lesson at the beginning of the semester and ended the semester accessing lesson material and the lesson problem set almost twice with each new lesson ($M = 1.94$). This trajectory represented the highest number of learners for monitoring activity with 126 and had an average grade of 73.39. Thus, learners in this trajectory sustained a moderate amount of monitoring activity and earned a passing grade in the course.

The fourth trajectory contained learners that started with a moderately high amount of monitoring activities ($M = 2.46$) but increased to a very high amount of monitoring activity as the semester ended ($M = 3.72$). This means that the 32 learners in this trajectory accessed the lesson material and the lesson problem set more than twice with each new lesson at the beginning of the semester but almost four times at the end of the semester. These learners also had the highest average grade out of all other monitoring trajectories with a mean grade of 86.15. Therefore, learners who increased their monitoring activities significantly over the semester also earned a high grade in the course.

The trajectories that were uncovered that utilized monitoring elements are like the ones found in learners' planning activities. For instance, learners who had higher levels of monitoring activity both at the beginning of the semester and the end of the semester had higher levels of academic achievement. Additionally, learners whose monitoring activity increased over the semester also obtained high levels of academic achievement. However, a key difference is that learners who possessed a consistently moderate amount of monitoring activity over the course of the semester earned a passing grade in the course, whereas learners who had consistently moderate planning activity over the semester did not earn a passing grade in the course.

Regulating Activities and Learners' Academic Achievement

Regulating activities were those that learners engaged with that helped reinforce knowledge. This study utilized the number of times a learner accessed the lesson solutions page to represent learners' regulating activity. From the analysis of learners' regulating activity, three trajectories were identified. Learners in the first trajectory started the semester with a moderately high amount of regulating activity ($M = 1.26$) that increased steadily as the semester concluded ($M = 1.87$). The 60 learners in this trajectory accessed the lesson solution set more than once at the beginning of the semester and almost twice at the end of the semester. Learners in this trajectory had a mean grade of 72.35. Thus, learners who had a high amount of regulating activity throughout the semester earned a passing grade in the course.

Learners in the second trajectory were consistently low with their regulating activity at the beginning of the semester ($M = 0.37$) as well as the end of the semester ($M = 0.29$). These learners did not access the lesson solutions consistently with each new lesson and rarely accessed the lesson solution at the end of the semester. There were 117 learners in this trajectory, and they had a mean grade of 71.18. Interestingly, although these learners had very low regulating activity; their grade was almost as high as those learners who possessed a high level of regulating activity. The author notes this as an unusual finding and is unsure why this may have occurred as most of the learners in this trajectory possessed high or moderate levels of planning and monitoring activities (Figure 4). One potential reason is that learners who had higher levels of accessing the lesson overview, lesson material, and lesson problem set may not have needed to access lesson solutions. It also could be true that perhaps regulating activities are not as important in grade obtainment as their planning and regulating counterparts.

Learners in the third trajectory began the semester with a moderate amount of regulating activity (M = 1.47) but decreased steadily to a low amount of regulating activity as the semester concluded (M = 0.51). These learners started the semester accessing lesson solutions with nearly every new lesson, but as the semester progressed, they significantly dropped off accessing lesson solutions with each new lesson. This trajectory contained 81 learners who had an average grade of 56.80, which was a failing grade in the course. Thus, learners whose regulating activity significantly decreased as the semester progressed also had lower grades.

A review of the results demonstrated that learners who had consistently high regulating activity and consistently low regulating activity earned almost the same grade in the course. In comparison, learners whose regulating activity significantly decreased as the semester progress performed poorly in the course. Next, the author situates the findings of the planning, monitoring, and regulating trajectories and their corresponding levels of academic achievement within SRL theory.

Planning, Monitoring, and Regulating Trajectories and SRL Theory

This section explores how the analysis across the planning, monitoring, and regulating domains from the previous section ties to SRL theory as well as how it extends what is currently know about learners' self-regulation. A review of the extant literature that utilizes cluster analysis to understand learners' SRL via LA data reveals that these findings are novel (Beheshitha et al., 2015; Pardo et al., 2016). Most of the previous studies focused on utilizing LA data to understand learner's behavior via a few data points within the semester, most commonly at the mid and/or the endpoint of the semester (Soffer & Cohen, 2018; Tempelaar, 2020; You, 2016; Zacharis, 2015). In comparison, this study considered how learners' SRL behavior changed over time through the utilization of more data points than previous work. Specifically, the current study used 13 different time points (e.g., lessons) across the semester to understand learner trajectories. Thus, the current study extends previous work by demonstrating the feasibility of utilizing learner's planning, monitoring, and regulating LMS data to understand learners' trajectories over time.

Another key takeaway from this study was the number of learners' SRL activity that was able to be understood through LMS data. Previous studies tended to understand or examine one aspect of SRL such as time management via LMS data (Baker et al., 2019; Li et al., 2020). In comparison, this study demonstrated that it is possible to understand learners' SRL behavioral patterns from LMS data on a broader set of activities. In particular, this study uncovered different learner patterns and trajectories for learners' planning, monitoring, and regulating activities. This is an important finding as it demonstrates the capacity of LMS data as a viable data source in understanding a variety of learners' SRL behaviors. Further studies should seek to leverage the longitudinal capability of LA data produced by an LMS to understand how learner behavior within an LMS changes over time.

Another key finding from the GMM and ANOVA analysis is that learners who engaged in higher levels of planning and monitoring activity earned higher grades in the course whereas learners with high and low levels of regulating activity earned nearly the same grade. Thus, this study confirms the well documented fact within SRL theory, learners who have higher levels of self-regulation also have higher levels of academic achievement (Hakan, 2016; Justice & Dornan, 2001; Peverly et al., 2003; Vrugt & Oort, 2008). However, previous studies have not examined how academic achievement differs across the planning, monitoring, and regulating domains. Thus, the current study adds to what is known about SRL and academic achievement by utilizing lesson variables gleaned from and LMS that served as indicators of learners' planning, monitoring, and regulating. In addition to extending what is known about SRL theory, the findings of the study can extend to other fields, such as student development theory.

Situating Self-Regulated Learning in Student Development Theory

One of the themes identified in chapter one was the connection this study could have between SRL and student development theory. As noted in the beginning chapter, the most appropriate student development theory to connect SRL to is Perry's Model of Cognitive Development (1999). According to Perry's theory, learners enter college as dualistic thinkers wherein they often knowledge as opposites and believe that an authority figure transmits knowledge to them. As learners grow and develop throughout their collegiate experience, the hope is that learners transition their thinking from dualism to relativism which is hallmarked by learners' ability to rely on themselves to create knowledge through intentional practice, reflection, and evaluation.

In the context of the current study, not many connections between SRL and Perry's theory were evident; however, there are a few key takeaways that demonstrate the need for future work to explore the tie between SRL and Perry's theory more intentionally. First, a key link between SRL and Perry's work is reflection. This study demonstrated that learners engaged in reflective practices multiple times across the semester as evidenced in their engagement with reflective activities such as accessing test solutions, accessing test solutions, and accessing lesson solutions. Even though an authority figure, such as the professor, provided the solutions, it could be that learners evaluated the merits of the skills and strategies employed based on whether they responded correctly. Thus, learners could adopt strategies used for correct responses and alter them based on incorrect responses for future implementation.

Second, and more broadly, it could be that self-regulation does not neatly fit into Perry's stages as he describes them, though that does not mean it is not something worthwhile to pursue. Rather, the skills and strategies that self-regulated learners accrue and possess over time are necessary to propel learners to higher stages in Perry's model. In other words, learners who do not possess self-regulation skills and strategies may not be able to reach Perry's higher stages. Though the author acknowledges this as a hypothesis, further work should be conducted to investigate the potential inherent tie between SRL and Perry's theory, in particular Perry's notion of commitment in which learners commit to a self-regulated learning strategy and complex conclusions.

Implications for Practitioners

This section considers implications for practitioners based on the findings of this study. The first is thinking about new ways to incorporate SRL within course design. Additionally, this section provides thoughts on imbuing SRL more deeply into pedagogy.

The second recommendation considers improving assessment practices on campus, specifically regarding the ability to include SRL as an assessment competency.

The Incorporation of SRL in Course Design

According to the findings of this study, higher grades were associated with learners who possessed higher levels of planning and monitoring activities. Thus, this study could be useful for instructors and practitioners to intentionally design courses that offer the ability for learners to engage within a wide array of planning, monitoring, and regulating activities. Course design, particularly in the online environment has been a hot topic in higher education over the past several decades (Jaggars & Xu, 2016; Strange & Banning, 2015; Vai & Sosulski, 2011). According to Strange and Banning (2015), the intentional design of courses in the virtual environment is a critical factor in learner success when it comes to academic achievement, learning, and retention. Thus, the prioritization of designing intentional virtual learning environments that foster learner success is of the utmost importance. Though it can be assumed that courses in the virtual environment are currently designed with a great deal of intention, the findings from the current study provide support and evidence for new ways of thinking about course design. Specifically, the results demonstrate the need for instructors and practitioners to design virtual courses with the ability for learners to develop and cultivate their SRL behaviors across the planning, monitoring, and regulating domains.

As for planning, it is key to develop and post material that helps set up the learner for success. The current study provides evidence that accessing the syllabus, accessing the weekly schedule, accessing announcements, and accessing the grades were key indicators of learners' self-reported self-regulation. Thus, instructors and practitioners should include these aspects within their course design as well as utilize and promote learner interaction with certain planning activities. These include the announcements tab, the grade book tab, as well as add additional items aside from the syllabus that can help learners organize their effort through the semester. Lastly, instructors should incessantly prompt learners to engage in planning activities throughout the semester as opposed to just the beginning of the semester.

As for monitoring, there are several activities that instructors and practitioners can implement that promote learners' self-regulated monitoring for knowledge acquisition. The current study provides several examples of monitoring strategies that instructors can implement throughout the semester such as learners taking practice quizzes, taking practice exams, or completing practice problem sets. The results from the GMM that utilized monitoring elements suggest that learners who engaged more frequently and consistently with monitoring activities earned higher grades in the course. Therefore, providing ample opportunity for learners to practice their knowledge acquisition must be prioritized within course design of the LMS.

Lastly, instructors and practitioners must provide the opportunity for learners to practice their regulating strategies and skills or activities that reinforce knowledge. Arguably, this is the most critical step in the SRL processes as much prior SRL literature supports SRL as a cyclical process wherein learners reflect on their learning (Zimmerman, 1989). Additionally, the incorporation of more regulating activities with the LMS could also promote learner's transition in thinking from dualism to relativism as presented in the previous section (Perry, 1999). While the results of the current study support the need for the incorporation of regulating activities within the course design, the findings suggest that learners did not perform as well as expected with higher levels of regulating activity. Though this could be because there may not have been many regulating activities that were included in the study. According to the results, the higher impact activities for learners' regulation were accessing quiz solutions, test solutions, or lesson solutions. Thus, it is important for instructors and practitioners to be sure that solutions to problem sets, exams, or quizzes are always available to learners. Lastly, instructors need to inform learners that review resources are available—and should be encouraged by the instructor—for learner success.

Equally important to course design is pedagogy. The findings from the study demonstrate that learners who engaged with higher levels of SRL planning, monitoring, and regulating had higher grades. Whereas it is unknown if learners' self-regulation caused the higher grades, this study presents a robust link between learners' self-regulation and higher grades earned. This was true for planning, monitoring, and regulating. Additionally, prior research on self-regulation demonstrates that learners that possess SRL skills and strategies are more likely to have higher levels of academic achievement (Matuga, 2009; Nota et al., 2004; Wibrowski et al., 2017; Zimmerman & Schunk, 2011). Thus, given the importance of the role SRL skills and strategies play in obtaining higher levels of academic achievement, institutions must further incorporate teaching SRL skills and strategies into curriculum as this is an identified area of opportunity within the SRL literature that can be remedied through existing courses (Schunk & Ertmer, 2000; Van Eekelen et al., 2005).

Leadership within institutions should prioritize identifying the appropriate individuals and course(s) in which SRL skills and strategies can be taught. There are two naturally occurring opportunities within the curriculum. First, a vast majority of institutions are incorporating a for-credit orientation-type course for first-year and transfer learners (Bauer-Wolf, 2019). These types of courses typically involve strategies for learners to be successful in college. Thus, it would follow logically that SRL skills and strategies would be incorporated into a course that is designed for learner success. Second and more recently, there has been a rise of professional skill-type courses at institutions, particularly within professional schools. As an example, at the institution where this study was conducted, each learner must take, and pass with a "C" or higher, a two-course, six-credit professional skills course sequence in the business school to graduate with a business degree. Included in these courses are activities aimed at increasing competence in learners' professional skills such as public speaking, critical thinking, ethical awareness, written communication, and teamwork. Thus, like orientation courses, professional skills courses appear to be a natural fit for the incorporation of SRL skills.

Lastly, instructors and practitioners should leverage previous literature that considers the incorporation of SRL within courses, specifically in the online environment. In their work, Krauel-Nix et al., (2019) propose a framework for developing and designing an online self-regulated course. Whereas their framework considers the incorporation of a separate SRL course that includes nine modules, there are many aspects of their course that could be adopted within any online course. As an example, one of their modules, “Methods for Learning” focuses on “how” learners learn as opposed to the “what” learners learn. Included in this module is an online assessment for learners to complete regarding their learning style. After, learners are encouraged to learn more about their specific learning style and associated strategies for success. In this example, learners can understand how they best learn, which connects to learners’ self-regulation, specifically metacognition. Specifically, if a learner is thinking about their learning style and strategies that would complement their learning style, then a learner is engaging with metacognition as this example demonstrates a learner engaging in thinking about their thinking. Thus, designing courses that include an understanding of learners’ preferred style of learning can foster learners’ self-regulation.

In review, this study demonstrates that course design and pedagogy matters. Within the study, a myriad of patterns were uncovered that tied learners who had higher levels of self-regulation to higher levels of academic achievement. Thus, future courses should consider ways in which learners can practice their self-regulation, specifically through the incorporation of planning, monitoring, and regulating activities. Lastly, institutions should embed the teaching of SRL skills and strategies into curriculum as this study complements that growing body of literature that supports the obvious benefits to learners who self-regulate (Pintrich, 2000; Winne, 1997; Zimmerman, 2000; Zimmerman & Schunk, 2011).

Ability to Assess SRL as an Assessment Competency

Over the past two decades, assessment on college campuses has risen considerably (Henning & Roberts, 2016; Kuh et al., 2014; Kuh & Ewell, 2010). As frequently noted in the assessment literature, key parts in the assessment processes include the identification of learning goals or learning competencies and how those learning goals or competencies are going to be objectively measured. Findings from this study can extend assessment practices both in the identification of learning competencies and assessment measurement.

Self-regulation is currently not a common assessment competency on college campuses according to the American Association of State Colleges and Universities, which provides rubrics for the most commonly assessed learning goals on campuses (Rhodes, 2010). Instead, most institutions choose to assess competencies such as critical thinking, written communication, oral communication, and ethical awareness among others. Although the exact reason may be unknown, one common reason why assessment competencies are chosen is due to the ability to measure the assessment competency from a more objective standpoint (Schuh & Upcraft, 2001). As established in chapter two, the current measurement methods of SRL such as self-report questionnaires, interviews, or think-aloud protocols are often subjective in nature. However, as the current study demonstrates, LA data gleaned from an LMS can be used as a more objective method to indicate learners' SRL, particularly when it comes to learners planning and regulating activities. Thus, the challenge of assessing learner's self-regulation due to measurement issues can be addressed by gathering learners' SRL data from an LMS.

Another way in which the current study can extend assessment practices is that instructors and practitioners are able to gather learners' SRL data in real-time as evidenced in the lesson activity trajectories. Building off the work of Klein and Hess (2018), this could enable instructors to identify trends during the semester in which students are struggling and prompt instructors to create interventions in real-time. This would serve as an upgrade from current practices within the assessment community whereby most analysis of assessment is conducted after the conclusion of the semester. Thus, most assessment work is reactionary. As a result, assessment findings are oftentimes not analyzed or understood until after the semester is completed. Therefore, learners in the previous semester are not the beneficiary of assessment work that is being conducted, which limits assessment data efficacy. However, this study offers promising results to understand learner activity on a week-to-week basis.

In review, the utilization of LA data as an indicator of learners' self-regulation has the potential to extend assessment practices by incorporating of SRL as a learning goal that can be measured by LMS data. Additionally, assessment practices can be enhanced by the production of real-time assessment data that can be gleaned from the lesson level that could help instructors design interventions within the current semester as opposed to waiting until after the semester has concluded.

Limitations

Although great care was taken to ensure a robust study, some limitations still exist. First, correlation does not mean causation. Even though there was ample correlation between LMS variables and learners' self-reported self-regulation, it cannot be definitively ascertained that clicking within the LMS is self-regulation. There could be a myriad of other reasons why learners clicked on the specific items within the LMS environment that may not necessarily relate to a learner's self-regulation. Thus, it is important to note that the correlation found in this study between LMS variables and learners' self-reported self-regulation is the same.

Additionally, another limitation of the study was the number of variables that were used in the GMM analysis. The model that was conducted for planning activity contained only the lesson overview variable, the model that was conducted for monitoring activities contained the lesson material and lesson problems variables, and the model that was conducted for regulating activity contained only the lesson solution variable. Although the low number of variables did not affect the ability to achieve optimal solutions, it would be informative to examine how the incorporation of more SRL behaviors /variables would potentially alter or enhance results. More variables may not necessarily equate to better models; however, there could be other variables that the current study is missing that might capture learners' self-regulation.

Lastly, another limitation was that this was a single institution study that was conducted within one business class at the institution of study. Thus, it could be that the results of this study could be limited in their generalizability outside of the context in which the study occurred. Though, the way in which the course in this study was designed was conducive to conducting this type of study. A limitation for replication in other online environments could be that the structure of other courses may not be conducive to this type of study. Additionally, it could be that different instructors utilize the LMS in different ways. Perhaps the online platform only represents a small portion of the course. In this case, it may not be possible to glean as much about learners' SRL in this type of environment. Therefore, it may not be possible to generalize to other uses of LMS by instructors.

Recommendations for Future Research

The findings from this study have the potential to be confirmed and extended via follow-up studies. As this was an exploratory study, more empirical work is needed to confirm or advance understanding of findings. First, there is a need to further interrogate the relationship between learner's self-report self-regulation and learner's behavior within the LMS. Although the findings of this study provided evidence that LA data can be utilized as indicators of SRL, more work must be conducted to replicate the patterns that were found in this study. Moreover, future work could build on the findings of this study to further confirm that LA data can be an appropriate measure for learners' self-regulation as traditional SRL measurement methods such as interviews or questionnaires. Moreover, follow-up work could confirm the relationships found between learners' self-reported SRL and the LMS data gather for learners' behavior in the planning and regulating categories as well as examine the monitoring category more fully. It would be worthwhile to investigate if follow-up studies also find a higher degree of correlation between learners' self-reported SRL and planning and regulating activities than between learners' self-reported SRL and monitoring activities or if that was a finding unique to this study.

Another area for future research is to further examine additional LMS variables that can potentially serve as an indicator of SRL. This study was limited to only the LMS variables that were available within the LMS of this course. It could be true that there are other LMS variables that exist that could enhance the findings of this study. For instance, there could be other LMS variables that could serve as an indicator of learners' planning, monitoring, or regulating. As an example, courses that utilize an LMS may enable a calendar feature which could be a critical factor in learner's planning. As another example, an instructor could require learners to utilize a Teaching Assistant's office hours, which could be an important factor in learner's monitoring as it could reinforce learner's accrued knowledge. However, future researchers must be thoughtful and intentional about which LMS variables could be important in ascertaining learner's self-regulation as an identified pitfall earlier in the paper was that oftentimes a multitude of variables are included in an analysis to see what correlates as opposed to being intentional and thoughtful about selecting appropriate variables for self-regulation.

Conclusion

This exploratory study sought to advance the understanding of the utilization of LMS data as an indicator of learners' self-regulation. To examine this further, the current study found correlation between learners' self-reported self-regulation and LMS elements, specifically within the planning and regulating categories. This suggests that LMS data, as compared to other analytics data sources, can serve as an indicator of learners' SRL. Additionally, the current study utilized 13 time points from across the semester to determine learner trajectories within the planning, monitoring, and regulating domains. Results demonstrated that learners who had high planning and high monitoring activities earned higher grades in the class. Thus, the results of this study provide hope and groundwork for future researchers to utilize LMS data to further examine its indication of learners' SRL.

APPENDIX A

INFORMED CONSENT

RESEARCH PROCEDURES

This research is being conducted to gain insight into student engagement patterns in the learning management system environment. Should you agree to be in this study, you will be asked to participate in an online survey. The online survey is comprised of consent questions, demographic questions, and questions related to your motivation, learning strategies, and engagement within Finance 303. The entire survey should take approximately 30 minutes. In addition, the second part of the study utilizes your Blackboard data and final grade. At the end of the semester, Mason's Information Technology Services unit will send your Blackboard data and final grade to the researcher. There is no time commitment for students for the second part of the study. Consent to participate in this research allows the researcher to use your data for research purposes.

Students' survey data, Blackboard data, and final grade data will be stored on a password-protected university computer and only the researcher will have access to the files. The files will be destroyed in 5 years.

RISKS

There are no foreseeable risks for participating in this research.

BENEFITS

There are no benefits to you as a participant in the study other than to further research on the understanding of student engagement patterns in the online environment.

CONFIDENTIALITY

The data in this study will be confidential. Since this research requires matching data from responses on the survey to Blackboard data, the student's G# will be a question on the survey as well as a data point received with the Blackboard data set. However, once both sets of data are obtained the student's G# will be replaced by a random number that is consistent between the survey data and the Blackboard data. Thus, the data will be de-identified after being received from GMU ITS, which will have access to the list of participants in order to provide the relevant data to the researchers. The de-identified data could be used for future research without additional consent from participants. While it is understood that no computer transmission can be perfectly secure, reasonable efforts will be made to protect the confidentiality of your transmission. The Institutional Review Board (IRB) committee that monitors research on human subjects may inspect study records during internal auditing procedures and are required to keep all information confidential.

PARTICIPATION

Your participation is voluntary, and you may withdraw from the study at any time and for any reason. If you decide not to participate or if you withdraw from the study, there is no penalty or loss of benefits to which you are otherwise entitled. There are no costs to you or any other party. All eligible participants are students enrolled in Finance 303: Financial Management for Spring 2021 semester. All participants must be 18 years of age.

Participants who participate fully in the study will be eligible for a $50 amazon gift card. Five winners will be drawn at random and receive a $50 Amazon gift card that will be sent directly to the participant's GMU email account. At the completion of the study, participants will be asked to enter email to be considered for the gift card. Under the U.S. federal tax law you may have individual responsibilities for disclosing the dollar value of the incentive received on this study.

CONTACT

This research is being conducted by Richard Hess and Angela Miller at George Mason University. Richard may be reached at 703-993-4446 or rhess5@gmu.edu or Angela can be reached at amille35@gmu.edu or 703-993-3678 for questions or to report a research-related problem. You may contact the George Mason University Institutional Review Board office at 703-993-4121 or IRB@gmu.edu if you have questions or comments regarding your rights as a participant in the research.

This research has been reviewed according to George Mason University procedures governing your participation in this research. The IRB reference number for this study is 1717683-1.

CONSENT

I have read this form, all of my questions have been answered by the research staff, and agree to participate in this study. To indicate consent to the study, please type your name and enter the date below:

Name:

Date:

Office of Research Integrity and Assurance

Research Hall, 4400 University Drive, MS 6D5, Fairfax, Virginia 22030
Phone: 703-993-5445; Fax: 703-993-9590

DATE:	March 1, 2021
TO:	Angela Miller
FROM:	George Mason University IRB
Project Title:	[1717683-1] Rick Hess Dissertation
SUBMISSION TYPE:	New Project
ACTION:	APPROVED
APPROVAL DATE:	March 1, 2021
REVIEW TYPE:	Expedited Review
REVIEW TYPE:	Expedited review categories #5 & 7

Thank you for your submission of New Project materials for this project. The George Mason University IRB has APPROVED your submission. This submission has received Expedited Review based on applicable federal regulations.

You are required to follow the George Mason University Covid-19 research continuity of operations guidance. You may not begin or resume any face-to-face interactions with human subjects until (i) Mason has generally authorized the types of activities you will conduct, or (ii) you have received advance written authorization to do so from Mason's Research Review Committee. In all cases, all safeguards for face-to-face contact that are required by Mason's COVID policies and procedures must be followed.

Please remember that all research must be conducted as described in the submitted materials.

Please remember that informed consent is a process beginning with a description of the project and insurance of participant understanding followed by a signed consent form unless the IRB has waived the requirement for a signature on the consent form or has waived the requirement for a consent process. Informed consent must continue throughout the project via a dialogue between the researcher and research participant. Federal regulations require that each participant receives a copy of the consent document.

Please note that any revision to previously approved materials must be approved by the IRB prior to initiation. Please use the appropriate revision forms for this procedure.

All UNANTICIPATED PROBLEMS involving risks to subjects or others and SERIOUS and UNEXPECTED adverse events must be reported promptly to the IRB office. Please use the appropriate reporting forms for this procedure. All FDA and sponsor reporting requirements should also be followed (if applicable).

All NON-COMPLIANCE issues or COMPLAINTS regarding this project must be reported promptly to the IRB.

This study does not have an expiration date but you will receive an annual reminder regarding future requirements.

Please note that all research records must be retained for a minimum of five years, or as described in your submission, after the completion of the project.

Please note that department or other approvals may be required to conduct your research in addition to IRB approval.

If you have any questions, please contact Katie Brooks at (703) 993-4121 or kbrook14@gmu.edu. Please include your project title and reference number in all correspondence with this committee.

GMU IRB Standard Operating Procedures can be found here: https://oria.gmu.edu/topics-of-interest/human-subjects/

This letter has been electronically signed in accordance with all applicable regulations, and a copy is retained within George Mason University IRB's records.

APPENDIX B

Survey to Learners

Intrinsic Goal Orientation

The following questions ask you about your study habits, your learning skills, your motivation, and engagement in this course. There are no right or wrong answers. Please respond to questions as accurately as possibility reflecting your own attitudes and behaviors in this course. For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

	not at all true of me						very true of me
	1	2	3	4	5	6	7
In a class like this, I prefer course material that really challenges me so I can learn new things.	○	○	○	○	○	○	○
In a class like this, I prefer course material that arouses my curiosity, even if it is difficult to learn.	○	○	○	○	○	○	○
The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.	○	○	○	○	○	○	○
When I have the opportunity in this class, I choose course assignments that I can learn from even if they don't guarantee a good grade.	○	○	○	○	○	○	○

Extrinsic Goal Orientation

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

	not at all true of me						very true of me
	1	2	3	4	5	6	7
Getting a good grade in this class is the most satisfying thing for me right now.	○	○	○	○	○	○	○
The most important thing for me right now is improving my overall grade point average, so my main concern in this class is getting a good grade.	○	○	○	○	○	○	○
If I can, I want to get better grades in this class than most of the other students.	○	○	○	○	○	○	○
I want to do well in this class because it is important to show my ability to my family, friends, employer, or others.	○	○	○	○	○	○	○

Task Value

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

	not at all true of me						very true of me
	1	2	3	4	5	6	7
I think I will be able to use what I learn in this course in other courses.	○	○	○	○	○	○	○
It is important for me to learn the course material in this class.	○	○	○	○	○	○	○
I am very interested in the content area of this course.	○	○	○	○	○	○	○
I think the course material in this class is useful for me to learn.	○	○	○	○	○	○	○
I like the subject matter of this course.	○	○	○	○	○	○	○
Understanding the subject matter of this course is very important to me.	○	○	○	○	○	○	○

Expectancy Component: Control of Learning Beliefs

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

	not at all true of me						very true of me
	1	2	3	4	5	6	7
If I study in appropriate ways, then I will be able to learn the material in this course.	○	○	○	○	○	○	○
It is my own fault if I don't learn the material in this course.	○	○	○	○	○	○	○
If I try hard enough, then I will understand the course material.	○	○	○	○	○	○	○
If I don't understand the course material, it is because I didn't try hard enough.	○	○	○	○	○	○	○

Affective Component: Text Anxiety

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

	not at all true of me					very true of me
	1	2	3	4	5	6	7
When I take a test I think about how poorly I am doing compared with other students.	○	○	○	○	○	○	○
When I take a test I think about items on other parts of the test I can't answer.	○	○	○	○	○	○	○
When I take tests I think of the consequences of failing.	○	○	○	○	○	○	○
I have an uneasy, upset feeling when I take an exam.	○	○	○	○	○	○	○
I feel my heart beating fast when I take an exam.	○	○	○	○	○	○	○

Expectancy Component: Self-Efficacy for Learning and Performance

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

	not at all true of me						very true of me
	1	2	3	4	5	6	7
I believe I will receive an excellent grade in this class.	○	○	○	○	○	○	○
I'm certain I can understand the most difficult material presented in readings for this course.	○	○	○	○	○	○	○
I'm confident I can understand the basic concepts taught in this course.	○	○	○	○	○	○	○
I'm confident I can understand the most complex material presented by the instructor in this course.	○	○	○	○	○	○	○
I'm confident I can do an excellent job on the assignments and tests in this course.	○	○	○	○	○	○	○
I expect to do well in this class.	○	○	○	○	○	○	○
I'm certain I can master the skills being taught in this class.	○	○	○	○	○	○	○
Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this class.	○	○	○	○	○	○	○

Cognitive and Metacognitive Strategies: Rehearsal

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best

	not at all true of me 1	2	3	4	5	6	very true of me 7
When I study for this class, I practice saying the material to myself over and over.	○	○	○	○	○	○	○
When studying for this class, I read my class notes and the course readings over and over again.	○	○	○	○	○	○	○
I memorize key words to remind me of important concepts in this class.	○	○	○	○	○	○	○
I make lists of important terms for this course and memorize the lists.	○	○	○	○	○	○	○

Cognitive and Metacognitive Strategies: Elaboration

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

	not at all true of me 1	2	3	4	5	6	very true of me 7
When I study for this class, I pull together information from different sources, such as lectures, readings, and discussions.	○	○	○	○	○	○	○
I try to relate ideas in this subject to those in other courses whenever possible.	○	○	○	○	○	○	○
When reading for this class, I try to relate the material to what I already know.	○	○	○	○	○	○	○
When I study for this course, I write brief summaries of the main ideas from the readings and the concepts from the lectures.	○	○	○	○	○	○	○
I try to understand the material in this class by making connections between the readings and the concepts from the lectures.	○	○	○	○	○	○	○
I try to apply ideas from course readings in other class activities such as lecture and discussion.	○	○	○	○	○	○	○
By now, there have been many statements that you have read, if you are reading this correctly, please respond to this question by selecting 1.	○	○	○	○	○	○	○

Cognitive and Metacognitive Strategies: Organization

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

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

	not at all true of me 1	2	3	4	5	6	very true of me 7
I often find myself questioning things I hear or read in this course to decide if I find them convincing.	○	○	○	○	○	○	○
When a theory, interpretation, or conclusion is presented in class or in the readings, I try to decide if there is good supporting evidence.	○	○	○	○	○	○	○
I treat the course material as a starting point and try to develop my own ideas about it.	○	○	○	○	○	○	○
I try to play around with ideas of my own related to what I am learning in this course.	○	○	○	○	○	○	○
Whenever I read or hear an assertion or conclusion in this class, I think about possible alternatives.	○	○	○	○	○	○	○

Cognitive and Metacognitive Strategies: Critical Thinking

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

	not at all true of me 1	2	3	4	5	6	very true of me 7
When I study the readings for this course, I outline the material to help me organize my thoughts.	○	○	○	○	○	○	○
When I study for this course, I go through the readings and my class notes and try to find the most important ideas.	○	○	○	○	○	○	○
I make simple charts, diagrams, or tables to help me organize course material.	○	○	○	○	○	○	○
When I study for this course, I go over my class notes and make an outline of important concepts.	○	○	○	○	○	○	○

Cognitive and Metacognitive Strategies: Metacognitive Self-Regulation

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

	not at all true of me 1	2	3	4	5	6	very true of me 7
During class time I often miss important points because I'm thinking of other things.	○	○	○	○	○	○	○
When reading for this course, I make up questions to help focus my reading.	○	○	○	○	○	○	○

	1	2	3	4	5	6	7
When I become confused about something I'm reading for this class, I go back and try to figure it out.	○	○	○	○	○	○	○
If course materials are difficult to understand, I change the way I read the material.	○	○	○	○	○	○	○
Before I study new course material thoroughly, I often skim it to see how it is organized.	○	○	○	○	○	○	○
I ask myself questions to make sure I understand the material I have been studying in this class.	○	○	○	○	○	○	○
I try to change the way I study in order to fit the course requirements and instructor's teaching style.	○	○	○	○	○	○	○
I often find that I have been reading for class but don't know what it was all about.	○	○	○	○	○	○	○
I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying.	○	○	○	○	○	○	○
When studying for this course I try to determine which concepts I don't understand well.	○	○	○	○	○	○	○
When I study for this class, I set goals for myself in order to direct my activities in each study period.	○	○	○	○	○	○	○
If I get confused taking notes in class, I make sure I sort it out afterwards.	○	○	○	○	○	○	○

Resource Management Strategies: Effort Regulation

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

	1 (not at all true of me)	2	3	4	5	6	7 (very true of me)
I often feel so lazy or bored when I study for this class that I quit before I finish what I planned to do	○	○	○	○	○	○	○
I work hard to do well in this class even if I don't like what we are doing.	○	○	○	○	○	○	○
When course work is difficult, I give up or only study the easy parts.	○	○	○	○	○	○	○
Even when course materials are dull and uninteresting, I manage to keep working until I finish.	○	○	○	○	○	○	○

Resource Management Strategies: Peer Learning

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

	1 (not at all true of me)	2	3	4	5	6	7 (very true of me)
When studying for this course, I often try to explain the material to a classmate or a friend.	○	○	○	○	○	○	○
I try to work with other students from this class to complete the course assignments.	○	○	○	○	○	○	○
When studying for this course, I often set aside time to discuss the course material with a group of students from the class.	○	○	○	○	○	○	○
By now, there have been many statements that you have read, if you are reading this correctly, please respond to this question by selecting 6.	○	○	○	○	○	○	○

Resource Management Strategies: Time and Study Environment

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

	not at all true of me 1	2	3	4	5	6	very true of me 7
I usually study in a place where I can concentrate on my course work.	○	○	○	○	○	○	○
I make good use of my study time for this course.	○	○	○	○	○	○	○
I find it hard to stick to a study schedule.	○	○	○	○	○	○	○
I have a regular place set aside for studying.	○	○	○	○	○	○	○
I attend class regularly.	○	○	○	○	○	○	○
I often find that I don't spend very much time on this course because of other activities.	○	○	○	○	○	○	○
I rarely find time to review my notes or readings before an exam.	○	○	○	○	○	○	○
By now, there have been many statements that you have read, if you are reading this correctly, please respond to this question by selecting 3.	○	○	○	○	○	○	○

Resource Management: Help Seeking

For each question, the same scale is employed. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, select the number between 1 and 7 that best describes you.

	not at all true of me 1	2	3	4	5	6	very true of me 7
Even if I have trouble learning the material in this class, I try to do the work on my own, without help from anyone.	○	○	○	○	○	○	○

	1	2	3	4	5	6	7
I ask the instructor to clarify concepts I don't understand well.	○	○	○	○	○	○	○
When I can't understand the material in this course, I ask another student in this class for help.	○	○	○	○	○	○	○
I try to identify students in this class whom I can ask for help if necessary.	○	○	○	○	○	○	○

Demographics

What is your race?

- ◯ African American
- ◯ Asian American
- ◯ Hispanic American
- ◯ Native American
- ◯ Pacific Islander
- ◯ White American
- ◯ Two or more
- ◯ International Student
- ◯ I prefer not to respond

What is your gender?

- ◯ Woman
- ◯ Man
- ◯ Transgender
- ◯ Non-binary/non-conforming
- ◯ I prefer not to respond

What is your major?

- ☐ Accounting
- ☐ Business Analytics
- ☐ Finance
- ☐ Financial Planning & Wealth Management
- ☐ Management Information Systems
- ☐ Management
- ☐ Marketing
- ☐ Supply Chain Management

Please enter your age.

Please select your transfer status.

- ◯ I started my collegiate career at George Mason University.
- ◯ I started my collegiate career elsewhere and transferred into George Mason University.

Please select your generation in college status: (Note: first-generation in college means that your parent(s) or guardian(s) did not complete a 4-year college or university degree).

- ◯ I am a first-generation college student.
- ◯ I am not a first-generation college student.

Please enter your Mason student ID number

If you would like to be considered for a $50 Amazon giftcard, please list your email address.

APPENDIX C

Email to Students

Dear Student-

Please consider participating in the following study entitled: Examining Learner Engagement Patterns within a Learning Management System. The intention of the study is to understand student's engagement patterns within Blackboard in hopes of improving student learning, and ultimately student grades.

The study consists of responding to a questionnaire regarding your learning strategies and behaviors in this course as well as demographic questions. The total time estimated to complete the questionnaire is approximately 25-30 minutes.

Participants who participate fully in the study will be eligible for a $50 Amazon gift card. Five winners will be drawn at random and receive a $50 Amazon gift card that will be sent directly to your GMU email account. At the completion of the study, you will be asked to enter your email to be considered for the gift card.

Your participation in this study will be of great importance in understanding how students learn in the online environment and how instructors and practitioners can design courses that leads to better student outcomes.

Please follow this link to participate in this study.

Thank you for your time and participation.
Richard Hess

The IRB reference number for this study is 1717683-1.

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