Online self-directed learning readiness and learning outcome in online statistics learning environment: The mediating roles of self-efficacy to learn statistics and 2x2 Achievement goal orientations

by

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Abstract

This study investigated the understanding of the effects of online self-directed learning readiness (OSDLR) on academic achievement. and course satisfaction for online learning statistics through the mediating variables of self-efficacy to learn statistics (SELS) and 2x2 achievement goal orientation. The current study sought to create awareness and inform learners and tutors engaging in online statistics courses how they can rely on self-directed learning readiness. The present study sought to investigate: i) the relationship between online self-directed learning readiness and academic outcomes as measured by course satisfaction and grades ii) how the relationship between OSDLR and learning outcomes (grade) is mediated by SELS iii) how the relationship between OSDLR and learning outcomes (grade) is mediated by achievement goal orientations iv) how the relationship between OSDLR and affective learning outcome (course satisfaction) is mediated by SELS and v) how the relationship between OSDLR and affective learning outcome (course satisfaction) is mediated by achievement goal orientations.

This study employs a quantitative research design and a correlational research design utilizing a cross-sectional mediation model to investigate the relationships among variables. Data collection for this study was conducted using an online survey with a set of questionnaires, including part 1 for demographics, part 2 for online learning readiness, part 3 for 2x2 achievement goal orientations, part 4 for self-efficacy to learn statistics, and part 5 for course satisfaction. The participants in the current study were students enrolled in and studying at a large public university in the Southeastern United States who had registered for at least one statistics course delivered online during the 2020 Fall semester.

Data analyses utilized path models, where a series of OLS regression analyses were performed. The analysis was divided into four different models: Model 1-1, Model 1-2, Model 2-

1, and Model 2-2. The study established that OSDLR was positively related to grades. OSDLR is also positively related to SELS, and SELS was not related to the grade, and as such, it was not a significant mediator between OSDLR and grade. It is also established that OSDLR was positively related to mastery-approach goal orientation (MAP) but showed no positive relationship with any other orientations (mastery-avoidance goal orientation (MAV), performance-goal orientation (PAP), or performance-avoidance goal orientation (PAV)) The results also showed that MAP was positively related to the grade; therefore, that MAP is the significant mediator between the relationship between OSDLR and grade. MAV was negatively related to grade and neither PAP nor PAV was significantly associated with the grade. OSDLR was positively associated with course satisfaction, and SELS was positively associated with course satisfaction. Finally, none of the 2x2 achievement goal orientations were associated with course satisfaction.

This study concludes with recommendations based on these findings, limitations of the current study, and implications of the present study. The findings of the current study provide a basis upon which future studies can be developed, as well as a basis upon which better educational programs can be implemented for online learning environments by instructors and institutions of higher learning.

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Chapter 1 - Introduction

Overview

In recent decades, the education system has been characterized by technological advancements that have enhanced its flexibility, variability, and accessibility. Online learning has been a significant development that has expanded learners' horizons, enabling them to save resources and time, enjoy increased flexibility in interacting with their educators and peers remotely, and access learning materials without geographical or temporal barriers. The success of online learning is dependent on students' academic self-efficacy, which depends on their educators' preparedness and the quality of the learning materials (Welter et al., 2022). Self-efficacy is considered a critical factor in learning since it determines a student's belief in their own abilities (Bandura, 1986). Pham et al. (2021) developed a framework for understanding the variables affecting the effectiveness of online learning, which include proactiveness, self-study ability, perceived efficacy, the characteristics or complexity of the course, faculty capacity, and usability content.

It has been reported that the online course completion rate is 12.6%; however, based on a study of 221 Massive Open Online Courses, this rate can vary dramatically from 0.7% to 52.1%. The concept of the efficacy of online courses has provided background information to justify this variation in completion rate (MOOCs; Jordan, 2015). At the same time, face-to-face learning offers more monitoring options for students since the ability of administrators and instructors to oversee students increases learning module completion rates. Basar et al. (2018) noted that while students who attend face-to-face learning options interact with their peers, engage in in-person group exercises, and see their instructors regularly, students taking online courses must practice effective time management, be more motivated, and assume complete accountability for their academic outcomes. This difference in the learning models' characteristics creates a difference in completion rates. The need for understanding approaches to online course completion has led to the study of the self-efficacy concept to address the psychological factors needed to increase learners’ commitments, attitudes, competencies, and motivations (Hayat et al., 2020).

The ability of online learning to provide accessible materials without geographical limitations or time constraints has enabled individuals to engage in flexible learning hours and self-directed learning (SDL). Self-directed learning allows individual learners to become empowered to take more responsibility for different learning decisions and to transfer study skills and knowledge from one situation to another. Self-directed learning does not necessarily occur in isolation but does occur on a personal level since it involves activities and resources such as participation in study groups, self-guided reading, electronic dialogues, reflective writing activities, and internships. Theories of self-directed learning, such as Knowles's theory, have enabled an understanding of the characteristics needed to engage in self-directed learning and any other factors that must be considered to facilitate the process (Manning, 2007).

Numerous studies of online self-directed learning readiness (OSDLR) have suggested that OSDL success depends on self-efficacy, which is characterized by a student’s attitude, self-determination, and motivation toward learning (Khodaei et al., 2022; Panisoara et al., 2020). Psychological factors such as anxiety, stress, and fear negatively affect students’ self-efficacy, directly resulting in poor academic performance (Yilmaz, 2017). For a better understanding of OSDLR, several studies have provided an online learning readiness survey as a platform for measuring constructs such as self-efficacy, learner characteristics, online skills, independent and dependent learning preferences, time management and self-discipline, communication, and social competencies (Martin et al., 2020; Wei & Chou, 2020). The survey instruments from these studies have aided in understanding the integrated competencies of self-directed learning, confidence, technical awareness, and communication.

Online Statistics Learning

Learning statistics online could have both advantages and disadvantages. For instance, students' opportunities to ask questions about a specific aspect of the course, a test, or calculations could be more limited. Al-Asfour (2012) recognized that while students were satisfied with online statistics courses overall, and they rated the assessment of their productivity and online instructions higher, they gave communication a lower rating. A study conducted by Blackburn (2015) revealed that online statistics courses were accepted with enthusiasm by students, who admitted that they were more interesting due to the presence of quizzes. Moreover, the online course decreased their statistics anxiety, taught them some interesting concepts, and led to positive feedback on the course overall. However, the same study showed that communication with instructors was rated lower than expected, and it was recognized that students benefit from previous knowledge of statistics before enrolling in the online course (Blackburn, 2015). Earlier research by DeVaney (2007) compared the attitudes, anxiety, and satisfaction levels of students enrolled in online statistics courses and traditional classrooms. They found that students' levels of statistics anxiety were significantly higher at the beginning of the online courses compared to the traditional classroom, yet at the end of the course, the level of statistics anxiety was lower in the online courses compared to the traditional classroom. Moreover, in some instances, anxiety increased among those learning in the traditional classroom, which affected overall satisfaction with the course (DeVaney, 2007). It is important to acknowledge, however, that each study analyzed a specific online or traditional statistics course, and the design and content of online courses can vary dramatically.

The success of online statistics learning could depend on students' attributes as well as factors related to the design and content of the course. For example, Dunn (2014) tested the impact of academic self-regulation, intrinsic motivation, and statistics anxiety on procrastination in online statistics. The findings revealed that in an online course, academic self-regulation and intrinsic motivation are critical to reducing passive procrastination and attaining success in online statistics learning. This study emphasized the importance of intrinsic motivation (mastery approach goal orientation) in decreasing procrastination and achieving success in an online statistics course. At the same time, Mills and Raju (2011) reported that, in most cases, students prefer a face-to-face statistics course over an online course primarily due to usability concerns, a lack of communication with the instructor, and problems with design, which affected their motivation to learn.

However, it is also critical to mention that this study analyzed online courses created more than ten years ago and did not consider the changes made over the years in terms of software and hardware progress. Larwin and Larwin (2011) showed that the positive attitude toward and satisfaction with online statistics courses had increased exponentially with the development and improvement of technologies, which provided more convenient, effective, and usable course designs. Further, since the COVID-19 global pandemic started, the amount of online learning has proliferated. Koehler et al. (2018) analyzed the impact of interactive instruments on learning statistics online, including student satisfaction, and revealed that learners were particularly satisfied with the possibility of having control over their learning and accessing education remotely.

Problem Statement

The COVID-19 crisis has led to drastic changes in the education system. Students were forced to shift from physical to online classes in response to government restrictions on face-to-face interactions. These restrictions were considered critical to preventing the spread of a global respiratory disease. Aguilera-Hermida (2020) explains that while numerous challenges accompanied these changes, they created an awareness of the role and advantages of engaging in online learning. Therefore, even after the risk of viral spread was reduced, the popularity of online learning remained high. Bashir et al. (2021) reported that Aston University adopted a hybrid mode of course delivery (combining online and face-to-face courses) as a post-COVID solution that recognized the popularity of online learning. A survey cited by Kelly (2021) asserted that 73% of students preferred studying fully online after the pandemic; however, only about 53% of faculty preferred teaching online.

Statistics courses have also been transferred online, with studies such as Ritzhaupt et al. (2020) revealing that students enrolled in the coursework experienced less anxiety, making the module preferable to in-person learning. The popularity of online statistics courses post-pandemic has created a demand for understanding this mode of learning and how learners and educators can organize their courses effectively. Further, demand for understanding the learning module has been created by studies such as Figueroa-Cañas and Sancho-Vinuesa (2020), which reported that the dropout rate of online statistics courses is higher than that of traditional statistics courses. This is a significant concern because, even though most learners prefer online learning, this same online model has seen higher dropout rates. However, Knowles' self-directed learning theory has encouraged scholars to focus on self-efficacy to improve online statistics courses (Manning, 2007). The current study sought to elucidate our understanding of the existing gap in the literature regarding the effects of self-efficacy, self-directed learning readiness (SDLR), and goal orientation on learning outcomes for an online statistics course.

Research Questions

The present study investigated the following research questions:

1. What is the extent of the relationship between online self-directed learning readiness and grades mediated by self-efficacy to learn statistics and each construct of achievement goal orientations in an online statistic learning environment?

1.1 What is the extent of the relationship between online self-directed learning readiness and grades in an online statistic learning environment?

1.2 What is the extent of the relationship between online self-directed learning readiness and grades mediated by self-efficacy to learn statistics in an online statistic learning environment?

1.3 What is the extent of the relationship between online self-directed learning readiness and grades mediated by each construct of achievement goal orientations (MAP, MAV, PAP, PAV) in an online statistic learning environment?

2. What is the extent of the relationship between online self-directed learning readiness and course satisfaction mediated by self-efficacy to learn statistics and each construct of achievement goal orientations in an online statistic learning environment?

2.1 What is the extent of the relationship between online self-directed learning readiness and course satisfaction in an online statistic learning environment?

2.2 What is the extent of the relationship between online self-directed learning readiness and course satisfaction mediated by self-efficacy to learn statistics in an online statistic learning environment?

2.3 What is the extent of the relationship between online self-directed learning readiness and course satisfaction mediated by each construct of achievement goal orientations in an online statistic learning environment?

Significance of the Study

The current study seeks to investigate the existing gap in our knowledge regarding the effects of self-efficacy, self-directed learning readiness (SDLR), and goal orientation on learning outcomes for learning statistics online. This investigation is especially relevant due to the increased demand for online courses after the pandemic. The study aims to create awareness and to inform learners and educators who engage in online statistics courses about how they can rely on self-efficacy and achievement goal orientations to improve their grade outcomes. Students, institutions, and tutors participating in online statistics courses will also understand the impact of self-directed learning readiness on online statistics course satisfaction and grade outcomes. The findings of the present study can be used to improve the dynamics of online statistics course grade outcomes and satisfaction from a psychological and academic perspective. As such, the present study has the potential to make important contributions to the body of academic literature, especially in the field of education.

Limitations of Study

This study has several limitations. First, students may not completely understand their achievement goal orientations, and some of the participants may adopt two or more goal orientations. Second, students were asked to report their grades from one of the courses they were enrolled in, but some of the participants who were enrolled in more than one statistics course could have reported their best grades regardless of their goal orientations and self-directed learning readiness. This also applies to course satisfaction. Third, the present study includes many variables, which increases the potential for introducing confounding variables that this study might fail to control. The presence of too many variables can lead to overfitting, which results in poor predictions using new data. As such, the study results could have a level of ambiguity due to overfitting. In addition, this study used self-reported questionnaires, which increases the possibility of participant bias. At the same time, the variables measured by this study are somewhat subjective in that they require feedback from students (participants') regarding goal orientation, self-efficacy, and SDLR. Lastly, this study focuses exclusively on online statistics learning from a large southeastern research institution; therefore, the generalizability of the results to other subjects and settings might be problematic.

However, these limitations do not seriously threaten validity or reliability.

Definitions of Terms

Achievement goal orientation (AGO): This is defined as part of the need to master goals. In a recent paper, it was classified as "an individual's perception of the purpose or meaning of engaging in an achievement activity, such as to demonstrate competency or to develop competency (Elliot et al., 1999; Lin, Chen and Zhang, 2021)."

Course satisfaction: In the context of this dissertation, course satisfaction refers to the level to which students are satisfied with their online statistics course.

Grade: A student assessment tool employed by a specific educational facility (Richardson & Newby, 2006).

Mastery approach goal orientation (MAP): Students who focus on developing competence-based learning, expanding their understanding of a topic, and improving their performance display a MAP goal orientation (Elliot et al., 1999; Mascret et al., 2017).

Mastery avoidance goal orientation (MAV): Students who focus on not losing knowledge, skills, or competence display a MAV goal orientation (Elliot & McGregor, 2001).

Online Learning Readiness Scale (OLRS): The OLRS is a scale measuring SDLR based on categories such as self-directed learning, motivation for learning, computer self-efficacy, learner control, and online communication self-efficacy (Hung et al., 2010).

Online self-directed learning readiness (OSDLR): OSDLR indicates that a learner has the attitudes, capabilities, and personality characteristics necessary for online self-directed learning (Sumuer, 2018).

Performance approach achievement goal orientation (PAP): Learners who demonstrate their competence by trying to outperform others demonstrate a PAP goal orientation (Wang et al., 2021).

Performance avoidance achievement goal orientation (PAV): Learners who focus on avoiding looking incompetent, making an error, or being outperformed by others display a PAV goal orientation (Partridge et al., 2014).

Self-efficacy: This describes people's judgments of their own capabilities to organize and execute courses of action required to attain designated types of performances (Bandura, 1986).

Self-efficacy in learning statistics (SELS): SELS refers to an individual's confidence in their ability to effectively learn the skills needed for their statistics course. It is rooted in social cognitive theory (Polm, 2016).

Organization of Study

The current study is organized into five sections: Introduction, Literature Review, Methodology, Results, and Discussion. Chapter 1 presents the introduction, which describes the research purpose, problem statement, and research question, the significance of the study, limitations of the study, the definition of terms, and the organization of the study. Chapter 2, the literature review, describes previous studies covering the research topic. This chapter not only brings together existing knowledge about self-directed learning, self-efficacy, 2x2 achievement goal orientation, and learning outcomes but also identifies an existing gap in the literature regarding the impact of the self-directed learning framework in an online learning setting and how this relationship is mediated by self-efficacy and 2x2 achievement goal orientations, which aid in establishing the unique contribution of the current study. Chapter 3 discusses the problem statement, research questions, research instruments, and participants' data collection and analysis procedures. Chapter 4 presents the demographic information of participants and survey results. The survey results will address how online self-directed learning readiness impacts learning outcomes, which are mediated by self-efficacy to learn statistics and achievement goal orientations. Finally, Chapter 5 provides implications for theory, practice, overall implications, and suggestions for future research.

Chapter 2 - Review of Literature

Overview

A review of the literature provides theoretical frameworks for the present study by discussing theories of achievement, goal orientation, self-directed learning (SDL), and self-efficacy. Self-directed learning, achievement goal orientation, and social cognitive theories are first discussed in Chapter 2. Specifically, the conceptual framework for this study includes self-directed learning readiness, online self-directed learning readiness, self-efficacy to learn statistics, and learning outcomes, such as cognitive and affective learning outcomes, as well as the achievement goal orientation theories of motivation. Following this conceptual framework, the literature review will focus on the relationship between online learning readiness, a 2x2 framework of achievement goal orientations, self-efficacy to learn statistics and learning outcomes such as academic achievement and course satisfaction.

Problem Statement

The COVID-19 global pandemic has led to drastic changes in educational systems around the world. Students were forced to shift from physical to online classes in response to government restrictions on face-to-face instruction. These restrictions were considered critical to preventing the spread of COVID-19. Aguilera-Hermida (2020) explained that while numerous challenges accompanied these changes, they also created an awareness of the role and advantages of engaging in online learning. Therefore, even after the risk of virus spread was reduced, the popularity of online learning remained high. Bashir et al. (2021) reported that Aston University adopted a hybrid mode of course delivery (combining online and face-to-face courses) as a post-COVID solution that highlighted the popularity of online learning among students. A survey cited by Kelly (2021) established that 73% of students preferred studying fully online after the pandemic; however, only about 53% of faculty preferred teaching online.

In recent years, many statistics courses have also been transferred online, with studies such as that conducted by Ritzhaupt et al. (2020) revealing that students enrolled in online coursework experience less anxiety, making online instruction preferable to in-person learning. The popularity of online statistics courses post-pandemic has created a demand for understanding this modality of learning and how learners and educators can organize their courses effectively. Further demand for understanding the learning modality has been created by studies such as those by Figueroa-Cañas and Sancho-Vinuesa (2020), which have reported that the dropout rate of online statistics courses is higher than that of traditional statistics courses. This is a significant concern because, even though most learners prefer online learning, this same online model has seen higher dropout rates. However, Knowles' self-directed learning theory has encouraged scholars to focus on self-efficacy to improve online statistics course outcomes (Manning, 2007). Thus, the present study seeks to explore the existing gap in the literature regarding the effects of self-efficacy, self-directed learning readiness (SDLR), and goal orientation on learning outcomes for learning statistics online.

Research Questions

1. What is the extent of the relationship between online self-directed learning readiness and grades mediated by self-efficacy to learn statistics and each construct of achievement goal orientations in an online statistic learning environment?

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Self-Directed Learning Theory

Self-directed learning (SDL) is a theoretical framework currently used by pedagogical experts and teachers to enhance self-efficacy in learners, promote transformational learning, and utilize components of social action and justice learning. Knowles (1975) defined SDL as a process by which individuals take initiative, through the assistance of others or on their own, to diagnose learning gaps and needs, formulate goals, identify resources, and implement strategies for learning. They also assess learning outcomes independently. Self-directed learning (SDL) allows individual learners to become empowered to take more responsibility for different learning decisions and to transfer study skills and knowledge from one situation to another (Alfaifi, 2016).

Knowles popularized the concept of self-directed learning in the US, while Tough, another scholar, embedded the term in Canadian discourse. In 1979, Tough published his book, *The Adult's Learning Projects*, an analysis of self-directed teaching activities. The term andragogy, coined by Knowles, with corresponding adult instructional processes, became popular in North America at the same time. Here, the principle of autonomy, which largely drives adult learning, is applied to more generalized notions of self-directed learning.

With the use of computer-assisted learning, many distance education efforts are using technology to facilitate self-directed learning, which requires new research and understanding (Hiemstra, 1994). In other words, it took the critical work of scholars like Gibbs (1988), Candy (1991), and Knowles (1997) to develop a framework for today’s 21st-century learning institutions. Brookfield (1993) disagrees with Candy (1991), arguing that democratic educational systems should be guided by SDL rather than institutions and governments. Some proponents of nationally oriented curricula consider SDL an abomination, while education better prepares students for the dominant culture. Today's schools are stronger, more diverse, and more multicultural and multiethnic than in the past. SDL increases cultural competence and awareness, according to research (Aldemir et al., 2022). Technology makes individuals more interconnected, making meaning-sharing more crucial. Building bridges of understanding requires skills and knowledge. The literature supports Brookfield's (1993) claim that, rather than contributing to cultural hegemony, an SDL pedagogical method assists students in a rapidly globalizing, technologizing, and diversifying environment.

Brockett and Hiemstra shaped SDL. The researchers analyzed learners' requirements, secured relevant resources, executed learning activities, and evaluated outcomes. Self-directed learning preparedness, self-concept, experience, and learning styles can influence SDL adoption. "Learner self-direction" is related to individual intentionality (Hiemstra, 1994). Hence, learners become naturally motivated if they thrive under the correct conditions and have enough confidence and self-concept to advance, interact with content, build knowledge, and use their abilities. Furthermore, Brockett and Hiemstra (1991) contributed to the discussion with their personal responsibility orientation model (PRO). The authors define PRO as taking ownership of one's actions and thoughts. The only way to take a proactive approach to learning is to accept responsibility for one's own education, and this comes from humanism, including the idea that individuals are independent, autonomous, and responsible for their own growth. In other words, it is virtually impossible for one to be independent if they are not accountable for their own actions, consequences, and choices. On the other hand, Brockett and Hiemstra (1991) believed that adult education instructors should boost student capability.

The PRO approach fits 21st-century needs, where information flows rapidly and is absorbed in large quantities, and knowledge management is crucial. Razzaq et al. (2019) observe that the public sector has recently prioritized knowledge management. As the world moves towards a service-based economy, managing knowledge is becoming a skill many professionals need. SDL may teach students early on how to manage knowledge for the economy and their jobs. Brockett and Hiemstra's (1991) PRO approach emphasizes accountability and responsibility, which are important for knowledge management.

Grow (1994) proposed the Staged Self-Directed Learning (SSDL) model, which gradually reduces an instructor's power over pupils. In the beginning, the instructor lectures, coaches, and gives criticism. At the second, "moderate" level, the pupil is independent, but still wants guidance. The teacher inspires conversation, goal setting, and lectures during this stage. At the third, "intermediate," stage, students engage in active learning. The teacher facilitates thought-inspiring dialogues by setting protocols and treating pupils equally. During this "self-directed" stage, the teacher acts as a consultant or delegate. Grow's model better defines SDL by incorporating a gradated system that assesses pupils' independence from their teachers.

Recent research confirms Knowles' fundamental work by demonstrating SDL's influence on learner autonomy, self-efficacy, and pleasant sentiments from the two (Terry, 2006). As they advance, learners prefer independent learning. According to Tekkol and Demirel (2008), self-directed learning requires planning, continuation, and assessment. Self-directed learning also requires independence (Hatcher, 1997; Nasri et al., 2020; Terry, 2006). According to Schweder and Raufelder (2022), positive emotions boost learning, and self-directed learning empowers students. Self-efficacy and autonomy create such good feelings and associations (Finnegan, 2022; Lemmetty et al., 2021). Nasri et al. (2020) also assert that SDL improves student competence and accountability.

Self-directed learning works well in a globalizing world, especially considering the lasting effects of COVID-19 (Liu et al., 2022). Self-directed learners engage in planning to learn, identify needs, and choose practical solutions (Gerard et al., 2022; Lai et al., 2022; Sahoo, 2016). Research supports learners supporting their own transformative learning. Internet communications technology (ICT) promotes students' participation in learning and is essential to SDL (Labonté & Smith, 2022), as portals can help students find information.

SDL andragogy is also significant. Adult learning takes place online, offline, or in hybrid adult-based learning programs. According to Pappas (2013), andragogy requires self-concept, adult learner experience, preparation, motivation, and orientation toward learning. ICT-supported learning settings combine online and remote learning with SDL, and ICT-enabled instruction aids SDL (Labonté & Smith, 2022).

In a world of instantaneous information, Guglielmino (2013) stressed the need for individual learning. Google CEO Eric Schmidt (2011) stated that at present, humans generate as much knowledge in two days as they did from the beginning of civilization through 2003. SDL helps students consume, control, and organize larger data sets, especially for classroom and professional use. Wang et al. (2021) propose that COVID-19 has forced migration to online learning, where the Internet collects and distributes vast volumes of data.

Frambach et al. (2012) emphasize that SDL can encourage learning and intellectual curiosity, but it also has drawbacks. SDL capacities and cultural and educational backgrounds were examined by medical school collaborators, who highlighted uncertainty regarding the level of student independence needed for autonomous learning, reliance on hierarchal pedagogical frameworks, and overemphasis on traditional learning modes and orientations as difficulties of the approach. Teacher-centered classrooms and pressure to get good grades were further issues faced by students in secondary schools.

Douglas (2010) assessed participants' perceptions of SDL adoption hurdles through a quantitative correlational study that identified dispositional, situational, and institutional limitations to self-directed learning. The researcher found that race, gender, class, and technology can be barriers to SDL. These can be situational, belief-based, or attitudinal.

Studies by Kohan et al. (2017) are consistent with the existing literature on SDL. While du Toit-Brits (2020) cites SDL's increasing efficacy in the 21st century, they also note its potential disadvantages and barriers. Kohan et al. (2017) studied barriers to SDL within virtual environments. Using semi-structured interviews and purposive sampling, the authors interviewed 23 postgraduate students in an Iranian medical sciences program. They then used inductive content analysis to interpret the data. Some of the identified barriers to participation in SDL included cognitive barriers, such as an overload of information and wandering minds, and barriers in communication (such as notetaking skills). Information overload was a common problem cited by the students. Participants were anxious about mismanaging large swathes of data within the eLearning context and had a difficult time sorting out which data was appropriate, feasible, and correct.

Other commonly reported issues included inadequate writing skills (i.e., preference for oral communication), time management, and role ambiguity. Role ambiguity refers to different expectations from students than those that they otherwise experience during the learning process. One post-secondary participant from Kohan et al.'s (2017) cohort suggested that a lack of face-to-face time created situations where instructors could not identify whether students had mastered important content. A common criticism among instructors using SDL was that they perceived SDL as a way of having students work completely on their own without any virtual assistance (Kohan et al., 2017). In other cases, students felt that they had more effective oral skills than writing skills but were required to submit responses to discussion questions online in text form. Students complained about time management problems, as they perceived online SDL learning to be more challenging to manage in terms of meeting deadlines and completing assignments.

It is important to remember that while SDL occurs within the context of the “self” (i.e., the individual), humans remain embedded in a cultural context, which may influence how they perceive the world around them. Thus, SDL does not and cannot occur in a vacuum. Even the most critically reflective educators cannot escape the determinants and influences of their own lives. SDL educators should reflect on the ongoing processes affecting themselves and their students while teaching. SDL can be a good way to teach students how to handle large amounts of information effectively. This type of pedagogy will become critical for fostering problem-solving and critical thinking skills in students in the 21st century.

Self-Directed Learning Readiness

Self-directed learning readiness (SDLR) has grown in popularity in recent years, especially in the field of higher education. Self-directed learners decide what they need to learn, according to Knowles (1975). They also plan where and how they will learn, which strategies will work best, and how they will measure their success. Chu and Tsai (2009) state that self-directed learning requires self-discipline, independence, autonomy, efficient organization, clear communication, openness to constructive criticism, introspection, and self-evaluation. The learner's self-directed learning readiness depends on their attitudes, abilities, and personality traits (Wiley, 1983).

SDLR for independent study requires many skills and traits. Students must assess their family, social, and academic situations. Through SDLR, adults are taught lifelong learning habits, techniques, and skills rather than passing the standardized tests. So, people must organize their issues and develop skills to accomplish so (Brown & Palincsar, 1989; Caffarella, 1993).

Self-directed students are more aware of their self-monitoring obligations, as they seek to enrich their education. These learners want to try new things. Self-directed adult learners perceive problems as challenges and are willing to learn and change; thus, they possess motivation, persistence, independence, self-discipline, self-confidence, and a goal-oriented perspective (Abdullah, 2007). Fisher et al. (2001) defined self-directed learning preparation as the extent to which a student takes responsibility for their education and accepts the independence that comes with focusing on relevant issues. The learner's mindset, approach, and skills determine their freedom. SDLR assumes; first, adults can self-direct, and SDL readiness can be considered a spectrum (Leach, 2000). Second, self-direction requires practice (Candy, 1991). The final premise is that SDL skills learned in one setting can be used in others. The biggest issue with defining SDL readiness is that high levels of readiness may not transfer to different circumstances and contexts (Fisher et al., 2001).

As mentioned, SDL preparedness is individualized and represents a continuum. Students who are unprepared show anxiety equivalent to that of those who are well prepared and put in a structured and instructor-guided environment.

Online Self-Directed Learning Readiness

In recent years, we have seen a rise in the idea of SDLR, especially in the context of higher education. For SDLR to be effective in independent study, a wide range of abilities and dispositions are needed. Therefore, students need to take stock of their circumstances, including their social support, study habits, and family life. There is less of a focus on standardized testing and more on developing the habits, strategies, and abilities necessary for lifelong learning in the adult population. As a result, people are required to arrange their personal challenges and cultivate traits that will serve them well in doing so (Brown & Palincsar, 1989; Caffarella, 1993). In this context, self-monitoring is an area in which self-directed students excel because they show more awareness of their responsibilities in this area as they strive to give their education a deeper purpose.

Self-directed learners develop an appetite for knowledge and a willingness to broaden their horizons by testing new activities, ideas, and abilities. Therefore, self-directed adult learning necessitates elevated motivation, tenacity, independence, self-discipline, self-confidence, and the attainment of a goal-oriented mindset, since independent learners see issues as challenges and are willing to learn and change (Abdullah, 2007).

As proposed by Fisher et al. (2001), the concept of self-directed learning preparedness investigates the extent to which the self-directed learner takes responsibility for their education and accepts the independence that comes with focusing on topics that are meaningful to them. The level of freedom a learner can achieve depends on their disposition, outlook, and skill set. There are assumptions regarding SDLR. First, adults have an intrinsic capacity for self-direction, and individuals' levels of SDL preparedness may be seen as falling somewhere along a spectrum (Leach, 2000). Secondly, skills in self-direction need time and effort to develop. Learning and practicing autonomous conduct is the best approach to comprehending and displaying self-directed behavior (Candy, 1991). The last assumption is that SDL skills acquired in one setting may be transferred to similar situations in another. High degrees of SDL readiness may not always transfer to new situations and contexts, which is perhaps the biggest problem when attempting to define SDL readiness (Fisher et al., 2001).

SDL readiness is seen as very personalized and representative across the spectrum, as was previously stated. Students who are not prepared for SDL and are then given an SDL assignment exhibit significant levels of anxiety that are comparable to those shown by students who are well prepared for SDL and are placed in surroundings with a great deal of structure and instructor guidance.

Self-Efficacy Theory

Self-efficacy is the primary element of Bandura's social-cognitive theory and has had a profound impact on the study of motivation and achievement in academic settings (Bryant, 2017). Self-efficacy describes an individual's confidence in their ability to control their motivation, behavior, and external environment, which manifests in the behaviors needed to achieve a particular performance and develops and forms as early as childhood (Bandura, 1986).

Self-efficacy is a domain-specific belief in one's ability to successfully perform a task, which influences engagement in and successful completion of the task (Bruning et al., 2013; Klassen, 2002; Pajares, 2003). Chemers et al (2001) defined Academic self-efficacy as "students' confidence in mastering academic subjects" (p. 56).

From the student's perspective, self-efficacy can be defined as a personal judgment regarding an individual's capability to reshape their behavior and accomplish academic goals. Gopal et al. (2018) defined self-efficacy theory as the cooperative interaction between the nature of the task assigned to the student and their thoughts, which determines their behavior and success rate. Self-efficacy is driven by four sources: physiological states, social persuasion, and vicarious and mastery experiences (Bandura, 1994, 1997). Mastery experiences are the major contributor to self-efficacy since they operate within a student's experiences on a subject matter. At the same time, vicarious experiences are based on what students observe and perceive when their peers perform a particular task, which aids them in manipulating their experiences through observation. A student's sense of self-efficacy is more positively impacted by others who experience success if common characteristics are shared, such as age, gender, and perceived similar abilities (Bryant, 2017). On the contrary, physiological states such as anxiety, mood swings, and stress control a student's capabilities in terms of success or failure. In such situations, a student’s self-efficacy may decrease after experiencing gloomy emotions and uncertainty regarding their abilities.

Pajares and Schunk (2002) insist that self-efficacy influences learners in very different ways and is pivotal in academic self-motivation (Bandura, Martinez-Pons, & Zimmerman 1992). A meta-analysis of empirical studies conducted over the last 20 years discovered that academic self-efficacy was the single strongest predictor of students' academic achievement and performance among nine commonly researched psychosocial constructs (Artino, 2012; Bryant, 2017).

Considering the above details, students at higher education levels tend to demonstrate higher levels of self-confidence and belief in their ability to perform. In other words, older students at higher learning levels have higher self-efficacy compared to younger students at lower learning levels. The study by Gore (2006) indicates that self-efficacy is a predictor of college students’ academic performance and persistence. The author attained such findings by examining first-year college students, their ACT scores, and a self-reported self-efficacy survey. Nonetheless, the results may not predict college success and could partially depend on “(a) when self-efficacy beliefs are measured, (b) what aspect of self-efficacy is being measured, and (c) what college outcome one wishes to predict” (Gore, 2006, p. 112). Gore’s (2006) findings also highlight the need to give students feedback on their performance, both social and academic, for them to assess their ability to achieve academic goals. The findings by Uchida, Michael, and Mori (2018) support such a perspective by indicating that giving feedback to college students enhances their self-efficacy, as they believed in their ability to succeed in subsequent tasks.

Moreover, Schunk (1991) underscored the role self-efficacy's in allowing students to recognize the need to achieve academic goals and superior grades, surpass other students, embrace new experiences, and diligently prove their intelligence through schoolwork. Students with low self-efficacy tend to negate the influence of intelligence on academic improvement. They feel unable to succeed, which undermines their focus on goals, mastery, and performance. Bandura (1977) hypothesized that individuals develop self-efficacy by interpreting the information received from the environment. This perspective aligns with the four sources of self-efficacy: mastery experiences, social experiences, vicarious experiences, and physiological experiences. Accordingly, interpreting one's own previous performance and mastery experience is a vital source of information (Klassen, 2004; Pajares et al., 2007).

Furthermore, students of various ages have shown a positive relationship between self-efficacy and higher achievement levels. The same trend is evident between learning and adaptive academic outcomes, including improved effort and persistence with difficult tasks in experimental and correlational studies (Bandura, 1997; Linnenbrink & Pintrich, 2002; Pintrich & Schunk, 2002). Such studies indicate that students with high self-efficacy tend to work harder, persist more, and achieve better results compared to those with low self-efficacy.

These explored areas imply that students with high expectations and those seeking challenging tasks tend to have stronger academic persistence compared to those with low expectations who tend to avoid or give up on their pursuit of learning (Brophy, 2004; Cleary & Chen 2009; Zeldin & Pajares, 2000). Similarly, students with high levels of self-efficacy are likely to develop challenging goals and draw on different strategies to accomplish them (Kizilgunes et al., 2009, as cited in Arquero et al., 2015). Walker et al. (2006) supports such findings by indicating a meaningful positive relationship between students' self-efficacy and cognitive learning outcomes.

Previous research has shown that students with higher self-efficacy were more eager to engage in difficult tasks, persist longer, and work harder (Bruning & Horn, 2000; Zimmerman, 2000;). Students with higher self-efficacy are able to become more resistant to the negative impacts of failure (Bandura, 1986). Williams and Williams (2010) attest that while students with high self-efficacy feel motivated to approach complicated tasks, students with low self-efficacy develop anxiety and nervousness. Higher self-efficacy may lead students to believe that they can regulate their learning and become inclined to set personal goals. For instance, efficacious students will select rigorous coursework and have the confidence to complete challenging material. Students with low self-efficacy may even perceive a task as more difficult than it really is and give up early.

Self-efficacy is a critical predictor of students' academic success. According to Clerge (2019), self-efficacy entails a person's perceived ability to perform the tasks necessary to attain their goals. As noted above, the four sources of self-efficacy, mastery experiences, verbal persuasion, vicarious experiences, and affective and physiological states, are essential in shaping various activities and underlying academic success. In their study, Medaille et al. (2022) indicated that some academic tasks, such as thesis writing, require students to demonstrate a high level of self-efficacy that is aligned with their belief in their ability to accomplish results. Educators should create adequate opportunities for students to develop self-efficacy for optimal academic achievement. The study by Bjørnebekk et al. (2013) covers the impact of self-efficacy, motives, and achievement goals on academic achievement in post-secondary education.

The researchers analyzed factors underlying achievement motives, self-efficacy, and achievement goals to improve student performance. The findings indicate that students developed self-efficacy by staying in programs for longer. However, their fear of failure influenced their performance. Students' perceptions of their self-efficacy shape the anticipatory scenarios they create and reiterate (Norton, 2013). Consequently, the findings indicate a negative correlation between self-efficacy and the fear of failing examinations. For instance, such fear hindered science students from achieving optimal performance (Bjørnebekk et al., 2013).

Self-efficacy influences individuals' well-being, thus enhancing performance. The study by Gutiérrez and Tomás (2019) emphasizes the role of self-efficacy and school engagement in enhancing autonomy and academic achievement. Self-efficacy also incorporates emotions, which influence learners' motivation, cognitive sources, satisfaction, mental health, and learning strategies, which in turn shape academic achievement (Hayat et al., 2020). The findings obtained by Thompson and Verdino (2019) support these viewpoints by indicating that enhancing self-efficacy among community college students is essential to addressing the achievement gap by enhancing motivation levels and persistence.

Additionally, improved academic achievement is vital to enhancing students' motivation. Motivation encompasses selecting, activating, and directing behavior toward a specific goal (Landry, 2003). A study by Bjornebekk et al. (2013) indicated that as learners transition from one level to the next, they tend to focus more on academic achievement. Study outcomes by Bong et al. (2012) support such a perspective by indicating that middle school students demonstrated a higher confidence level in mathematics compared to elementary students. Yokoyama (2019) supports the explored findings by indicating that students with high self-efficacy are highly motivated to learn, leading to higher academic achievement. These details demonstrate the need for educators to foster students' motivation by emphasizing the need for self-efficacy, self-determination, self-esteem, and academic identity, among other positive attributes (Gannouni & Ramboarison-Lalao, 2018).

Doménech-Betoret et al. (2017) postulate the relationship between self-efficacy, course satisfaction, and expectancy-value beliefs. According to their study, process expectations relate to students' feelings during their interactions with their teacher and are likely to play a salient role in describing learners' satisfaction levels. However, this process can be influenced by the student's self-efficacy or expected performance levels. In other words, students with robust self-efficacy beliefs are more likely to visualize success scenarios that guide performance and provide supportive resources. Consequentially, these students tend to experience more satisfaction with the learning process. Doménech-Betoret et al. (2014) focused on the mediator role played by students' beliefs, such as self-concept, self-esteem, self-efficacy, and outcomes. The study shows a positive relationship between self-efficacy and achievement expectations, cost (expected dedication), and enjoyable learning expectations, which in turn led to achievement expectations that eliminated avoidance strategies.

Self-Efficacy to Learn Statistics

Widyastuti et al. (2019) define statistics as a branch of mathematics that is used as a tool to help humans solve their problems mathematically. It can also be defined as the science that deals with presenting, collecting, analyzing, processing, and concluding data when information is available at both variable and limited levels. Beyth-Marom et al. (2008) claim that numerous studies aim to improve statistical education and practice. The concept of statistical cognition (a notion that learning simply involves developing and testing hypotheses) has aided in improving statistical education. The science of statistics has been attributed to the most normative field of statistical cognition, which includes simple rules such as the conjunction rule of probability, models, theorems, and laws. Statistics can be understood from a descriptive, normative, or perspective approach, with the normative approach proven to be the best. In this context, self-efficacy will be considered an approach to improving statistical education through improved reasoning and information retention. The self-efficacy concept improves learning by doing, authentic learning, and situated cognition.

Widyastuti et al. (2019) established three facets of statistical cognition that aid in understanding the mediating role of self-efficacy in statistics. Normative facets represent statistical techniques that can be applied correctly within a given situation and integrate the full body of knowledge of mathematical statistics. On the other hand, descriptive facets integrate the knowledge of how people think regarding statistical concepts, misconceptions, and biases in the field and the messages they acquire when interpreting statistical information (Iwuanyanwu, 2022). At the same time, perspective statistics rely on knowledge of how to achieve successful statistical education and information.

Self-efficacy, which concerns an individual's performance capability, is dependent on judgment capability, which makes it a critical factor in statistics (Iwuanyanwu, 2022). Self-efficacy influences how individuals think, motivate themselves, and feel toward a subject by promoting fluency, ease, and confidence. Welter et al. (2022) established a correlation between the three facets of statistical cognition (prescriptive, normative, and descriptive), with the implication that students must be aware of these processes of acquiring knowledge when they attempt to explain statistical concepts. At the same time, this correlation depends on a clear perception of the difference between values and variables, which affects the student's ability to use symmetric variables and, for example, their ability to interpret the data and represent it on the 2x2 tables.

Yousafzai et al. (2020) used the cognitive inference model to understand how self-efficacy can be used to improve statistical performance. They found that the cognitive interference model affects students' statistics anxiety, and performance. Based on the cognitive inference model, if anxiety overloads a student's working memory during an exam, this might affect their ability to perform during the examination period. Bárkányi (2021) also established a direct relationship between reduced student performance, self-efficacy, and increased anxiety levels. According to Macher et al. (2015), a student's ability to prepare for an exam can cause anxiety, which is mainly triggered by procrastination during the preparation period.

At the same time, Feldhammer-Kahr et al. (2022) showed that maladaptive coping strategies in the study process were averse to using self-regulated learning strategies, which then triggered statistical anxiety, indirectly impacting the study process. According to the researcher, self-regulated learning includes forethought, performance, and self-reflection. Anxiety reduces students' self-efficacy at the forethought stage since such students have maladaptive beliefs regarding statistics, making them struggle to keep up with classwork as early as the beginning of classes. These students avoid completing their homework and use procrastination as an escape throughout the process. Furthermore, they fail to help themselves view class materials in a less threatening way in order to learn productively. Such students are also afraid of asking their tutors for help, thereby placing themselves in situations where they experience repeated failure cycles. Self-efficacy, therefore, becomes a critical component for students aiming to achieve success in statistics, since it helps them feel that they have what it takes to develop the skills needed to master the presented concept, even if it demands that they work through setbacks (Yousafzai et al., 2020). Samuel and Warner (2021) define a self-efficacious statistics student as one with an analytical mindset who can cultivate the skills required to meet the given learning objective since they acknowledge that the required skills can be attained with effort. From the beginning, the student can set clear, realistic, and challenging goals attributed to the mastery of objectives in the statistics course.

Self-efficacy builds the skills needed to utilize underperformance feedback as a platform for identifying new strategies for overcoming failure. Hoegler and Nelson (2018) support the claim that students with self-efficacy beliefs have an additional 7% variability in their exams because they controlled the environment of success before sitting the test. Samuel and Warner (2021) aimed to study how to improve statistical performance by improving self-efficacy and reducing anxiety levels. Based on the research, self-efficacy was judged as a state of psychological arousal that enables people to measure their anxiety levels or other emotionally arousing situations. The detrimental effect of anxiety on student statistics performance demands self-efficacy models that can enable students to prepare for exams, modify positive beliefs surrounding their coursework, and eliminate any misguiding beliefs that might prevent them from seeking help by eliminating maladaptive approaches that might hinder the preparation process.

Statistical self-efficacy is domain-specific since it includes factors relating to application and reasoning, which arise from the quantitative nature of statistical calculations. Perepiczka et al.'s (2011) study on the relationship between statistics self-efficacy and statistics anxiety focused on environmental, dispositional, and situational variables. Dispositional antecedents are intrapersonal issues that bring students into the classroom. The researchers discovered that, at the developmental stage, factors influencing students' perceptions of their abilities affected their concerns regarding evaluation and fear of failure, which triggered statistical anxiety.

Environmental antecedents involve interpersonal factors related to the classroom experience, including interactions between the lecturer and the student. Finally, situational variables are the factors that surround the students' previous experiences with statistics. Hoegler and Nelson's (2018) study showed that students who had failed mathematics courses had a negative perception of statistics.

Attitude is also a contributing factor in self-efficacy statistics. Perepiczka et al. (2011) found that attitude determined the knowledge gap and the need for students to fill the gap provided by statistics courses. The study also reviewed the impact of gender on statistics, where males were found to have a more positive attitude than their female counterparts towards self-efficacy in statistics. Students who viewed statistics as a road towards achieving their degree and career also had better attitudes than their counterparts, which had a positive impact on their performance.

Perceived social support establishes the basis of statistical self-efficacy since it forms a personal self-identity based on family, friends, and significant others. The perceived social support process creates a potential buffering effect on attitudes and anxieties (Althauser, 2015). Walker et al. (2017) showed that statistics attitudes are not unidimensional; instead, they integrate cognitive competence, affect, interest, effort, value, and difficulty variables. Students with self-efficacy possess the attitudes required to improve throughout the semester, thereby contributing to higher performances. Widyastuti et al. (2019) focused on the role of motivation as a self-efficacy variable in statistics which could increase students' abilities to complete learning tasks. Saeid and Eslaminejad (2017) defined motivation as the driving force that triggers all human actions. Students with high motivation levels achieve maximum statistical learning outcomes, since a motivated psychological state helps them maintain the needed intensity throughout their learning process (Althauser, 2015).

Finney and Schraw (2003) aid in developing a measure of statistical self-efficacy that can be used to examine students' self-efficacy throughout the semester. To achieve valid results in statistics, the authors recommended avoiding general measures of self-efficacy since they can decontextualize self-efficacy judgment. Instead, the design process should focus on task-specific activities, such as computing standard deviation, instead of domain-specific activities, such as learning statistics. Self-efficacy judgment offers better predictors of performance since it enables the establishment of a particular learning outcome criterion concerning what is being compared. It can be challenging to develop a direct relationship between self-efficacy and statistical achievement, which then interferes with the process of devising measurement standards (Althauser, 2015).

Nevertheless, self-efficacy to learn statistics (SELS) and current statistics self-efficacy (CSSE) have proven to be reliable methods of measuring self-efficacy levels during numerous challenges (Gomez et al., 2022). CSSE defines a student's confidence in solving tasks related to statistics, while SELS measures a student’s confidence in building the skills required to solve specific statistics-related tasks. Therefore, combining the two measures can show the skill growth towards the desire to learn statistics and the psychological outcome of learning statistics. This then enables an understanding of how statistical self-efficacy can contribute to improved performance.

Goal Orientation Theory

Achievement goal-oriented theories (GOT), which became popular among educators studying academic motivation in the 1980s, may be defined as a social-cognitive theory of achievement motivation. The difference between GOT and other theories hinges on their overall focus. While other motivational theories tend to concentrate on "learners'" beliefs regarding their performances, GOT focuses on what stimulates students to be concerned with and engage in learning while considering why the goal is important to them (McCollum & Kajs, 2007; Woolfolk-Hoy & Hoy, 2006). Meece et al. (1988) defined goal orientation as "a set of behavioral intentions that determine how students' approach and engage in learning activities."

Early versions of GOT focused on the dichotomy between mastery-goal and performance-goal orientations (Ames, 1992). In this dichotomous view of this process, mastery goal orientation could be identified as an intention to attain competence, expand knowledge, and improve understanding by using effortful learning (Ames, 1992). In other words, an individual focuses on improving their skills by concentrating on the process of learning attained through effort. Here, goal orientation is the product of effortful learning.

By contrast, a performance-goal orientation could be defined as the intention to achieve positive appreciation or feedback from others (Ames, 1992). In other words, learners with a performance-goal orientation focus on the opinions of their peers, society, and instructors when involved in a learning task. In the original dichotomy, learners were divided into these two categories. Performance goal orientation is generally understood as self-enhancing goal orientation (Skaalvik, 1997) and ego-involved goal orientation (Nicholls, 1984)

According to this dichotomous view, mastery-oriented learners were able to use self-regulation and self-monitoring skills by adapting to their learning process. Mastery goal orientation allows students to complete complex tasks, as they invest their effort in the process due to their interest in the subject and the learning process (Butler, 1987). In this case, learners must be able to invest their efforts rather than have an intrinsic ability to learn. According to this dichotomous view of GOT, mastery goal orientation is an indicator of effective academic performance (Elliot & McGregor, 2001). According to Ames (1992), mastery-oriented learners have the possibility to experience pride and satisfaction with not only their results but also the entire process of learning. Overall, it was considered that learners must lean towards a mastery orientation to attain their academic goals.

As performance-oriented learners aim to outperform others, they find no intrinsic value in goal orientation, which limits their learning ability (Dweck, 1986). This dichotomous approach to learning implies that learners with a performance orientation are more likely to shift their focus from goals to acquire new skills, abilities, or knowledge to goals revolving around outperforming others, thus limiting their attention and focus. Since the main objective of performance-oriented students was to outperform others rather than appreciate the process of learning, the intrinsic value of learning was not attained (Dweck, 1986). According to the dichotomous view, performance-oriented learners relate their success or failure to the difficulty of the task or their own abilities.

Such an approach undermines the importance of effort (which is present in mastery-oriented learners), which limits learners' abilities to attain success in challenging and complex tasks. According to this approach, performance-oriented learners could generate only limited information processing and use simple memorization as their primary means of learning (Dweck, 1986, Butler, 1987). Such students are more likely to avoid challenging tasks due to the risk of failure and the requirement of effort in attaining their goals. Performance orientation was associated with a negative perception of a subject.

It is believed that students with a performance orientation tend to quit tasks early, avoid challenging assignments, and lose their motivation once they start performing better than the rest of the class (Tan & Miksza, 2019). Nevertheless, this approach to GOT has lost favor over time, particularly as researchers began to analyze people's motivations for learning.

Hence, the dichotomous approach to GOT gave way to a new model of PAV (performance-avoidance) goal orientation. For instance, Elliot and Harackiewicz’s (1996) study on mastery- and performance-oriented learners produced mixed results, reporting that the latter could still manifest intrinsic orientation and invest their efforts in attaining their goals. The authors criticized the dichotomous approach for its inability to distinguish between approach and avoidance characteristics. They used Atkinson's (1957) theory to develop a new framework in which orientation characteristics are essential when classifying learners (approach vs. avoidance). This theory claims that some learners are oriented toward success as their goal (approach), while others focus on avoiding failure (avoidance).

Specifically, PAP-focused learners focus on positive feedback regarding their competencies in relation to others. By contrast, PAV-focused learners concentrate on avoiding negative feedback regarding their competencies (McCollum & Kajs, 2007). Thus, learners who use the PAP strategy try to receive better grades than their peers, while those who use the PAV strategy strive to avoid earning lower grades than their peers. Consequently, the trichotomous GOT model, including the approach and avoidance strategies, becomes more reliable when explaining learning styles (Elliot & Harackiewicz, 1996; McCollum & Kajs, 2007).

The trichotomous approach to GOT points to PAV as a negative goal orientation strategy, as avoidance integrates intrinsic motivation. Students who use this strategy lack effort and persistence; their intention to learn is triggered by their fear of failure, and they focus primarily on low-performing peers rather than on high-performing peers (Elliot et al., 1999). A PAV orientation is associated with superficial information processing, poor organization, and lower academic performance (Elliot et al., 1999). On the contrary, a PAP goal orientation has been connected to high academic performance (Barron & Harackiewicz, 2001). PAP orientation emphasizes the importance of orientation toward successful peers in the form of competition rather than considering mediocre performance as the primary goal.

The trichotomous version of GOT depicts PAV as an ineffective approach to goal orientation as it does not allow learners to attain ultimate success (Barron & Harackiewicz, 2001). In other words, fear of failure is seen as a destructive feeling that limits learners' capabilities. However, the development of research in this area has challenged theorists to develop a new and more complex approach to goal orientation and GOT. For instance, academic procrastination, which is typical of learners who utilize an avoidance goal orientation, is associated with poor academic achievement (Dikmen & Bahadır, 2021). By contrast, a goal-oriented approach mediates the relationship between academic procrastination and academic achievement by preventing or minimizing procrastination (Dikmen & Bahadır, 2021).

The next installment of GOT is the 2x2 model of goal orientation. Elliot et al. (1999) pointed out that in addition to PAV, learners could have a MAV goal orientation, wherein they avoid self- or task-referential incompetence. The 2x2 model contrasts the MAP goal orientation with the MAV goal orientation.

In this model, MAV learners strive to avoid losing their competencies, skills, and academic success, and this desire drives their learning process (Elliot & McGregor, 2001). While PAV orientation is based on avoidance of failure, MAV orientation indicates that learners want to avoid losing their attained success. While a MAV orientation indicates a lack of intrinsic motivation, it is not entirely devoid of this type of motivation, unlike PAV. Elliot and McGregor (2001) constructed a 2x2 achievement goal framework, wherein an intrapersonal approach versus a normative and valence approach versus an avoidance approach were presented in two dimensions, as shown in Figure 1. In this model, the "intrapersonal approach" refers to the goals set by individuals concerning their previous performance, whereas the "normative approach" stems from the orientation of an individual toward external stimuli (Elliot & McGregor, 2001).

Table 1

2x2 Achievement Goal Orientation Theory

		Intrinsic	Normative
Valence	Approaching Success	Mastery-Approach Goal	Performance-Approach Goal
	Avoiding Failure	Mastery-Avoidance Goal	Performance-Avoidance Goal

Note. This model was developed by Elliot &McGregor (2001)

The 2x2 model has similar rules to the trichotomous view of GOT. Avoiding failure is seen as a negative approach to learning and goal orientation. Regardless of whether the avoidance takes the form of MAV or PAV, these learners rely more on fear of failure or losing their status and knowledge than on intentions to gain success (Elliot & McGregor, 2001). Even though the PAP model orients toward environmental or normative factors, it is still possible for such learners to encounter success in goal orientation (Elliot & McGregor, 2001).

Here, intrinsic orientation is not viewed as the only determinant of successful goal orientation or academic performance. Valence is also considered. In their comparison of the trichotomous and 2x2 frameworks of goal orientation, Simamora and Mutiarawati (2021) found that the 2x2 model is more suitable for and more accurate at measuring goal orientation among learners. Keklik and Keklik (2013) validated the 2x2 AGO framework by showing that the achievement goal orientation scale (AGOS) was able to distinguish among the four categories of learners (MAP, MAV, PAP, and PAV). An analysis of learners' success according to their form of goal orientation showed that self-efficacy for performance and learning was an effective tool in predicting goals, especially academic achievement goals (Keklik & Keklik, 2013).

An empirical analysis of the 2x2 framework showed that the approach method has positive but limited statistical significance. While it had a positive impact on intrinsic motivation, it was not the best measure of exam performance (Korn & Elliot, 2016). At the same time, performance-oriented goals may not be suitable for integration in one-time performance examinations as they do not allow learners to focus on their results (Korn & Elliot, 2016). Failure-avoidance goals are associated with an adverse empirical profile, as they cannot stimulate intrinsic motivation and do not encourage students to achieve good performances (Korn & Elliot, 2016).

The combination of avoidance and performance orientation is the least effective when measuring and producing outcomes since it does not allow learners to foster their efforts or motivation to learn (Korn & Elliot, 2016). Erturan et al. (2020) confirmed the efficacy and validity of the 2x2 model in the context of physical education goal orientation. The 2x2 achievement goal model has proven to be a better framework for interpreting the relationships between achievement goals and learning approaches (Üztemur, 2020). Wolters (2004) found that mastery structure (based on six items that asked students to report on whether the instructional practices in their math class emphasized learning as much as possible) and mastery orientation.

Based on five items that reflect the student's desire to learn as much as possible and engage in challenging coursework are directly associated with adaptive outcomes for all students. The facet has proven to be the most effective approach when defining goal orientation. Overall, this study recognized that, although performance success can be associated with multiple factors, goal orientation plays an essential role.

Achievement Goal Orientations and Online Learning

By using the 2x2 achievement goal orientation theory as a model of measurement of learners' goal orientation, it is possible to determine their probability of success and the possibility of attaining their academic and professional goals. As was noted earlier, students had to change their mode of learning by transferring from face-to-face to virtual learning due to the COVID-19 pandemic. Only a few studies have analyzed the 2x2 achievement goal orientation framework in the context of virtual learning.

For instance, Yeh et al. (2019) used a 2x2 framework as a basis for measuring students' online learning environments. Their study showed that students with higher mastery-approach goals were able to implement different self-regulating learning strategies and supportive online learning behaviors, which predicted their positive academic outcomes (Yeh et al., 2019). On the contrary, students with mastery-avoidance goals failed to adopt effective self-regulating learning strategies and supportive online learning behaviors, which limited their performance outcomes (Yeh et al., 2019). Moreover, performance-approach and performance-avoidance goals revealed the limited capabilities of students applying effective self-regulating strategies and online learning behaviors, especially what concerns the avoidance model (Yeh et al., 2019). Overall, this study supports the theorization of the 2x2 model, yet it does not support a positive attitude toward performance-approach goals.

Another study conducted by Yang et al. (2016) revealed that performance-approach goals predicted online help-seeking behavior differently compared to those using the performance-avoidance approach. Students who used avoidance approach goals (mastery or performance-oriented) reported more help-seeking, while those with approach-oriented goals were less likely to seek help when learning online (Yang et al., 2016). It was implied that online courses must be designed to satisfy the demands and needs of all learners, despite the approach to goal orientation that they tend to choose (Yang et al., 2016).

Xu (2021) recognized that self-regulation of online assignment behavior among students with different goal-orientation approaches showed different results. Students with mastery-approach and performance-approach achievement goal orientations were more likely to use better self-regulating assignment behavior compared to those who were failure-avoidance oriented (Xu, 2021). Overall, studies exploring the use of goal orientation theory in the context of the online environment are limited. A 2x2 achievement goal orientation theory is the most suitable theoretical framework for this study, as it allows one to assess the goal orientation of learners in a more complex and comprehensive manner using four criteria and two levels of definition and valence. Moreover, this theory allows one to assess goal orientation among learners enrolled in online courses, which is one of the goals of this study. In addition, the 2x2 model is more detailed and comprehensive in evaluating learners' initial core orientation (to master skills or receive praise) and their valence (avoiding failure or seeking success), which is critical for this study.

Learning Outcomes

Learning outcomes are the products of reactions triggered by experiences that aim to acquire intelligence through practice and effort (Triwahyuni et al., 2021). They are usually measured and observed at the end of the learning experience. In the field of science, the abilities a student acquires can be measured in three aspects of mastery: psychomotor, affective, and cognitive (Sinar, 2018). Cognitive development describes a student's ability to understand principles or concepts concerning the components of thinking and believe that these principles or concepts will be understood, applied, remembered, analyzed, evaluated, and developed to create learning outcomes. Suartama et al. (2020) defined cognitive outcomes as those related to acquiring information, knowledge, and intellectual skills. In this context, intellectual skills are the generic and domain-specific abilities involved in thinking, reasoning, decision-making, and broad comprehension. Broad abilities are self-regulated skills that refer to goal setting, time management, task strategy, self-evaluation, and environmental structuring. At the same time, knowledge can be measured as academic achievement or conceptual knowledge (knowledge acquired from the course under different topics and units).

On the contrary, the affective domain focuses on students' feelings, emotions, and values. It teaches reactions to stimulation, internalization, sensitivity in receiving, and the willingness to organize the values chosen. Supena (2017) explains that high and low student learning outcomes are dependent on internal factors (a student's attributes) or external factors (the school environment, learning methods, family, and so on). The achievement of cognitive learning outcomes can be assessed through written tests taken before and after the learning experience. At the same time, affect outcomes are measured through observation during learning. Gray and DiLoreto (2016) emphasize the need for OLRS to give students quality time throughout the learning process, thereby enhancing effective outcomes.

Triwahyuni et al. (2021) hypothesized that cognitive outcomes could be measured by a student's general background and mathematical competencies in statistics. At the same time, self-efficacy, attitudes towards statistics, and satisfaction were the affective outcomes being measured since they determine the students' beliefs regarding their abilities and feelings towards the course. Instruments like surveys, user data, observations, and interviews are used as external evaluation tools to explore the different aspects of affective statistics outcomes (Wei et al., 2021). However, questionnaires are the most frequent instruments used to survey learners. User data is frequently used to obtain information regarding how students behave. This data includes the number of replies, posts, and comments students make in discussion forums, the time/duration spent watching video lectures, and their submission and completion of assessments throughout the learning process. This data can also help the researcher understand the complex and differentiated pathways of the learning process. Mahauad et al. (2018) explain that user data can be used to understand the pathway of learners' access to learning resources, which then identifies the self-regulated strategies, problem-solving patterns, and social networks that emerge in the process.

Course Satisfaction as an Affective Learning Outcome

Affective learning is focused on impacting change in learners' attitudes and beliefs. Learning strategies and student emotions have been strongly associated with learning achievement and have been considered critical elements in students' learning satisfaction (Wu et al., 2021). Satisfaction is an outcome of affective learning since it is the measure of affective responses or aggregate feelings towards various factors (Hoque, 2017). Satisfaction in this domain manifests through outcomes such as self-esteem, confidence, and motivation. Affective learning supports learners' psychological wellbeing. Hence, affective learning has been increased to achieve positive outcomes regarding young people's mental health (Teraoka et al., 2021). Overall, satisfaction manifests through positive emotional responses, which are the core elements of affective learning. A few affective teaching strategies can be applied to increase satisfaction as a learning outcome. These strategies encourage feedback and ask deductive questions.

Gray and Di Loreto (2016) focused on the different dynamics that impact the affective elements in determining course satisfaction. The authors used course structure and organization, learner interaction, instructor presence, student engagement, infrastructural reliability, and perceived learning to investigate the elements that determine course satisfaction. The study used a survey that asked students if the online course enabled them to prepare to be future leaders or enhanced their probability of achieving their life goals. They found that students who perceived the online course as an improvement opportunity had a higher probability of being satisfied with the classes than others. This enabled them to increase their commitment to the classes.

Students have shown higher levels of course satisfaction in cases where they felt that their tutors communicated effectively, had a good rapport, and encouraged or facilitated their learning process (Allen & Seaman, 2016). Moreover, students' course satisfaction levels increased with their perceptions of the class having a sense of community and teachers' presence with asynchronous video feedback, which provided higher satisfaction levels than text feedback (Gray & Di Loreto, 2016). Students believed that video feedback made the nuance of the communication clearer and that lecturers had a higher probability of caring about them when using this form of communication.

Di Loreto and Gray (2016) explained that motivated students who excel in their courses or who are involved or invested in their desire to learn and are willing to place an extra effort in doing so have a higher probability of being engaged in their education. Course engagement extends beyond traditional approaches to understanding instructional effectiveness and includes students' mastery, retention, and satisfaction perceptions. The diverse nature of online courses has allowed the gathering of information regarding student satisfaction, which aids in improving the dynamics of online courses. Course organization and structure integrate the design of the course schedule, curriculum, instructional strategies, methodologies, and general planning of the course throughout the learning process (Allen & Seaman, 2016). Lack of technological infrastructure and reliable expertise to use the online teaching and learning resources can be a source of negative perception and can promote attitudes and behaviors that hinder independent learning and lead to course dissatisfaction.

Self-Directed Learning Readiness and Learning Outcomes

Learning and teaching experiences have evolved due to significant changes in educational technology. Using digital tools in learning encourages students to be more active in their studies outside the classroom. Learners can gain access to a plethora of materials via the intranet or the internet. This allows them to practice SDLR. SDL is a process in which learners can take the lead in determining their learning needs and managing their learning strategies and outcomes, with or without the assistance of others. Relatedly, SDLR examines the abilities, attitudes, and personality traits required for self-directed learning (Chen, 2022). Self-directed learning readiness plays a significant role in improving student outcomes, grades, and course satisfaction. Students can develop various essential aspects, such as research skills and self-discipline traits. Through this research, students can continually develop an urge to gain new knowledge and skills. Gagnon et al. (2013) conducted a study wherein students in a control group were required to purchase course notes, while those in the intervention group had electronic access to similar notes and were even allowed to make copies. According to the researcher, a few students from the intervention group who did not have to purchase notes found it less favorable. Nonetheless, the study found no difference in the level of course satisfaction between the two groups, thus leading to the conclusion that the "unfair" situation did not affect outcomes. Such findings show that teaching methods lack a direct and significant effect on SDLR, knowledge acquisition, and satisfaction. Students that exhibited low motivation levels in the intervention group performed relatively better than those in the control group, while the level of motivation exhibited a positive association with course satisfaction in both groups. According to Kuo et al. (2013), the first dimension of a learner's readiness is internet self-efficacy and a computer, and this is rarely addressed. At the same time, the researchers point to existing evidence supporting the influence of SDLR and self-efficacy on satisfaction.

Mead (2011) hypothesized that students with a high level of SDLR were most likely to exhibit high satisfaction with online courses. According to the findings, the association between a student's course satisfaction rating and their level of SDLR was moderate but significant. Researchers such as Fisher et al. (2001) have also established a relatively strong association between SDLR and overall learning satisfaction. Grow (1991) proposed the staged self-directed model to encourage students to become more SD learners. In the proposed model, the researcher discovered that a student would likely become more used to a set goal to increase their SD thinking levels. With this, the researcher concluded that if a perceived grade could be termed a form of goal setting, perhaps students could discover new levels of self-directedness that, as a result, would lead to higher course satisfaction levels.

Cho and Kim (2021) found a positive correlation between self-directed learning readiness and learning satisfaction from the study investigating the effects of face-to-face flipped learning and non-face-to-face flipped learning on learning satisfaction, self-directed learning readiness, and interactions between instructors and learners among undergraduate nursing students. Online classes where the instructor and the learner operate in different times and spaces require higher levels of self-directed learning. Therefore, it is harder for teachers to manage learning for their students in these settings. The results supported Yoo's research (2020), which demonstrated the importance of self-directed learning,

In Monroe's (2016) study, which considered participants' differences as variables, there was a lack of a combination of students' grades that could overwhelmingly predict the aptitude for SDL. Considering the importance of improving SDL skills among medical students, there was a need for a more pragmatic and reliable approach to measuring the relationship between SDL and test scores. However, the data analysis offered no definite means of documenting the SDLR of the medical students based on the evaluation metrics. Regarding the academic level, Örs (2018) discovered that the SDLR scale presented a trend where students in the low-grade level received a lower mean score than their high-grade counterparts. Therefore, it can be assumed that SDLR increases with an increase in academic level.

Shokar et al. (2002) discovered a positive correlation between students' scores on the SDLR scale and their course grades. Despite the link between SDLR and a student's academic performance, other factors that constrain the association might be at work. The researcher assumed the possibility that the type of curriculum (such as the problem-based curriculum for medical school students) impacts the strength of the association, since students who are low in SDLR are more likely to be enrolled in such a curriculum.

Self-Directed Learning Readiness and Self-Efficacy

KOÇ and Turan (2018) investigated how SDLR impacts critical thinking and self-efficacy in the context of physical education and sports school. They established that SDLR affects self-efficacy and critical thinking characteristics in the same way as it affects other aspects related to education, such as course satisfaction and grades. The authors also found that SDLR predicts general self-efficacy and critical thinking by 50.5%. KOÇ and Turan (2018) argued that SDLR tends to have a positive impact on critical thinking and self-efficacy.

Tuong and Trường (2021) also investigated SDLR and its impact on self-efficacy among students at Vietnam University and found a strong positive correlation between SDLR and self-efficacy. The authors acknowledge the limited research on the relationship between these variables. They added that the greatest impact of SDLR was on the learner's self-management factors. They recommended that by emphasizing improving students’ self-efficacy, the university is likely to improve education outcomes such as course satisfaction, grades, and self-directed learning readiness.

A study by Yao (2021) regarding nursing students’ ability to solve workplace problems found that SDLR had a significant positive impact on academic self-efficacy. This finding was also confirmed in other studies, including a study by Murniati et al. (2022), who also investigated university students, and Coros and Madrigal (2021), who obtained the same results in their study of high school students.

Self-Directed Learning Readiness and Achievement Goal Orientations

Achievement goal orientations measure students' general tendencies in approach, engagement, and evaluation of their academic progress and performance. Understanding SDLR as a high level of motivation to learn can help predict the success of the learning process. This can lead to satisfactory achievement in student learning (Siddiqui, 2021).

Achievement goal orientation can be a construct formed by dividing students' achievement intentions into two types: a general approach and a performance orientation. The general approach is characterized by students being well-organized, autonomous, proactive, and self-directed toward learning. By contrast, performance-oriented students can be highly persistent and focused on task completion. Well-organized students can designate clear goals, adopt a goal-oriented strategy, and practice self-confidence in their learning (Wong, 2021). This is essential, as it helps them be self-directed in the learning process. Wong (2021) suggested that self-directed learning boosts students' motivation in autonomy experiences. SDLR is controlled by learners' levels of autonomy, which is a key aspect of building strong core competence in self-direction. For instance, when students feel more autonomous about their SDLR process, they tend to become more comfortable expressing their ideas and views. However, learners who experience low levels of autonomy gradually learn to work within the framework of their instructor's or teacher's expectations. As a result, they can only work effectively under the teacher's guidance.

Learners motivated by self-direction show their willingness to take on challenging tasks (Bonk & Lee, 2017). Such students tend to adopt effective, goal-oriented strategies to improve their learning outcomes and achievement. Moreover, when SDLR is implemented based on self-direction, learners can increase their levels of persistence and motivation. For example, a learner who takes an active role in goal setting, monitoring, and evaluating their performance will be motivated to learn and produce better grades. Similarly, learners with positive self-direction experience are likely to increase their levels of persistence in tackling difficult tasks.

Ariffin et al. (2020) argued that when the learners' motivations are situated between external goal setting and performance motivation, they are likely to experience low persistence. Students tend to be less oriented when they are less motivated. This, as a result, affects their learning outcomes regarding general tendencies in approach, engagement, and evaluation of their studies. The authors emphasize that SDLR helps learners achieve goal orientation and develop their skill sets in a manner that allows them to perform well. Through SDLR, students can set achievement goals that help them improve competence and performance. Adopting SDLR aids learners in effective approach, engagement, and evaluation. This ensures that the 2x2 AGO is satisfied and that learning outcomes are improved. Simply put, SDLR is an essential part of the learning process, as it enhances academic performance and overall achievement.

Self-Efficacy and Learning Outcomes

Liu et al. (2010) integrated cooperative learning, problem-solving skills, and LEGO robotics into the design of a suitable robotics course for preservice teachers. Their findings indicated that the level of preservice teachers perceived self-efficacy positively impacted satisfaction with the learning environment, learning content, and method. In addition, Wang et al. (2013) used structural equation modeling to examine the association between SRL, student characteristics, self-efficacy in technology, and course results. Based on the findings, students who had previous e-learning experience exhibited a more effective strategy when taking their online courses. Therefore, they had a higher motivation level throughout their time as students. An increase in course satisfaction and technological self-efficacy was also noted. Lastly, students recorded better final scores with high course satisfaction and technology self-efficacy.

Jan (2015) assessed 103 graduate students who took online courses regarding various factors, including computer and academic self-efficacy, prior online learning experience, and student satisfaction rates. Their findings indicated a significant positive association between computer self-efficacy and prior online learning experience and between student satisfaction and self-efficacy. Similarly, there was a positive association between computers and academic self-efficacy and between student satisfaction and prior online learning experiences. However, the study failed to establish a significant or positive association between student satisfaction and computer self-efficacy. Alqurashi (2016) found that internet and computer self-efficacy are strong predictors of students' performances and satisfaction with online learning, and other studies failed to exhibit this link.

Self-efficacy and emotions such as anxiety were presumed to directly impact students' grades (Barrows et al., 2013). Self-efficacy strongly influences how individuals believe in their capacities, which, as Bandura (1993) stated, affects their academic performance. It is, therefore, reasonable to assume that students with higher self-efficacy are less worried about their grades/test scores. Abdi et al. (2012) discovered similar results in their study of high school students. According to the researchers, there is a significant relationship between self-efficacy and overall test score.

Moreover, regression analyses have established that self-efficacy is an accurate predictor of academic performance. According to Barrows et al. (2013), empirical evidence supports the association between self-efficacy and overall academic success. The findings furthered the empirical literature by exhibiting an association between text anxiety, self-efficacy, and single test grades. Additionally, it was discovered that self-efficacy failed to moderate test grades or anxiety, which, interestingly, implicated future researchers in discovering the existence of a moderator between self-efficacy and test grades.

According to Gray (2018), persistence and retention rates in online classes were relatively lower compared to those of traditional online courses for adults. Based on the study's findings, online learning educators and instructional designers of online courses are likely to reduce attrition by purposely designing online courses to increase students' SDLR. For existing courses, instructors can examine students' SDLR at the beginning of the course to identify those who might be more likely to exit the course. Here, grades can aid instructors in providing additional support to students more likely to drop the course.

Achievement Goal Orientations and Learning Outcomes

Goal orientation theory has been extensively researched in educational psychology, as it tries to explain students' motivations concerning learning and postulates that a person's goal orientation will impact their insight. Studies on goal orientation have emphasized the benefits of learning and performance as two crucial goals that drive learners' motivations and boost their course satisfaction (Yeh et al., 2019). Mastery goals describe a student's motivation for obtaining knowledge and developing skills and competencies. Studies have related mastery goal orientation to active cognitive engagement, learning satisfaction, persistence, and improved effort. In their studies of high school students, Ames and Archer (1998) revealed that course satisfaction is one of the main facets of mastery goals. They explained that learners who use both mastery and performance approach goals tend to exhibit equal responses regarding learning and course satisfaction.

The two dimensions of mastery and performance goals help learners understand the need to master a task and develop higher self-competence. Achievement goal theory determines learners' desired goals for engaging in learning. It is, therefore, closely linked with their learning strategies, learning outcomes, and level of satisfaction. Dubey (2000) confirmed that only avoidance goals were undesirably connected to online participation, satisfaction, and accomplishment.

Cho and Shen (2013) examined the roles that goal orientation and academic self-efficacy played toward a student's achievement in tandem with effort regulation and online interaction regulation. The results indicated that intrinsic goal orientation and self-efficacy were clear paths toward metacognitive self-regulation. There was no type of self-regulation prediction that could be determined from extrinsic goal orientation. This study showed that students' intrinsic goal orientations at the individual level and self-efficacy in academic courses directly impacted their overall academic achievement.

According to Standage and Treasure (2002), task and ego accomplishment goal orientations impact students' intrinsic motivations regarding physical education. The researchers noted that according to the theory of self-determination (Deci, 1985), the unidimensional construct of intrinsic motivation states that intrinsic motivation is only a single form of motivation. Therefore, this study aimed to determine the relationship between achievement goal orientations and situation-motivating factors in the case of physical education. Data was collected using structured questionnaires distributed among 182 male and 136 female middle school children with an average age of 13.2 years. The results indicated that task orientation was positively associated with more self-efficacy for situational motivation, and ego orientation was found to have reduced effects on self-determined motivation. The research also split the study population into goal groups. The analysis of the resulting data revealed that groups with high task orientation reported better motivational adaptation than those with low task orientation.

Klein et al. (2006) investigated how learning goal orientation (LGO), learning mode (either in physical locations or blended learning), perceived barriers, and enablers related to students' motivation affected overall learning and course outcomes. A study size of 600 students either enrolled in physical classrooms or involved in blended learning was used. The results highlighted that students who were involved in blended learning conditions with high goal orientations and those who viewed environmental factors as enablers rather than barriers to learning recorded higher learning motivation. The motivation to learn positively impacted their academic performances in terms of grades, satisfaction, and metacognition.

Moeller et al. (2012) stated that the relationship between goal orientation and student motivation is an area of study of particular interest to researchers. Still, the connection between goal setting and the academic achievement of students at the classroom level has arguably remained unexplored. Their study analyzed the findings from a five-year quasi-experimental study that examined goal orientation and student achievement in a Spanish-language high school classroom. LinguaFolio, a portfolio focusing on self-assessment, goal setting, and evidence collection of language understanding among students, was implemented in 23 high schools with 1,273 students. The researchers used a hierarchical linear model to analyze the relationship between goal orientation and student performance at the individual levels of teachers and students. The resulting correlational analysis revealed a significant relationship between goal orientation and language proficiency achievement.

In statistics, most learning outcome assessments use assignments, tests, writing projects, and exams to test students' cognitive development. These measures are also used to understand the extent to which learners have absorbed the information presented on the subject matter. They are also integrated to be part of the cognitive assessment outcomes. Graded assignments aid in examining the required learning outcomes and compromise the mandatory final course grade. In statistics courses, explicit and standardized answers are used to assess learners. Moreover, autograded and short-answer questions with feedback have proven effective for many students in understanding their performance, while exams focus more on practice and disciplinary-related skills.

Achievement goal theory tries to outline and forecast students' school-related performances. Wang et al. (2021) show a significant association between the four subscales of achievement goal orientation and academic performance. Initially, achievement goal orientation was characterized by students' task commitment. They were distinguished by two types: mastery goals, which focus on competence growth, and performance goals, which are concerned with demonstrating competence. Wang et al. (2021) proposed that goal orientation positively predicts academic adjustments and performance. In a recent study, students with high mastery-oriented goals presented a considerable aptitude for adapting to penalties and showing motivation and good academic ability compared to those with weak mastery (Wang et al., 2021). Mastery-oriented students tend to spend most of their time studying and, as a result, receive good grades. This also shows that students who use mastery ability and performance-based goals have two-sided advantages. They are likely to use intellectual tactics and make extra efforts to attain better academic performance due to their high motivation. Lastly, students with performance-oriented goals risk obtaining poor grades because they experience burnout, higher test anxiety, and more significant challenges compared to the group that uses mastery goals.

Achievement goal theory offers academic institutions a priceless understanding of how their students respond when they encounter academic activities. A study by Alrakaf et al. (2014) on pharmacy students in Australia shows how performance approaches correlate with good grades. The students in the first year who used the approach recorded higher grades (Alrakaf et al., 2014), which is consistent with prior findings that indicate a positive association between academic achievements and a performance approach.

Yeh et al. (2019) examined the underlying relationship between goal orientation and academic achievement among online learners. The researchers simultaneously investigated the structural relationships between 2x2 achievement goal orientation, online courses with instructors' support, self-paced learning strategies, and the expected academic performance among several online courses with both undergraduate and graduate student respondents. The effects of self-paced learning and online instructors' supportive learning behaviors mediated the relationship between achievement goal orientations regarding students' academic expectations. Results showed that mastery-approach and avoidance goals were vital in predicting self-regulated learning strategies and online instructor-led behaviors. They also helped predict students' academic performance outcomes in their online courses. The authors noted that students with higher mastery-approach goals usually adopt multiple types of self-regulated learning strategies and utilize different supportive online learning mediums to enhance their learning experiences, further increasing the chances of better academic outcomes. By contrast, those students with higher mastery avoidance goals were less likely to adapt self-paced learning strategies and online instructor behaviors, resulting in poor academic performance.

According to Cazan (2014), online learning is usually individual and student-centered. This is because the learning environment requires learners to have a sense of self-regulation and to be learner focused. The online learning experience demands that students possess self-regulatory skills in setting up goal orientations, monitoring their progress, seeking clarification and help from their instructors whenever needed, and efficiently managing their time. According to the author, self-regulated learning positively impacts students' academic achievements and performances in online courses. This study aimed to determine the relationship between self-regulated learning and academic performance in the case of online learning. Undergraduate student participants enrolled in online courses were the subjects of the study. The researchers noted that all learning objectives, including submitting quizzes, summative assessments, and learning resources, were done online via electronic resources. The results of an online questionnaire on self-regulated learning revealed two groups of learners: those with low levels of self-regulation and those with high levels of self-regulation. An analysis of the results indicated that self-regulated learning positively impacts academic achievement for students with high self-regulation in online courses. Moreover, linear regression analysis outlined that computer self-efficacy and online self-regulation were good predictors of grades at semester closing for the online courses. The study recommended that future research focus on epistemological beliefs, motivations for learning, and anxiety related to computers to better explain the concept of self-regulated learning in online settings.

Pulkka and Niemivirta (2013) investigated whether students' goal orientations and perceptions of their study environment affected their academic achievement. Data was collected from 169 students from the Finnish National Defense College, and students' goal orientations and learning environment evaluations were assessed twice every four months. The study group was then subdivided into four subgroups, and each group was compared against the others. The study revealed that students with different goal-orientation personalities displayed different levels of effort, attainment, and participation. Students with an orientation channeled toward increased competence and mastery goals registered more success and positive outcomes in their evaluations. On the other hand, students who avoided goal-oriented efforts displayed incompetence and poor academic achievement.

Summary

This chapter reviewed the literature on the effects of OSDLR on grades and course satisfaction for online learning statistics through the mediating variables of self-efficacy and 2x2 achievement goal orientations. The chapter was divided into two main sections. The first discussed the theoretical framework of this thesis, which uses self-directed learning, 2x2 achievement goal orientation, and self-efficacy theory, which is a subset of Bandura's social cognitive theory. The second discussed the empirical literature, which focused on the relationship between SDLR, self-efficacy, 2x2 achievement goal orientations, and learning outcomes. The learning outcomes examined in this chapter were self-efficacy, course satisfaction, grades, and 2x2 achievement goal orientation. The chapter also identified four achievement goal orientations: mastery approach (MAP), mastery avoidance (MAV), performance approach (PAP), and performance avoidance (PAV). The chapter summarized important relationships between SDLR and different learning outcomes from previous research, and hypotheses will be developed based on these findings.

Previous research has suggested that learners with a mastery goal orientation have a higher probability of learning and developing competencies, whereas those with a performance goal orientation tend to demonstrate their competencies by outperforming others. There is considerable research that exists between goal orientations and learning outcomes. It has also suggested a positive relationship between mastery goal orientations and learning. However, it has been established that, thus far, there is limited research on self-directed learning readiness and different learning outcomes, and as such, a gap in the literature exists. By investigating the effects of self-efficacy, SDLR, and goal orientation on learning outcomes for learning statistics online, this study hopes to make important contributions toward filling this gap.

The current study covers the existing gap in information regarding the effects of SDLR, self-efficacy, and goal orientations on learning outcomes for learning statistics online with the increased demand for online courses after the pandemic. The study aims to create awareness and to inform learners and tutors in online statistics courses on how they can rely on self-efficacy and 2x2 achievement goal orientations to improve their grades and course satisfaction. The audience will also understand the impact of self-directed learning readiness on online course satisfaction and grade outcomes. Even though previous studies have covered online readiness and self-efficacy as independent variables, the current study introduces the dynamics of 2x2 achievement goal orientations in improving self-directed learning readiness in the online learning environment. Previous studies such as Üztemur (2020) have only covered the 2x2 achievement goal as an independent variable in improving the performance of online statistics. Such studies focus on either a combination of two components of the AGO framework (i.e., MAP and PAV) (Korn & Elliot, 2016) or AGO as a framework for improving learning approaches and goal achievement (Üztemur, 2020).

The current study focuses on how the combination of the four elements in the AGO frameworks can improve course satisfaction and grade outcomes at the same time. It, therefore, covers the existing gaps where the previous researchers failed to focus on the dynamics of both the grade outcome and course satisfaction using the four elements of the framework. The current study will not view self-efficacy alone as a determinant of improved grade outcomes as in previous studies (Domenech-Betoret et al., 2017, Betoret et al., 2014). On the contrary, self-efficacy and the 2x2 AGO goal can act as mediators for improving online statistics course readiness, grade outcomes, and course satisfaction. Therefore, this study bridges the independent variables of self-efficacy, grade outcomes, course satisfaction, and online course readiness to provide information on how students taking online statistics courses can improve their commitment to finishing the course and reach the goals that they established when enrolling in the classes. The study provides information from the preparation stage (online readiness) to setting goals and maintaining the required psychological and academic characteristics (self-efficacy, 2x2 AGO model) to the final stage of learning to achieve results (grade outcome and satisfaction). The study's ability to cover all stages of learning in online statistics makes it superior to other studies that only focus on single stages. For example, Betoret et al. (2014) and Walker and Brake (2017) focused on maintaining students' psychological states when participating in online courses, while Bárkányi (2021) and Macher et al. (2015) focused on the final, or outcome, stages. At the same time, Tang et al. (2021) and Yilmaz (2017) focused on the online readiness component without considering its impact throughout the whole study process. By contrast, the current study will combine the variables and cover the existing gap by showing the role of online readiness, self-efficacy, and 2x2 AGO frameworks in online statistics grade outcomes and satisfaction.

The current study will also seek to conduct research that should help fill some of the gaps in the previous literature in this area, such as how students can fully transition into the hybrid or online statistics course model after the COVID-19 pandemic or how tutors can enable their students to shift swiftly. Second, online learning has undergone drastic changes over the past decade, rendering past studies in the field obsolete. The absence of newer studies covering the topics to be analyzed emphasizes the lack of modern contexts for online learning and its impact on the learning process and students. Since online learning has become an increasingly relevant educational model, the lack of current studies in this area could be detrimental to the fields of education and statistics. Third, the instruments used in past studies differ across the research spectrum. For example, SDLR can be measured according to problem-solving ability, creativity, ability to accept change (Guglielmino, 1978), self-management, desire for learning, self-control (Fisher et al., 2001), motivation for learning, computer self-efficacy, self-directed learning, online communication, and learner control (Hung et al., 2010). Different approaches to measuring relevant concepts create a certain level of ambiguity in analyzing the topics mentioned above. Lack of specificity in the measurement and determination of such concepts as self-efficacy and SDLR indicates the need for an in-depth analysis.

Finally, this study focuses on 2x2 achievement goal orientation and its relation to self-efficacy, SDLR, and learning outcomes in online statistics. No relevant studies in this area have been detected. Also, since this study focuses on online statistics courses, it was important to analyze studies conducted in this field. Yet, only limited inquiries have been conducted in this area, indicating a paucity of research on the topic. Consequently, this study will help fill this gap and expand knowledge on the relationships among goal orientation, self-efficacy, self-directed learning readiness, and learning outcomes (grade and course satisfaction) in online statistics learning.

Chapter 3 - Method

Overview

The purpose of this study was to investigate the relationship between online self-directed learning readiness and learning outcomes such as grade and course satisfaction through the potential mediators of self-efficacy to learn statistics and 2x2 achievement goal orientations (AGO) in online statistics learning. The present study includes an analysis of data gathered from a self-report questionnaire, which was voluntarily completed by students who were studying at a large Southeastern U.S. research institution during the Fall 2020 semester. The questionnaires chosen to collect data for this research were the online self-directed learning readiness (online SLDR) questionnaire developed by Hung et al. (2010), self-efficacy to learn statistics questionnaire (Finney and Schraw, 2003), the achievement goal questionnaire – revised version (AGQ-R) developed by Elliot and Murayama (2008), and the course satisfaction questionnaire (Kuo et al., 2013). This chapter is comprised of the following sections: 1) research questions; 2) research design; 3) participants and sampling procedures; 4) instruments; 5) data collection procedures; and 6) data analysis.

Problem Statement

COVID-19 is a health crisis that has caused drastic changes in the education system. Students were forced to shift from physical to online classes in response to government restrictions on face-to-face interactions, which were considered critical in preventing the spread of respiratory disease. Aguilera-Hermida (2020) explains that these changes have led to new challenges; however, they have also created awareness of the role and advantages of engaging in online learning. Therefore, even after the pandemic waned, the popularity of online learning remained high. Bashir et al. (2021) reported that a university adopted a hybrid (a combination of online and face-to-face courses) mode of course delivery as a post-COVID solution that recognized the popularity of online learning. Kelly's (2021) survey reported that 73% of students prefer to take fully online courses, and 68% prefer learning using a hybrid solution.

Statistics courses have also been transferred online, with studies such as Ritzhaupt et al. (2020) revealing that students enrolled in the class experience less anxiety, making the module preferred. The popularity of online statistics post-pandemic has created a demand for understanding this learning module and how learners and educators can organize the course effectively. Further demand for understanding the learning module has been created by studies such as those conducted by Figueroa-Cañas and Sancho-Vinuesa (2020), which have reported that the dropout rate of online statistics courses is higher than that of traditional statistics courses. However, through grounded research in theories such as those espoused by Knowles on self-directed learning, scholars have focused on self-efficacy as an approach to improving online statistics. The current study seeks to help close the existing knowledge gap regarding the effects of self-efficacy, SDLR, and goal orientation on learning outcomes for learning statistics online.

Research Questions

1. What is the extent of the relationship between online self-directed learning readiness and grades mediated by self-efficacy to learn statistics and each construct of achievement goal orientations in an online statistic learning environment?

    1.1 What is the extent of the relationship between online self-directed learning readiness and grades in an online statistic learning environment?

    1.2 What is the extent of the relationship between online self-directed learning readiness and grades mediated by self-efficacy to learn statistics in an online statistic learning environment?

1.3 What is the extent of the relationship between online self-directed learning readiness and grades mediated by each construct of achievement goal orientations (MAP, MAV, PAP, PAV) in an online statistic learning environment?

2. What is the extent of the relationship between online self-directed learning readiness and course satisfaction mediated by self-efficacy to learn statistics and each construct of achievement goal orientations in an online statistic learning environment?

2.1 What is the extent of the relationship between online self-directed learning readiness and course satisfaction in an online statistic learning environment?

2.2 What is the extent of the relationship between online self-directed learning readiness and course satisfaction mediated by self-efficacy to learn statistics in an online statistic learning environment?

2.3 What is the extent of the relationship between online self-directed learning readiness and course satisfaction mediated by each construct of achievement goal orientations in an online statistic learning environment?

Research Design

This study employs a quantitative survey research design. Specifically, a correlational research design utilizing a cross-sectional mediation model was used in this quantitative study to investigate the relationships among variables of online self-directed learning readiness, self-efficacy to learn statistics, 2x2 achievement goal orientations, course satisfaction, and grades in online statistics learning. A correlational study is non-experimental and focuses on collecting data to determine the degree to which a relationship exists between at least two variables where little, or no effort has been made to control extraneous variables (Mohajan, 2020). The mediation role employed during the current study investigated how OSDLR affects learning outcomes such as grades and course satisfaction through 2x2 AGO and SELS as mediating variables. Previous studies have shown that correlational studies aim to predict possible outcomes and explain human behaviors (Fraenkel et al., 2014), justifying the appropriateness of using a correlational research design in the current study. According to recommendations by Pollack et al. (2012) and Verhulst et al. (2012), correlation studies do not establish causal relations between variables; instead, mediation analysis should be applied to test the connection between meditating, dependent, and independent variables. As such, mediation analysis is the most suitable statistical approach for examining the research questions in this study.

A cross-sectional study design simultaneously collects data on relevant variables from different subjects, people, or phenomena (Spector, 2019). The single-data collection process usually takes place within a short time frame. The process enables researchers to gather preliminary evidence for the relationships that may exist among constructs and provide the foundation for future avenues of research using cross-sectional correlation analysis (Martin et al., 2019). However, the outcome variable (variable Y, i.e., the explained, response, dependent, or predicted variable) and the exposure variable (variable X, i.e., predictor, explanatory, independent variable, which, at times, is referred to as a factor), which are measured simultaneously, are the most critical elements of cross-sectional studies (Gregorich et al., 2021). Nevertheless, in the current study, it was impossible to ensure that the exposure preceded the outcome because there was no follow-up over time.

Participants and Sampling Procedure

The present study explored the relationships among students' OSDLR, SELS, and AGO, and learning outcomes included course satisfaction and grade during the online statistics learning process. The current study used convenience sampling, which is a type of non-probability sampling method where the researcher selects participants who are easily accessible and readily available to participate in the study. This method is commonly used in research studies with time, budget, or logistical constraints (Jager et al., 2017). Convenience sampling is a quick and easy way to collect data, as participants are selected based on their availability and willingness to participate. It can be a cost-effective research method, as there are no extra expenses related to recruiting participants, such as advertising or incentives (Bhardwaj, 2019). This method can also be helpful for researchers with limited access to a large population or difficulty recruiting participants from a specific population (Jawale, 2012). The current study participants were students enrolled in a large public university in the Southeastern United States who had registered for at least one statistics course delivered online during the 2020 fall semester. These students were selected as possible participants because they were enrolled as students at the university and were 19 years old or older.

Instruments

Achievement Goal Questionnaire-Revised (AGQ-R)

Elliot and McGregor (2001) are the pioneers of the Achievement Goal Questionnaire (AGQ) instrument, which aims to evaluate AGOs conceptualized in the 2x2 achievement goal framework. However, in 2008, the questionnaire was revised and improved by Elliot and

Murayama (2008), as cited by Sánchez Rosas (2015), who renamed it the Achievement Goal Questionnaire-Revised Version (AGQ-R). The updated version was designed as a hierarchical model that integrated approach and avoidance achievement motivations. The new version allows for the inclusion of the four AGOs, including MAP-goal orientation, MAV-goal orientation, PAP-goal orientation, and PAV-goal orientation, as it is grounded in a 2x2 achievement goal orientation theoretical framework.

Learners with a mastery goal orientation have a higher probability of learning and developing competencies, whereas those with performance goal orientations tend to demonstrate their competencies by outperforming others (Lin, 2021). Therefore, MAP goal orientation focuses on understanding and learning course materials, whereas MAV goal orientation focuses on avoiding losing one's competencies or skills. PAP goal-oriented learners focus on outperforming their peers, whereas PAV goal-oriented learners strive not to appear incompetent (Elliot & McGregor, 2001).

The AGQ-R survey uses a 12-item, 7-point Likert scale that ranges from 1 (strongly disagree) to 7 (strongly agree; Diaconu-Gherasim et al., 2019). The items evaluate students' goals concerning their academic performances; therefore, they rely upon statements such as, "When studying, I aim at mastering the *materials* presented in class completely," and "My studying objective is to perform better than other students." Different studies have used the AGQ scale when measuring AGO. The Cronbach's alpha of mastery approach-goal orientation, mastery avoidance-goal orientation, performance approach-goal orientation, and performance avoidance-goal orientation are 0.84, 0.88, 0.92, and 0.94, respectively (Diaconu-Gherasim et al., 2019; Rosas, 2015). Overall, the results suggested that the AGQ-R is a reliable instrument.

Self-Efficacy to Learn Statistics (SELS)

The self-efficacy to learn statistics (SELS) scale was developed by Finney and Schraw (2003) to measure students' confidence and ability to learn statistics. The instrument has 14 items, and each item is based on a 6-point Likert scale ranging from 1 (no confidence) to 6 (complete confidence) using questions associated with statistics-related tasks, with scores ranging from 14 (low level of statistical self-efficacy) to 84 (high level of statistical self-efficacy). Alhazzani et al.'s (2021) study measured the scale's internal consistency with a

Cronbach's alpha value of 0.975 which shows the scale's good reliability. The study established a negative correlation between SELS and anxiety scores. At the same time, a positive correlation was established between attitudes toward statistics and SELS.

Online Self-Directed Learning Readiness (OSDLR)

Hung et al.'s (2010) self-reported, 18-item scale, the Online Learning Readiness Scale (OLRS), was used in the survey to evaluate online readiness. The OLRS is a multidimensional scale consisting of five sub-dimensions associated with online readiness: self-directed learning (5-item), motivation to learn (4-item), learner control (3-item), computer/internet self-efficacy (3-item), and online communication self-efficacy (3-item). Answers are provided on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Self-Directed Learning consists of the first part of OLRS, which seeks to explore how learners take the initiative to understand their learning needs, establish learning goals, identify the required learning resources, choose, and implement appropriate learning strategies, and evaluate learning outcomes (Knowles, 1975). Computer/internet self-efficacy assesses students' abilities to use technology to accomplish online learning. This includes the ability to use computers to accomplish certain tasks and to apply higher-level internet self-efficacy skills. Motivation for learning is concerned with motivational and cognitive variables influencing online learning. This includes both intrinsic and extrinsic motivation. The learner control dimension is concerned with the autonomy and flexibility of the learner in using study materials. The online communication self-efficacy dimension measures the computer-mediated communication involved in online learning. The reliability of the questionnaire was validated with a composite reliability between 0.73 and 0.87 (Hung et al., 2010). Liu (2019) supported the previous study on the role of the OLRS survey in evaluating online readiness, where a Cronbach's alpha value of 0.82 was found. This means

OLRS is a reliable instrument. Items such as: "I repeated the online learning materials based on my needs," "I am open to new ideas when learning online," and "I feel confident in using online tools to communicate with others" were used to measure OLRS.

Course Satisfaction

Course satisfaction cannot be measured using a single template across the different studies (Gray & DiLoreto, 2016; Kuo et al., 2013) instead, it is adjusted according to the course structure, which enables an understanding of students' opinions regarding online learning settings. Kuo et al.'s (2013) study relied on a self-reported, 5-item blended-learning satisfaction scale with answers ranging from 1 (strongly disagree) to 5 (strongly agree). The study demonstrated high internal consistency, which concludes that this scale is reliable, as shown by Cronbach's alpha of 0.8. The study provided items such as "I enjoyed being an online student," "Online learning met my needs as a student," and "I find the experience beneficial," which was used in the current study.

Data Collection Procedures

Data collection for this study was conducted using an online survey with a set of questionnaires, including part 1 for demographics, part 2 for online learning readiness, part 3 for 2x2 achievement goal orientations, part 4 for self-efficacy to learn statistics, and part 5 for course satisfaction. Emails were sent to the Department of Mathematics and Statistics, which was asked to distribute the survey through group emails to the students who were enrolled in at least one statistics course. Invitation emails were then sent through a third party every two weeks over a period of six weeks to all students enrolled in the Department of Mathematics and Statistics. The survey was approved by the Institutional Review Board (IRB) (See Appendix D).

At the beginning of the data collection process, participants were informed of the purpose of the research and the expected time required to take the survey. They were also informed that their participation in the survey was completely anonymous and voluntary. Participants were informed that no foreseeable risks were associated with the study. Furthermore, they were asked to describe how well the survey statements described their online learning readiness, self-efficacy to learn statistics, achievement goal orientations, course satisfaction, and self-reported grades. They were assured that there were no right or wrong answers for each item. In addition, participants were informed that all their personal information and responses would be kept confidential. One-hundred-sixty-eight students participated in answering the survey in the fall semester of 2020, and 121 respondents, or 72.02%, were usable.

Data Analysis Procedures

Data collected from the online survey will be analyzed using IBM SPSS Statistics (Version 26). Statistical analyses will include descriptive statistical analysis, correlational analysis, reliability estimates, and a series of OLS regressions to analyze the path models. First, descriptive statistics for age, gender, grade levels, ethnic/racial identification, major (STEM/Non-STEM), and self-reported grade in one of the statistics courses students were enrolled in were used to portray the characteristics of this research sample. A correlational research design utilizing a mediation model was used to investigate how OSDLR transmits its effect on learning outcomes (grade and course satisfaction) through intervening variables or "mediators" such as SELS and 2x2 AGO. Pearson's correlations will be computed to see whether there are significant relationships among variables. To test the proposed mediation model as diagrammed in Figure 1 through Figure 4 and answer Research Questions 1.1, 1.2, 1.3, 2.1, 2.2, and 2.3 path analysis will be used to investigate the mediating roles of SELS and 2x2 AGO.

There are four different models to answer research questions in the current study. The first two regression analyses from Model 1-1 examined whether the antecedent variable of self-directed learning readiness was associated with the consequent variables of cognitive outcome (grade) (Equation 1) and self-efficacy to learn statistics (i.e., the potential mediator) (Equation 2). The third regression analysis from Model 1-1 included self-directed learning readiness and self-efficacy to learn statistics as predictors of cognitive learning outcomes (Equation 3). In Model 1-2: 2x2 achievement goal orientations of mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance are included as potential mediators in Equations 5 through 8, which show how self-directed learning readiness is associated with each mediator. The last equation from Model 1-2 is the regression analysis that probes whether grade can be predicted by self-directed learning readiness and each construct of 2x2 achievement goal orientations together (Equation 9). Regression analyses from Models 2-1 and 2-2 examined how self-directed learning readiness was directly associated with affective learning outcomes (course satisfaction) and the potential mediators of 2x2 achievement goal orientation and self-efficacy to learn statistics, respectively. The following equations for each model represent the estimation of the statistical diagram of the mediation model, where *a1, a2, a3, a4, a5, a6, a7, a8, a9, a10, b1, b2, b3, b4, b5, b6, b7, b8, b9, c1, c2, c3, c4, c'1, c'2, c'3,* and *c'4* are the unstandardized regression coefficients given to the predictors in the proposed mediation model in the estimation of the outcomes, and e*1* through *e17* denote the errors in estimation. The first and last regression analyses yielded direct effect and total effect, respectively, and the rest of the analyses indicated the indirect effect of self-directed learning readiness on affective learning outcomes (course satisfaction) and cognitive learning outcomes (Grade) (See Figures 1, 2, 3, and 4):

Figure 1

Model 1-1: The statistical model in which the effect of online self-directed learning readiness on grade is mediated by self-efficacy to learn statistics

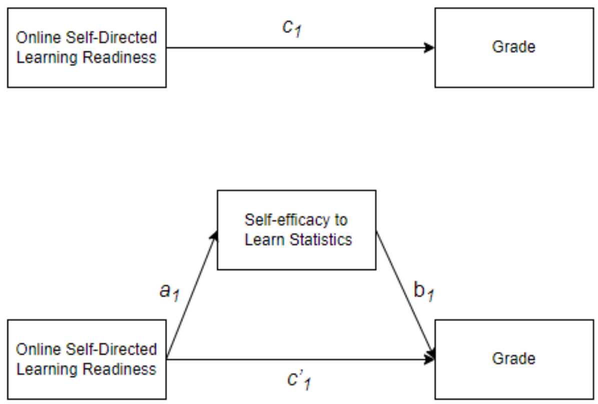


Figure 2

Model 1-2: The statistical model in which the effect of online self-directed learning readiness on grade is mediated by each construct of 2x2 achievement goal orientations

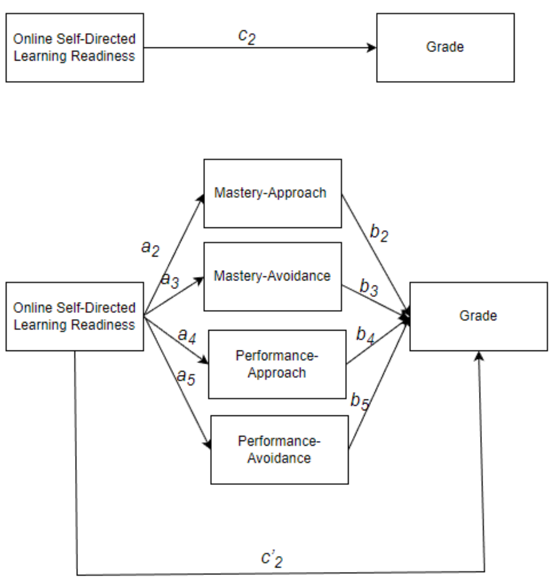


Figure 3

Model 2-1: The statistical model in which the effect of online self-directed learning readiness on course satisfaction is mediated by self-efficacy to learn statistics

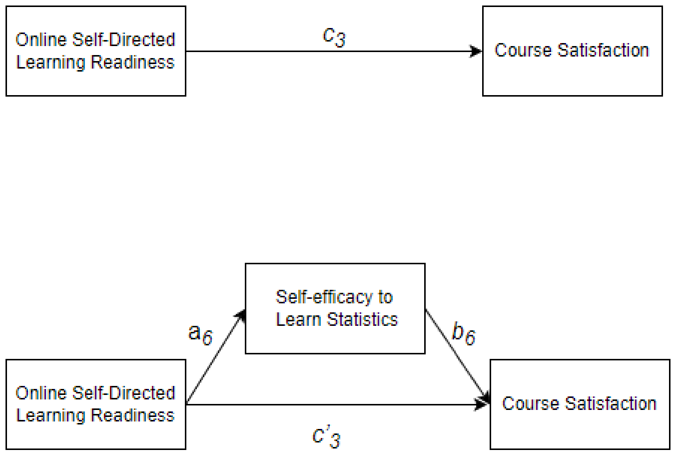
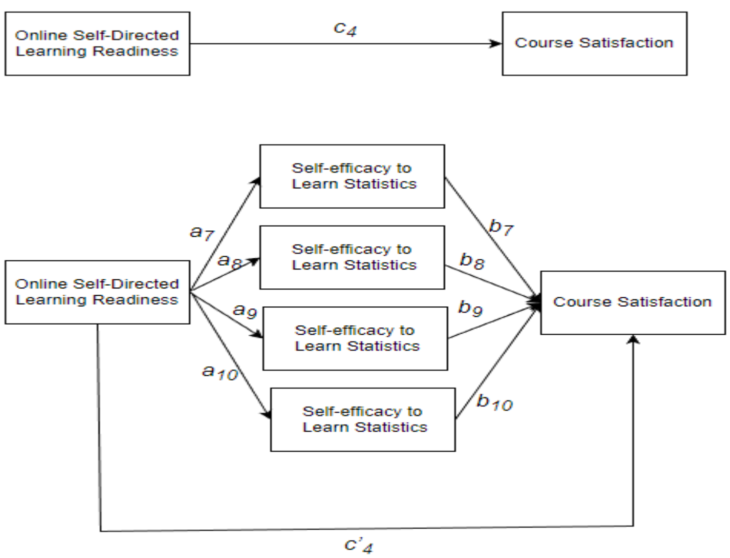


Figure 4

Model 2-2: The statistical model in which the effect of online self-directed learning readiness on course satisfaction is mediated by each construct of 2x2 achievement goal orientations



Model 1-1

$$Grade = \beta 0 + (c1 \times self - directed\ learning\ readiness) + e0 \qquad (1)$$

$$Self-efficacy\ to\ Learn\ Statistics\ =\ \beta 0\ +\ (a1\times\ self-directed\ learning\ readiness)\ +\ e1 \quad (2)$$

$$Grade\ =\ \beta 0\ +\ (c'1\ \times\ self-directed\ learning\ readiness)\ +\ (b1\ \times\ SELS)\ +\ e2 \quad (3)$$

Model 1-2

$$Mastery-Approach =\ \beta 0 +\ (a2\ \times\ self-directed\ learning\ readiness)\ +\ e3 \quad (4)$$

$$Mastery-Avoidance =\ \beta 0\ +\ (a3\ \times\ self-directed\ learning\ readiness)\ +\ e4 \quad (5)$$

$$Performance-Approach =\ \beta 0\ +\ (a4\ \times\ self-directed\ learning\ readiness)\ +\ e5 \quad (6)$$

$$Performance-Avoidance =\ \beta 0\ +\ (a5\ \times\ self-directed\ learning\ readiness)\ +\ e6 \quad (7)$$

$$Grade =\ \beta 0\ +\ (c'2\ \times\ self-directed\ learning\ readiness)\ + (b2\ \times\ MAP)\ +\ (b3 \times\ MAV)\ +\ (b4\ \times\ PAP) + (b5\ \times\ PAV) + e_7 \quad (8)$$

Model 2-1

$$Course\ Satisfaction =\ \beta 0\ +\ (c3\ \times\ self-directed\ learning\ readiness)\ +\ e8 \quad (9)$$

$$Self-efficacy\ to\ Learn\ Statistics\ =\ \beta 0\ +\ (a6\times\ self-directed\ learning\ readiness)\ +\ e9 \quad (10)$$

$$Course\ Satisfaction\ =\ \beta 0\ +\ (c'3\ \times\ self-directed\ learning\ readiness)\ +\ (b6\ \times\ SELS)\ +\ e10 \quad (11)$$

Model 2-2

$$Mastery-Approach =\ \beta 0\ +\ (a7\ \times\ self-directed\ learning\ readiness)\ +\ e11 \quad (12)$$

$$Mastery-Avoidance =\ \beta 0\ +\ (a8\ \times\ self-directed\ learning\ readiness)\ +\ e12 \quad (13)$$

$Performance - Approach = \beta0 + (a9 \times self - directed\ learning\ readiness) + e13$ (14)

$Performance - Avoidance = \beta0 + (a10 \times self - directed\ learning\ readiness) + e14$ (15)

$Course\ Satisfaction = \beta0 + (c'4 \times self - directed\ learning\ readiness) + (b7 \times MAP) + (b8 \times MAV) + (b9 \times PAP) + (b10 \times PAV) + e15$ (16)

The total effect of self-directed learning readiness on grades

The total effect of SDLR on grades is simply quantified and estimated with the regression coefficient c in the proposed mediation model shown in Equations 1. The interpretation of the total effect is that two cases that differ by one unit on SDLR are estimated to differ by c units on grade.

The total effect of self-directed learning readiness on course satisfaction

The total effect of SDLR on course satisfaction is simply quantified and estimated with the regression coefficient c in the proposed mediation model shown in Equations 9. The interpretation of the total effect is that two cases that differ by one unit on SDLR are estimated to differ by c units on course satisfaction.

The direct effect of self-directed learning readiness on grades

The direct effect of self-directed learning readiness on grade is quantified as c' and is interpreted as the extent to which two cases differ by one-unit self-directed learning readiness but are equal on self-efficacy to learn statistics (Equation 3), and 2x2 achievement goal orientations (Equation 8) are estimated to differ by c' units on grade.

The direct effect of self-directed learning readiness on course satisfaction

The direct effect of self-directed learning readiness on course satisfaction is quantified as c' and is interpreted as how the extent to which two cases differ by one-unit self-directed learning readiness but are equal on self-efficacy to learn statistics (Equation 11), and 2x2 achievement goal orientations (Equation 16) are estimated to differ by c' units on course satisfaction.

The indirect effect of self-directed learning readiness on grades

The effect of self-directed learning readiness on grades has yielded indirect effects in the proposed mediation model (see Figure 1 and 2). The indirect effect of self-directed learning readiness through self-efficacy to learn statistics only (Indirect effect 1 = $a1 \times b1$; Equation 3), mastery-approach only (Indirect effect 2 = $a2 \times b2$; Equation 8), mastery-avoidance only (Indirect effect 3 = $a3 \times b3$; Equation 8), performance-approach only (Indirect effect 3 = $a4 \times b4$; Equation 8) and performance-avoidance only (Indirect effect 4 = $a5 \times b5$; Equation 8). Each indirect effect is used to test the research questions.

The indirect effect of self-directed learning readiness on course satisfaction

The effect of self-directed learning readiness on course satisfaction has yielded indirect effects in the proposed mediation model (see Figure 3 and 4). The indirect effect of self-directed learning readiness through self-efficacy to learn statistics only (Indirect effect 5 = $a6 \times b6$; Equation 11), mastery-approach only (Indirect effect 6 = $a7 \times b7$; Equation 16), mastery-avoidance only (Indirect effect 7 = $a8 \times b8$; Equation 16), performance-approach only (Indirect effect 8 = $a9 \times b9$; Equation 16) and performance-avoidance only (Indirect effect 9 = $a10 \times b10$; Equation 16). Each indirect effect is used to test the research questions.

Table 2

Explanation of Variables of Models and Research Questions

Research Question	Model	Outcome	Mediator	Path Model
RQ 1.1	1-1	Cognitive Learning Outcome (Grade)	Direct effect	SDL → Grade
RQ 1.2				SDL → SELS → Grade
RQ 1.3.	1-2		Indirect Effect	SDL → MAP → Grade SDL → MAV → Grade SDL → PAP → Grade SDL → PAV → Grade
RQ 2.1	2-1	Affective Learning Outcome (Course Satisfaction)	Direct effect	SDL → Satisfaction
RQ 2.2				SDL → SELS → Satisfaction
RQ 2.3.	2-2		Indirect Effect	SDL → MAP → Grade SDL → MAV → Grade SDL → PAP → Grade SDL → PAV → Grade

The current study can use the bootstrapping method and beta coefficient to achieve its objective of understanding the statistical significance of the relationship between variables. Kim and Park (2019) defined statistical significance as the level at which the measure of the probability of the null hypothesis will be true or vary as per accepted standards. The beta coefficients estimate the strength and direction of the relationship between latent or observed variables and the associated errors. Indirect effects are calculated by acquiring the difference between total effects and direct effects. The direct effects are predictor variables of an outcome that do not account for the effects of the mediating variables in the relationship. For the current study, the beta coefficient will be determined as the product of the beta coefficient of online self-directed learning readiness and mediating variables (2x2 achievement goal orientations and self-efficacy to learn statistics). The effect of online self-directed learning readiness on grades and course satisfaction will yield indirect effects in the proposed mediation model.

Bootstrapping is a popular method to infer mediation (Shrout & Bolger, 2002) wherein the indirect effect is computed using a specified re-sampling method (e.g., 5000 iterations). This method generates a p-value, confidence intervals, and a standard error, which are used to interpret mediation. If the confidence interval does not include 0, one may conclude that the indirect effect differs from 0 and is statistically significant at the .05 level (Kenny, 2018). The model parameters are known as the unstandardized regression coefficients that are quantified and estimated using PROCESS version 4.3 with the 95% bootstrap confidence interval, as re-sampling methods implemented for the indexes of mediation inference (Hayes, 2013, 2018; Preacher & Hayes, 2008).

Bootstrapping is a widespread technique in research for several reasons. First, it does not require normalization assumptions. Unlike traditional statistical inference methods, such as t-tests or ANOVA, bootstrapping does not require the assumption of data normality. It creates a robust method for analyzing data that may not follow a normal distribution (Awang, Afthanorhan & Asri, 2015). It can also handle complex data structures. Bootstrapping can estimate the variability of statistics for complex data structures, such as clustered or longitudinal data, which can be challenging to analyze using traditional methods (Deen & de Rooij, 2020). It can also provide more accurate estimates. By generating numerous re-samples from the original data, bootstrapping can provide more accurate estimates of the variability of statistics compared to traditional methods (Awang et al., 2015). Bootstrapping is an alternative approach to null hypothesis testing that can be employed to assess the indirect effect and ascertain whether it differs significantly from zero (Hayes, 2013). When utilizing null hypothesis testing for an indirect effect, one assumption is that ab follows a normal distribution (i.e., if the study were repeated numerous times, resulting in the determination of ab for each iteration, the distribution of ab would be normal). However, since we lack knowledge about the true distribution of the indirect effect in the population, bootstrapping is preferable as it doesn't rely on the assumption of normality for ab. Bootstrapping, as described by Hayes (2013), is a resampling technique. However, there are also some limitations to using bootstrapping in research. Firstly, generating numerous re-samples from the original data can be computationally intensive and may require large amounts of computing power and time (Bestgen & Vincze, 2012). Secondly, it may not work well for small sample sizes, as the re-samples may not adequately represent the population (Davidson & Flachaire, 2008). Accordingly, it could be susceptible to bias if the original data set is biased, as this bias may be propagated to the re-samples (Wehrens, Putter & Buydens, 2000).

Summary

This chapter provided a review of the methodology used to investigate the relationships between online learning readiness, self-efficacy to learn statistics, 2x2 achievement goal orientations, and learning outcomes such as course satisfaction and grade in the online statistics learning environment. The chapter covered the participants, data collection methods, instruments, and data analysis procedures. The population used in this study were students enrolled in a large research institution in the Southeastern U.S. during the Fall 2020 semester. The instruments used for data collection were a combination of AGQ-R, self-efficacy to learn statistics, and parts of the online learning readiness and course satisfaction scales. Bivariate correlation and path analysis were used to analyze quantitative data. The next chapter will discuss the findings and results of the study.

Chapter 4 - Findings

Overview

In this chapter, demographic findings, statistical assumptions, and preliminary analyses including reliability, descriptive findings, and correlations between measures and findings from the data analysis will be presented. The results and findings for each research question are described along with the tables and figures from the data analysis.

Problem Statement

The COVID-19 crisis has led to drastic changes in the education system. Students were forced to shift from physical to online classes in response to government restrictions on face-to-face interactions. These restrictions were considered critical to preventing the spread of respiratory disease. Aguilera-Hermida (2020) explains that while numerous challenges accompanied these changes, they created an awareness of the role and advantages of engaging in online learning. Therefore, even after the risk of spread was reduced, the popularity of online learning remained high. Bashir et al. (2021) reported that Aston University adopted a hybrid mode of course delivery (combining online and face-to-face courses) as a post-COVID solution that recognizes the popularity of online learning. A survey cited by Kelly (2021) established that 73% of students preferred studying fully online after the pandemic; however, only about 53% of faculty preferred teaching online.

Statistics courses have also been transferred online, with studies such as Ritzhaupt et al. (2020) revealing that students enrolled in the coursework experience less anxiety, making the module preferable to in-person learning. The popularity of online statistics courses post-pandemic has created a demand for understanding this module of learning and how learners and educators can organize the course effectively. Further demand for understanding the learning module has been created by studies such as those by Figueroa-Cañas and Sancho-Vinuesa (2020), which have reported that the dropout rate of online statistics courses is higher than that of traditional statistics courses. This is a significant concern because, even though most learners prefer online learning, this same online model has seen higher dropout rates. The current study covers the existing gap in the literature regarding the effects of self-efficacy, self-directed learning readiness (SDLR), and goal orientation on learning outcomes for learning statistics online.

Research Questions

1. What is the extent of the relationship between online self-directed learning readiness and grades mediated by self-efficacy to learn statistics and each construct of achievement goal orientations in an online statistic learning environment?

1.1 What is the extent of the relationship between online self-directed learning readiness and grades in an online statistic learning environment?

1.2 What is the extent of the relationship between online self-directed learning readiness and grades mediated by self-efficacy to learn statistics in an online statistic learning environment?

1.3 What is the extent of the relationship between online self-directed learning readiness and grades mediated by each construct of achievement goal orientations (MAP, MAV, PAP, PAV) in an online statistic learning environment?

2. What is the extent of the relationship between online self-directed learning readiness and course satisfaction mediated by self-efficacy to learn statistics and each construct of achievement goal orientations in an online statistic learning environment?

2.1 What is the extent of the relationship between online self-directed learning readiness and course satisfaction in an online statistic learning environment?

2.2 What is the extent of the relationship between online self-directed learning readiness and course satisfaction mediated by self-efficacy to learn statistics in an online statistic learning environment?

2.3 What is the extent of the relationship between online self-directed learning readiness and course satisfaction mediated by each construct of achievement goal orientations in an online statistic learning environment?

Demographic Findings

A total of 168 students participated and completed the survey. Among the total participants, 47 students were removed because of the high level (above 10%) of missing data (Hair, Black, Babin, & Anderson, 2010). After excluding these respondents, the data analyzed in the present study was drawn from a valid sample of 121 participants. Table 2 presents the demographic characteristics of a valid sample of participants, including age, gender, ethnicity, international/domestic students, degree level, stem major, and final grade. Participants' ages ranged from 18 to 57 (M=25.31, SD=8.72). More than 66.9% of students (n=81) were reported as female, and 33.1% of participants (n=41) were reported as male. Seventy-four of the participants (61.2%) were undergraduate students, and 47 of the participants (36.8%) were graduate students.

Table 3

Descriptive Statistics for Study Variables (N=121)

Demographic	Category	Frequency	Percentage
Gender			
	Male	40	33.1%
	Female	81	66.9%
Age			
	17-24	81	66.9%
	25-34	25	20.7%
	35-44	7	5.8%
	44~	8	6.6%
Ethnicity			
	White	90	74.4%
	African American	8	6.6%
	Asian	11	9.1%
	Hispanic	9	7.4%
	Other	3	2.5%
International			
	Domestic Student	103	85.1%
	International Student	18	14.9%
Degree Level			
	Undergraduate	74	61.2%
	Graduate	47	38.8%
Stem Major			
	STEM	93	76.9%
	Non-STEM	28	23.1%
Final Grade			
	A	68	56.2%
	B	33	27.3%
	C	17	14%
	D	1	0.8%
	F	2	1.7%

Measures of Reliability

Using the Cronbach Coefficient Alpha test, the results of the tests for online self-directed learning readiness, self-efficacy to learn statistics, 2x2 achievement goal orientations, and course satisfaction are presented in Table 3. A value of 0.70 or higher was considered evidence of very good reliability, a value between 0.6 and 0.7 is acceptable, a value between 0.5 and 0.6 is considered poor reliability, and a value below 0.5 is unacceptable (Becker, 2000). The value of Cronbach's alpha for online self-directed learning readiness (OSLR) is 0.61, and for self-efficacy to learn statistics (SELS) is 0.79. The values of Cronbach's alpha for mastery-approach goal orientation (MAP), mastery-avoidance goal orientation (MAV), performance-approach goal orientation (PAP), and performance-avoidance goal orientation (PAV) were 0.65, 0.85, 0.83 and 0.77, respectively. The value of Cronbach's alpha for course satisfaction (CS) was 0.81. According to Becker (2000), all Cronbach's alpha values of variables in this study were acceptable to use.

Table 4

Reliability for Study Variables

	N	**Cronbach's α**	**Previously reported Cronbach's α**
OSDLR	5	0.61	0.72
SELS	14	0.80	0.97
Achievement goal orientations			
MAP	3	0.65	0.84
MAV	3	0.85	0.88
PAP	3	0.83	0.92
PAV	3	0.77	0.94
Course satisfaction	5	0.81	0.79

Statistical Assumptions

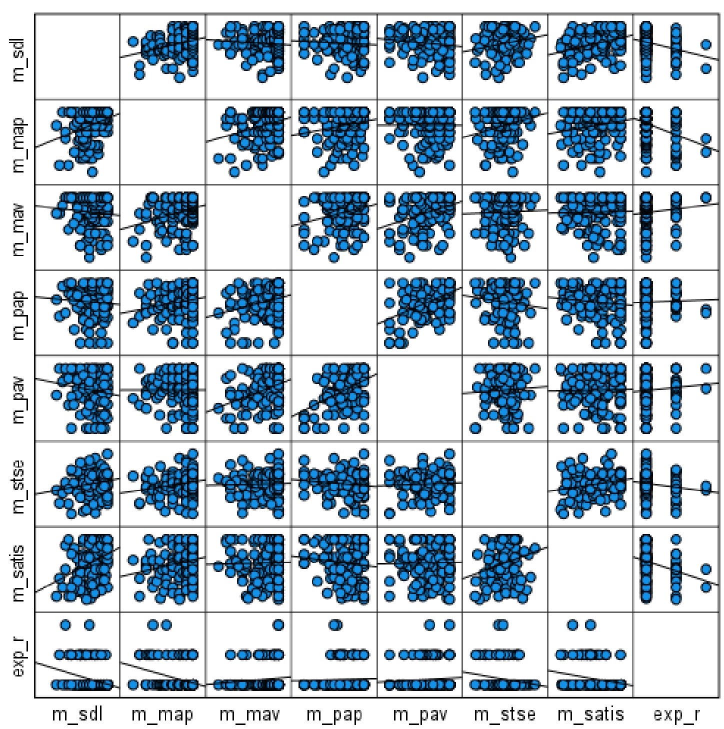
Prior to performing an OLS regression-based path analysis, statistical assumptions including linearity, normality, independent errors, homoscedasticity, normally distributed errors, multicollinearity, and multivariate outliers were tested.

Linearity

The linearity assumption is one of the most important assumptions to be satisfied in multivariate analysis methods. In order to run path analysis, one of the assumptions is that any predictor should be linearly associated with the outcome variable (Field, 2013). The linearity assumption was checked with the matrix scatterplots between each variable. The result of scatterplots for each predictor variable in this study represents a linear pattern for the outcome variable. Therefore, we can conclude that the inspection of the scatterplots did not reveal any evidence of nonlinear relationships between the variables, indicating that the linearity assumption is reasonable (see Figure 6).

Figure 5

Matrix scatterplot of the relationships between self-directed learning readiness, each construct of 2x2 achievement goal orientations, self-efficacy to learn statistics, and reported grade.



Normality

Skewness and kurtosis were used to determine whether the data was normally distributed or not. An absolute skew value larger than 2 or smaller than -2 or an absolute kurtosis value larger than 7 or smaller than -7 may indicate non-normality (Bryne, 2010; Hair et al, 2010). According to Table 3, normality testing results represented the range for kurtosis between -.895 and .479 and the range for skewness between -1.154 and -.283. Both values of skewness and kurtosis demonstrated that the shape of the data distribution for each variable in the research is acceptable (Kline, 2011; Tabachnick & Fidell, 2013)

Table 5

Summary of Normality Statistics

Variable	Skewness	Kurtosis
OSLDR	-0.60	0.09
SELS	-0.33	0.54
MAP	-1.15	0.48
MAV	-1.02	0.18
PAP	-0.87	0.38
PAV	-0.60	-0.28
Course Satisfaction	-0.28	-0.90

Independence of Errors

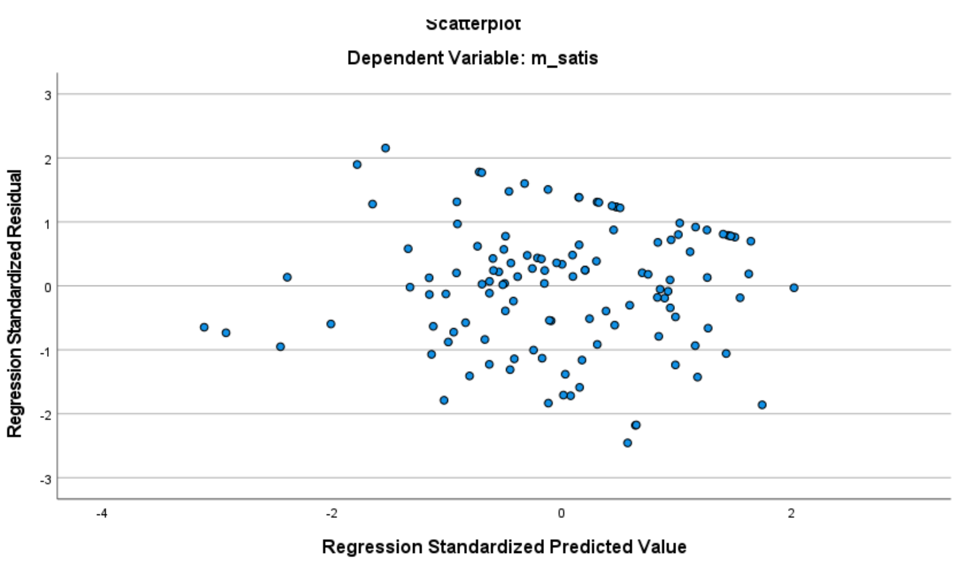
The assumption of independence of errors should be met when the errors of any two observations are not correlated to each other. The Durbin-Watson test was used to examine the assumption of independent errors. The Durbin-Watson value between 1.5 and 2.5 indicates that the independent error assumption is tenable (Neter et al., 1996). According to Field (2013), the conservative criterion of the assumption of independent errors is that Durbin-Watson values “less than 1 or greater than 3 should definitely raise alarm bells” (p. 337). The Durbin-Watson statistics were computed to be 1.79 and 2.13, which is within the acceptable range. Therefore, the assumption of independent errors has been satisfied.

Homoscedasticity

The assumption of homoscedasticity states that the outcome variable should exhibit the same levels of variance at each level of each predictor (Hair et al., 2010). Violating this assumption indicates heteroscedasticity. Homoscedasticity was investigated graphically by plotting the standardized predicted values (ZPRED) against the standardized residuals (ZRESID). If the graph looks like a random array of scatter plots, this is indicative of a situation in which the homoscedasticity assumption has been met. Based on the scatterplot of ZPRED vs. ZRESID (see Figure 7), the assumption of homoscedasticity is not violated because it presents a random pattern. Consequently, the variance of the course satisfaction values is relatively equal across the range of predictor(s), thereby indicating homoscedasticity (Field, 2013; Hair et al., 2006).

Figure 6

Scatterplot of ZRESID vs. ZPRED

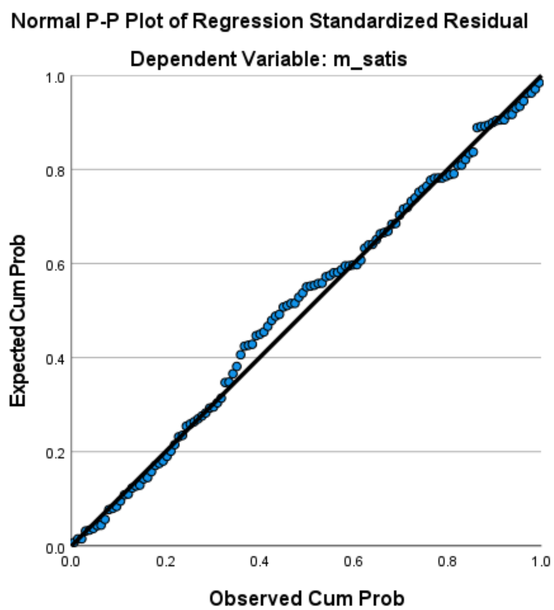


Normally distributed errors

The assumption of normally distributed errors examines whether the residuals in the model are normally distributed, which means that there are no differences between the observed data (little dots) and the model (diagonal line). To test the assumption, the P-P plot of the regression standardized residual plot was used (see Figure 8). Ideally, this plot should look like the little dots (observed data) and should follow the normality line. Thus, it can be concluded that the residual is normally distributed.

Figure 7

Normal P-P plot of Regression Standardized Residual



Multicollinearity

The assumption of multicollinearity is to be met by having no perfect multicollinearity between predictors (i.e., two predictors) or among predictors (i.e., more than two predictors). Ideally, the predictor variables in the model should be highly correlated with the outcome variable but have zero or little correlation between or among themselves. Multicollinearity indicates that the predictors actually have shared variance with each other, which challenges the ability to predict and explain the outcome as well as discover the relative importance of each predictor in the model. I used VIF to assess multicollinearity, applying the guidelines provided by Field (2013), where VIF values of up to 5 are acceptable levels of multicollinearity. To check this assumption, I ran a multiple linear regression with course satisfaction and grade as outcome variables and OSDLR, SELS, and 2x2 achievement goal orientations as predictors. Table 4 indicates the summary of multicollinearity statistics for this research. The VIF's values ranged from 1.12 (SELS) to 1.46 (PAV). Given that none of the VIF values have violated the cutoff value of 5, I can conclude that multicollinearity is not a concern for the research model.

Table 6

Summary of Multicollinearity Statistics (N = 121)

Variable	VIF
OSDLR	1.18
SELS	1.12
MAP	1.36
MAV	1.29
PAP	1.41
PAV	1.46

Multivariate Outliers

The OLS regression works best when the assumption of having no multivariate outliers is met. Outliers can be very influential in correlation and, therefore, regression. A thorough initial data analysis should be used to review the data and identify outliers (both univariate and multivariate). Mahalanobis distance, which describes the distance of a case from the centroid of the remaining cases, where the centroid is the point created at the intersection of the means of all the variables, was used to detect multivariate outliers. Chi-square tests of significance are usually used to determine outliers.

The Mahalanobis distance (MD) on p of variables is used as a multivariate outlier detection measure and is compared with a chi-square distribution on p degrees of freedom (Rousseeuw and Van Zomeren,1990; Samson, 2014). For a p-dimensional vector, x(i), on observation i with a corresponding mean vector, mean, and a sample covariance matrix, C, we have (see equation 19):

$$MD(i) = Square\ Root\ of\ (x(i) - mean)T\ C - 1\ (x(i) - mean) \tag{19}$$

If MD(i) is greater than χ2(p,0.999) then this suggests that observation i is an outlier. This high level of significance, which corresponds to $p<0.001$, is recommended (Tabachnich and Fidell, 1996; Hair et al, 1998).

Mahalonobis distance was calculated from the SPSS, and a chi-square distribution with the same degrees of freedom was compared. The degrees of freedom correspond to the number of variables that were grouped together to calculate the Mahalanobis distance. The Mahalonobis distance was represented by MAH_1, and the p-value of the right-tail of the chi-square distribution p-value was calculated by the expression 1 – CDF.CHISQ(X1, X2); X1 was substituted with the Mahalanobis distance variable that was created from the regression, and X2 was substituted with the degrees of freedom—which corresponds to the number of variables being examined. There was no observation with the values of the new probability variable less than 0.001; thus, I concluded that this data was usable without any multivariate outliers.

Preliminary Analyses

Descriptive Findings and Correlations among Measures

Table 5 displays the descriptive statistics of means and standard deviations and the Pearson correlation coefficient of the variables in this research except for grade. Grades were reported as an ordinal variable; thus, the correlation between grades and other variables in this study was measured with Kendall's coefficient of rank correlation, τb, which is represented in the 8th row of the table below.

The results of the bivariate correlations showed that online self-directed learning readiness is positively related to self-efficacy ($r = 0.19$, $p < 0.05$), mastery-approach goal orientation ($r = 0.31$, $p < 0.001$), and course satisfaction ($r = 0.35$, $p < 0.001$). Moreover, mastery-approach goal orientation ($r = 0.20$, $p < 0.05$) and self-efficacy to learn statistics ($r = 0.24$, $p < 0.001$) are positively correlated with course satisfaction and master-approach goal orientation is positively associated with grade (τb = 0.24 $p < 0.001$). On the other hand, performance-avoidance goal orientation is negatively correlated with grade (τb = -0.14, p <0.05).

Table 7

Intercorrelations for Study Variables

	1	2	3	4	5	6	7	8
1. Online self-directed learning readiness	--							
2. Self-efficacy to learn statistics	.19*	--						
3. Mastery-approach	.31**	.21*	--					
4. Mastery-avoidance	-.09	.03	.29**	--				
5. Performance-approach	-.07	-.12	.19*	.26**	--			
6. Performance-avoidance	-.14	.05	.001	.35**	.46**	--		
7. Course satisfaction	.36**	.24**	.20*	.02	-.11	.02	--	
8. Grade	.14	.03	.24**	-.08	.03	-.14*	.21**	--
Mean	3.89	3.99	6.34	5.78	5.11	4.86	3.43	4.35
SD	.77	1.11	.76	1.26	1.53	1.65	1.16	.87

Note. **p< .05, **p< .001*

Results

This section reports the results of the assessment of the proposed mediation model in the current study. This hypothesized model was estimated using an ordinary least squares (OLS) regression-based path analysis with the PROCESS macro for SPSS (Hayes, 2013, 2018; Preacher & Hayes, 2008).

OLS Regression

The proposed mediation model in Figures 2, 3, 4 and 5 from Chapter 3 has four different models. Each model has one total effect, one direct effect, and one indirect effect for mediator SELS and four indirect effects for mediator 2x2 achievement goal orientations of OSDRS on cognitive and affective learning outcomes, such as grade and course satisfaction. The focus of this study is to specify the indirect effects of each model, passing through a mediator(s) of: (a) SELS between OSDLR and grade; (b) 2x2 achievement goal orientations between OSDLR and grade; (c) SELS between OSDLR and course satisfaction; and (d) 2x2 achievement goal orientations between OSDLR and course satisfaction. Each indirect effect is tested based on research questions. In addition to the estimation of the indirect effects, the parameters c and c' estimate the total effect and direct effect of OSDLR on cognitive and affective learning outcomes, respectively. The model parameters are known as the unstandardized regression coefficients that are quantified and estimated using PROCESS version 4.3 with the 95% bootstrap confidence interval as a resampling method implemented for the indexes of mediation inference (Hayes, 2013, 2018; Preacher & Hayes, 2008).

Research Questions 1.1 and 1.2

Research question 1.1 for the current study asked: What is the extent of the relationship between online self-directed learning readiness and cognitive learning outcomes (grades) in an online statistic learning environment? Research question 1.2 asked: What is the extent of the relationship between online self-directed learning readiness and cognitive learning outcomes (grades) mediated by self-efficacy to learn statistics in an online statistic learning environment? The primary intention of this question is to test whether self-efficacy was a potential mediator of the relationship between online self-directed learning readiness and cognitive learning outcomes. This was examined by measuring the indirect effect, which was quantified as the product of the effect of online self-directed learning readiness (*a1*) and the effect of self-efficacy to learn statistics (*b1*).

The results of the mediation model analysis for Research Questions 1.1 and 1.2 are presented in Table 8. As shown in Table 8, self-directed learning readiness was positively related to self-efficacy to learn statistics (B= 0.28, SE = 0.12, t (119) = 2.17, p = 0.03), but there is no evidence of an association between self-efficacy to learn statistics and cognitive learning outcome (grade) when controlling for SDL (B = 0.05, SE = 0.07, t (119) = 0.64, p = 0.52). As can be seen in Table 8, a_1 = 0.28, and b_1 = 0.05. Therefore, multiplying *a1* and *b1* does not yield any significant indirect effect, where $a_1 \times b_1$ = (0.28) (0.04) = 0.0129 (see Table 9). A resampling method using 5,000 bootstrap samples was applied to generate a 95% bias-corrected bootstrap confidence interval as the inferential test for indirect effect ($a_1 \times b_1$ = 0.01), and this was found to be around zero (-0.03 to 0.07). The first indirect effect is statistically non-significant because the confidence interval includes zero (Preacher & Hayes, 2008). Therefore, the results of this analysis do not support research questions 1.1 and 1.2, which assume that self-efficacy to learn statistics mediates the relation between online self-directed learning readiness and grade.

Table 8

Model Summary Information for the Proposed Mediation Model Portrayed in Figure 1 (N = 121)

Predictors		Output						
		SELS				Grade		
		$B(\beta)$	SE	p		$B(\beta)$	SE	p
OSDLR	$a_1 \rightarrow$	0.28 (.19)	0.12	0.03	c'_1	0.24 (0.21)	0.10	0.04
SELS					$b_1 \rightarrow$	0.05(0.06)	0.07	0.52
Constant		2.91	0.51	< 0.001		3.25	0.45	< 0.001
		R^2= 0.04, F (1, 119) = 4.72, p =0.03				R^2= .05, F (1, 118), p = 0.04		

Note. B = Unstandardized regression coefficient; β = Standardized regression coefficient.

Table 9

Summary of the Mediation Model 1-1 Analysis

Effect	Mediator	Equation	Estimate	SE	95% CI LL	95% CI UL
Indirect	SELS	$a_1 \times b_1$	0.01	0.02	-0.03	0.07
Direct		c_1'	0.24	0.10	0.03	0.44
Total		c_1	0.25	0.10	0.05	0.45

Note. CI = confidence interval; LL = lower limit; UL = upper limit. If the confidence interval does not include zero, it reveals a significant effect.

Research Question 1.3

Research question 1.3 for the present study was: what is the extent of the relationship between online self-directed learning readiness and cognitive learning outcome (grade) in an online statistics learning environment mediated by each construct of achievement goal orientations (MAP, MAV, PAP, PAV)? The primary intention was to test whether each construct of achievement Goal Orientations (MAP, MAV, PAP, PAV) was a potential mediator of the relation between online self-directed learning readiness and cognitive learning outcome. This was examined by an indirect effect, which was quantified as the product of the effect of online self-directed learning readiness (a_2) and the effect of MAP (b_2), MAV (b_3), PAP (b_4), and PAV goal orientations (b_5).

The results of the mediation model analysis are presented in Table 10. As shown in Table 10, self-directed learning readiness was positively related to MAP (B = 0.30*, SE* = 0.09*, t (119)* = *3.52, p* < 0.001), and MAP was also positively associated with cognitive learning outcomes (grades) when controlling for SDLR (B = 0.45, SE = 0.11, t (119) = 4.05, p < 0.001). As can be seen in Table 10, a_2 = 0.30, and b_2 = 0.45. Therefore, multiplying a_2 and b_2 yielded the indirect effect of a_2b2 = (0.30) (0.45) =0.13 (see Table 11). A resampling method using 5,000 bootstrap samples was applied to generate a 95% bias-corrected bootstrap confidence interval as the inferential test for indirect effect (a_2b_2 = 0.13), and this was found to be totally above zero (0.04 to 0.27). The indirect effect is statistically significant because the confidence interval does not include zero (Preacher & Hayes, 2008). Therefore, the result of this analysis supports research question 1.3, which assumes that MAP mediates the relationship between online self-directed learning readiness and cognitive learning outcomes (grades).

The results of the mediation model analysis for MAV are presented in Table 10. As shown in Table 8, self-directed learning readiness was not related to MAV (B = -0.14, SE = 0.15, t (119) = -0.96, p = 0.33, and there is evidence of an association of MAV with cognitive learning outcomes (grades) controlling for SDLR (B = -0.17, SE = 0.07, t (119) = -2.50, p = 0.01). As can be seen in Table 10, a_3 = -0.14, and b_3 = -0.17. Therefore, multiplying $a3$ and $b3$ does not yield any significant indirect effect; a_3b_3 = (-0.14) (-0.17) = 0.02 (see Table 11). A resampling method using 5,000 bootstrap samples was applied to generate a 95% bias-corrected bootstrap confidence interval as the inferential test for indirect effect (a_3b_3= 0.02), and this was found to involve zero (-0.02 to

0.08). The indirect effect is statistically non-significant because the confidence interval includes zero (Preacher & Hayes, 2008). Therefore, the results of this analysis do not support research question 1.3, which assumes that MAV mediates the relationship between online self-directed learning readiness and cognitive learning outcomes (grades).

The results of the mediation model analysis for PAP are presented in Table 10. As shown in Table 10, self-directed learning readiness was not related to PAP (B = -0.13, SE = 0.18, t (119) = -0.77, p = 0.44), and there is no evidence of an association of PAP with cognitive learning outcomes (grades) when controlling for SDLR (B = -0.00, SE = 0.06, t (119) = -0.01, p = 0.99). As can be seen in Table 10, a_4 =-0.13 and b_4 = -0.00. Therefore, multiplying $a4$ and $b4$ does not yield any significant indirect effect; a_4b_4 = (-0.00) (-0.00) = 0.00 (see Table 9). A resampling method using 5,000 bootstrap samples was applied to generate a 95% bias-corrected bootstrap confidence interval as the inferential test for indirect effect (a_4b_4 = 0.00), and this was found to involve zero (-0.02 to 0.03). The indirect effect is non-significant because the confidence interval includes zero (Preacher & Hayes, 2008). Therefore, the results of this analysis do not support research question 1.3, which assumes that PAP mediates the relationship between online self-directed learning readiness and cognitive learning outcomes (grades). The results of the mediation model analysis for PAV are presented in Table 8. As shown in Table 10, self-directed learning readiness was not significantly related to performance-avoidance (B = -0.30, SE = 0.19, t (119) = -1.55, p = 0.12), and there is also no evidence of an association between PAV and cognitive learning outcomes (grades) when controlling for SDLR (B = -0.03, SE = 0.05, t (119) = -0.58, p = 0.12). As can be seen in Table 10, a_5 =-0.30, and b_5 = -0.03. Therefore, multiplying $a5$ and $b5$ does not yield any significant indirect effect; a_5b_5 = -0.30 (-.017) = 0.01 (see Table 11). A resampling method using 5,000 bootstrap samples was applied to generate a 95% bias-corrected bootstrap confidence interval as the inferential test for indirect effect (a_5b_5 = 0.01), and this was found to involve zero (-0.02 to 0.06). The indirect effect is non-significant because the confidence interval includes zero (Preacher & Hayes, 2008); therefore, the results of this analysis do not support research question 1.3, which assumes that PAV mediates the relationship between online self-directed learning readiness and cognitive learning outcomes (grades).

Models 1-2 were statistically significant, or the total indirect effect was significant, as can be seen from Tables 10 and 11. Adding the product of $a_2\times b_2$, $a_3\times b_3$, $a_4\times b_4$, and $a_5\times b_5$ yielded a statistically significant total indirect effect; $a_2\times b_2 + a_3\times b_3 + a_4\times b_4 + a_5\times b_5$; 0.17, and this was found not to involve zero (0.06 to 0.30). The overall indirect effect is statistically significant because the confidence interval does not include zero (Preacher & Hayes, 2008).

Table 10

Model Summary Information for the Proposed Mediation Model Portrayed in Figure 2 (N = 121)

		Outcome																		
Predictors		MAP (M 1)				MAV (M 2)				PAP (M 3)				PAV (M 4)				Grade		
		B(β)	*SE*	*p*		*B(β)*	*SE*	*p*		*B(β)*	*SE*	*p*		*B(β)*	*SE*	*p*		*B(β)*	*SE*	*p*
OSDLR	$a_2 \rightarrow$	.30 (.31)	0.09	<.001	$a_3 \rightarrow$	-. 14 (-.09)	0.15	0.33	$a_4 \rightarrow$	-0.13 (-0.07)	0.18	0.44	$a_5 \rightarrow$	-0.30 (-0.14)	0.19	0.12	$c_2' \rightarrow$	0.08 (0.07)	0.10	0.42
MAP																	$b_2 \rightarrow$	0.45 (0.39)	0.11	< 0.001
MAV																	$b_3 \rightarrow$	-0.17 (-0.24)	0.07	0.01
PAP																	$b_4 \rightarrow$	-0.00 (-.00)	0.06	0.99
PAV																	$b_5 \rightarrow$	-0.03 (-0.06)	0.05	0.56
Constant		5.18	0.34	< .001		6.34	0.59	< .001		5.65	0.71	< .001		6.02	0.76	< .0001		2.30	0.70	< 0.01
		$R^2 = 0.09$, F (1, 119) = 12.42, $p <$ 0.001				R^2 =0 .01, F (1, 119) = 0.93, p = 0.34				$R^2 = 0.01$, F (1. 119)= 0.59, p = 0.44				$R^2 = 0.02$, F (1, 119) = 2.41, p = 0.12				$R^2 = 0.19$, F (1, 115) =5.51, $p <$ 0.001		

Note. B = Unstandardized regression coefficient; β = Standardized regression coefficient.

Table 11

Summary of the Mediation Model 1-2 Analysis

Effect	Mediator	Equation	Estimate	*SE*	95% CI *LL*	95% CI *UL*
Indirect	MAP	$a_2 \times b_2$	0.13	0.06	0.04	0.27
Indirect	MAV	$a_3 \times b_3$	0.02	0.02	-0.02	0.08
Indirect	PAP	$a_4 \times b_4$	0.00	0.01	-0.02	0.03
Indirect	PAV	$a_5 \times b_5$	0.01	0.*02*	-0.02	0.06
Total indirect		$a_2 \times b_2 + a_3 \times b_3 + a_4 \times b_4 + a_5 \times b_5$	0.17	0.06	0.06	0.30
Direct		c_2'	0.08	0.10	-0.12	0.28
Total		c_2	0.25	0.10	0.05	0.45

Note. CI = confidence interval; LL = lower limit; UL = upper limit. If the confidence interval does not include zero, it reveals a significant effect.

Research Questions 2.1 and 2.2

Research questions 2.1 and 2.2 asked: what is the extent of the relationship between online self-directed learning readiness and affective learning outcomes (course satisfaction) mediated by self-efficacy to learn statistics in an online statistic learning environment? The primary intention of the question was to test whether self-efficacy was a potential mediator of the relationship between online self-directed learning readiness and course satisfaction. This was examined by an indirect effect, which was quantified as the product of the effect of online self-directed learning readiness (a_6) and the effect of self-efficacy to learn statistics (b_6).

The results of the mediation model analysis are presented in Table 12, which shows that self-directed learning readiness is related positively to self-efficacy to learn statistics (B = 0.28, SE = 0.12, t (119) = 2.17, p = .035) and self-efficacy to learn statistics is associated with affective learning outcomes (course satisfaction) when controlling for SDLR (B = 0.18, SE = 0.09, t (119) = 2.03, p = 0.04). As can be seen in Table 12, a_6 = 0.28, and b_6 = 0.18. However, multiplying *a6* and *b6* does not yield any significant indirect effect; a_6b_6 = (0.28) (0.18) = 0.05 (see Table 13). A resampling method using 5,000 bootstrap samples was applied to generate a 95% bias-corrected bootstrap confidence interval as the inferential test for indirect effect (a_6b_6 = 0.05), and this was found to be around zero (-0.01 to 0.14). This indirect effect is non-significant because the confidence interval includes zero (Preacher & Hayes, 2008). Therefore, the results of this analysis do not support research questions 2.1 and 2.2, which assume that SELS mediates the relationship between online self-directed learning readiness and affective learning outcomes (course satisfaction).

Table 12

Model Summary Information for the Proposed Mediation Model Portrayed in Figure 3 (N = 121)

		Outcomes						
Predictors		SELS				Satisfaction		
		B(β)	*SE*	*P*		*B(β)*	*SE*	*P*
OSDLR	$a_6 \rightarrow$	0.28 (0.19)	0.12	0.03	c_3'	0.48 (0.17)	0.12	< 0.001
SELS					$b_6 \rightarrow$	0.18 (0.32)	0.09	0.04
Constant		2.91	0.51	< 0.001		0.83	0.57	0.14
		R^2= .04, F (1, 119) =4.72, p < 0.05				R^2=.15, F (1,118) = 10.84, p < 0.001		

Note. B = Unstandardized regression coefficient; β = Standardized regression coefficient.

Table 13

Summary of the Mediation Model 2-1 Analysis

					95% CI	
Effect	Mediator	Equation	Estimate	*SE*	*LL*	*UL*
Indirect	SELS	$a_6 \times b_6$	0.05	0.04	-0.01	0.14
Direct		c	0.48	0.13	0.22	0.74
Total		c_3	0.53	0.13	0.28	0.79

Note. CI = confidence interval; LL = lower limit; UL = upper limit. If the confidence interval does not include zero, it reveals a significant effect.

Research Question 2.3

Research question 2.3 for the present study asked: what is the extent of the relationship between online self-directed learning readiness and affective learning outcomes (course satisfaction) mediated by each construct of 2x2 achievement goal orientations (MAP, MAV, PAP, PAV) in an online statistic learning environment? The primary intention was to test whether each construct of 2x2 achievement goal orientations (MAP, MAV, PAP, PAV) is a potential mediator of the relation between online self-directed learning readiness and course satisfaction. This was examined by an indirect effect, which was quantified as the product of the effect of online self-directed learning readiness (a_7) and MAP goal orientation (b_7), MAV goal orientation (b_8), PAP goal orientation (b_9), and PAV goal orientation (b_{10}).

The results of the mediation model analysis are shown in Table 14, which reveals that self-directed learning readiness is positively related to MAP (B = 0.30, SE =0 .09, t (119) = 3.52, $p <$ 0.001), and there is no evidence of an association between MAP and affective learning outcomes (course satisfaction) when controlling for SDLR (B = 0.21, SE = 0.15, t (119) = 1.38, p = 0.17). As can be seen in Table 14, a_7 = 0.30, and b_7 = 0.21. Therefore, multiplying a_7 and b_7 does not yield the indirect effect, a_7b_7 = 0.30(.21) = 0.06 (see Table 15). A resampling method using 5,000 bootstrap samples was applied to generate a 95% bias-corrected bootstrap confidence interval as the inferential test for indirect effect (a_7b_7 = 0.06), and this was found to involve zero (-0.02 to 0.18). The indirect effect is non-significant because the confidence interval includes zero (Preacher & Hayes, 2008). Therefore, the results of this analysis do not support research question 2.3, which assumes that MAP mediates the relationship between online self-directed learning readiness and affective learning outcomes (course satisfaction).

As shown in Table 12, analysis did not provide evidence of a relationship between self-directed learning readiness and MAV (*B* = -0.14, SE = 0.15, *t* (119) = -0.96, *p* = 0.33), and MAV is also not associated with affective learning outcomes (course satisfaction) when controlling for SDLR (*B* = 0.01, *SE* = 0.09, *t* (119) = 0.10, *p* = 0.92). As can be seen in Table 14, a_8 =-0.14 and *b8* =0.01. Therefore, multiplying *a8* and *b8* does not yield any significant indirect effect; a8b8 = -0.14 (.01) = -0.00 (see Table 15). A resampling method using 5,000 bootstrap samples was applied to generate a 95% bias-corrected bootstrap confidence interval as the inferential test for indirect effect (*a8b8*= -0.0013), and this was found to involve zero (-0.04 to 0.03). The indirect effect is non-significant because the confidence interval includes zero (Preacher & Hayes, 2008). Therefore, the results of this analysis do not support research question 2.3, which assumes that MAV mediates the relationship between online self-directed learning readiness and affective learning outcome (course satisfaction).

As shown in Table 14, self-directed learning readiness is not related to PAP (*B* = -0.13, *SE* = 0.18, *t* (119) = -0.77, *p* = 0.44), and there is no evidence of an association between PAP and affective learning outcomes (course satisfaction) when controlling for SDLR (*B* = -0.14, *SE* =0 .07, *t* (119) = -1.9, *p* = 0.06). As can be seen in Table 14, a_9 =-0.13 and b_9 = -0.14. Therefore, multiplying *a9* and *b9* does not yield any significant indirect effect; a_9b_9 = -0.13 (-0.14) = 0.02 (see Table 15). A resampling method using 5,000 bootstrap samples was applied to generate a 95% bias-corrected bootstrap confidence interval as the inferential test for indirect effect (a_9b_9 = 0.02), and this was found to involve zero (-0.02 to 0.09). The indirect effect is non-significant because the confidence interval includes zero (Preacher & Hayes, 2008). Therefore, the results of this analysis do not support research question 2.3, which assumes that PAP mediates the relationship between online self-directed learning readiness and affective learning outcomes (course satisfaction).

As shown in Table 14, self-directed learning readiness is not related to PAV (B = -0.30, SE = 0.19, t (119) = -1.55, p = 0.12), and there is no evidence of an association between PAV and affective learning outcomes (course satisfaction) when controlling for SDLR (B = 0.11, SE = 0.07, t (119) = 1.47, p = 0.14). As can be seen in Table 12, a_{10} =-0.30, and b_{10} = 0.11. Therefore, multiplying *a10* and *b10* does not yield any significant indirect effect; $a_{10}\, b_{10}$ = -0.30 (-.11) = -0.03 (see Table 15). A resampling method using 5,000 bootstrap samples was applied to generate a 95% bias-corrected bootstrap confidence interval as the inferential test for indirect effect ($a_{10}\, b_{10}$ = -0.03), and this was found to involve zero (-0.10 to 0.02). The indirect effect is non-significant because the confidence interval includes zero (Preacher & Hayes, 2008). Therefore, the results of this analysis do not support research question 2.3, which assumes that PAV mediates the relationship between online self-directed learning readiness and affective learning outcomes (course satisfaction).

The results show that the model was non-significant, or the total indirect effect is non-significant, as can be seen from Tables 14 and 15. Adding the product of $a_7 \times b_7$, $a_8 \times b_8$, $a_9 \times b_9$, and $a_{10} \times b_{10}$ does not yield a statistically significant total indirect effect, where $a_7 \times b_7$, $a_8 \times b_8$, $a_9 \times b_9$, and $a_{10} \times b_{10};$ 0.05, and this was found to involve zero (-0.06 to 0.19). The overall indirect effect is non-significant because the confidence interval includes zero (Preacher & Hayes, 2008).

Table 14

Model Summary Information for the Proposed Mediation Model Portrayed in Figure 4 (N = 121)

		Outcome																			
Predictors		MAP (M 1)				MAV (M 2)				PAP (M 3)				PAV (M 4)				Course Satisfaction			
		B(β)	*SE*	*p*		*B(β)*	*SE*	*p*		*B(β)*	*SE*	*p*		*B(β)*	*SE*	*p*		*B(β)*		*SE*	*p*
SDLR	$a_7 \rightarrow$	0.30 (0.31)	0.09	<0.001	$a_8 \rightarrow$	-0. 14 (-.09)	0.15	0.33	$a_9 \rightarrow$	-0.13 (-.07)	0.18	.44	$a_{10} \rightarrow$	-.30 (-.14)	.19	.12	$c'_4 \rightarrow$	.48 (.32)		.14	<.001
MAP																	$b_7 \rightarrow$	.21 (.13)		.15	.17
MAV																	$b_8 \rightarrow$	.01 (.01)		.08	.92
PAP																	$b_9 \rightarrow$	-.14 (-.18)		.07	.06
PAV																	$b_{10} \rightarrow$	.11 (.15)		.07	.14
Constant		5.18	0.34	< .001		6.34	.59	< .001		5.65	.71	< .001		6.02	.76	< .001		.41		0.95	0.66
		$R^2 = 0.09$, F (1, 119) = 12.42, $p < 0.001$				$R^2 = 0.01$, F (1, 115) = 4.57, $p < 0.001$				$R^2 = 0.01$, F (1. 119)= 0.59, $p = 0.44$				$R^2 = 0.02$, F (1, 119) = 2.41, $p = 0.12$						$R^2 = 0.16$, F (1, 115) =4.57, $p <$ 0.001	

Note. B = Unstandardized regression coefficient; β = Standardized regression coefficient.

Table 15

Summary of the Mediation Model 2-2 Analysis

					95% CI	
Effect	Mediator	Equation	Estimate	*SE*	*LL*	*UL*
Indirect	MAP	$a_7 \times b_7$	0.06	0.05	-0.02	0.18
Indirect	MAV	$a_8 \times b_8$	-0.00	0.02	-0.04	0.03
Indirect	PAP	$a_9 \times b_9$	0.02	0.03	-0.03	0.09
Indirect	PAV	$a_{10} \times b_{10}$	-0.03	0.03	-0.10	0.02
Total indirect		$a_7 \times b_7 + a_8 \times b_8 + a_9 \times b_9 + a_{10} \times b_{10};$	0.05	0.06	-0.06	0.19
Direct		c_4 ‘	0.48	0.14	0.21	0.76
Total		c_4	0.53	0.13	0.28	0.79

Note. CI = confidence interval; LL = lower limit; UL = upper limit. If the confidence interval does not include zero, it reveals a significant effect.

Table 16

Explanation of Variables of Models and Research Questions

Research Question	Model	Outcome	Mediator	Path	Results
RQ 1.1	1-1	Cognitive Learning	Direct effect	SDL → Grade	Significant

RQ 1.2		Outcome (Grade)	Indirect Effect	SDL → SELS → Grade	Not Significant
RQ 1.3	1-2			SDL → MAP → Grade	Significant
				SDL → MAV → Grade	Not Significant
				SDL → PAP → Grade	Not Significant
				SDL → PAV → Grade	Not Significant
RQ 2.1	2-1	Affective Learning Outcome (Course Satisfaction)	Direct effect	SDL → Satisfaction	Significant
RQ 2.2			Indirect Effect	SDL → SELS → Satisfaction	Not Significant
RQ 2.3	2-2			SDL → MAP → Grade	Not Significant
				SDL → MAV → Grade	Not Significant
				SDL → PAP → Grade	Not Significant
				SDL → PAV → Grade	Not Significant

Figure 8

Model summary information for the hypothesized mediation model portrayed in Figure 1

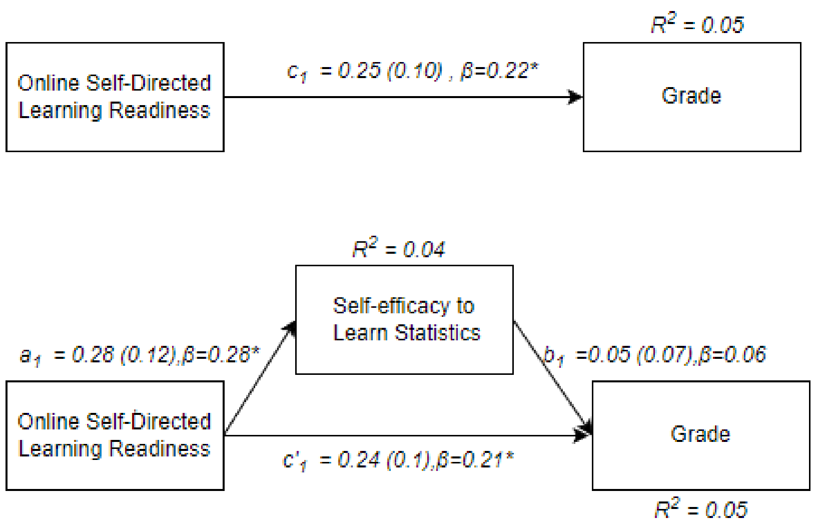
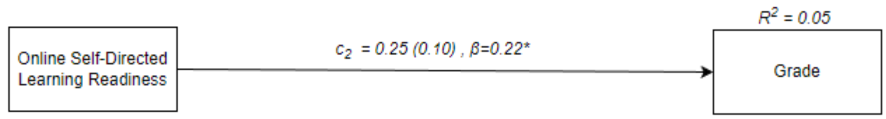
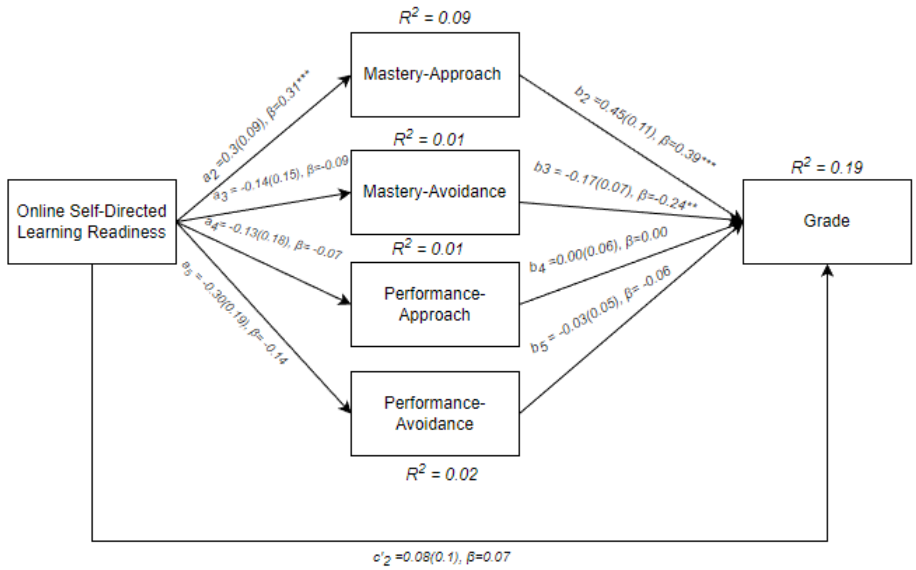


Figure 9

Model summary information for the hypothesized mediation model portrayed in Figure 2



Online Self-Directed Learning Readiness
c_2 = 0.25 (0.10) , β=0.22*
R^2 = 0.05
Grade



Online Self-Directed Learning Readiness
R^2 = 0.09
Mastery-Approach
R^2 = 0.01
Mastery-Avoidance
R^2 = 0.01
Performance-Approach
Performance-Avoidance
R^2 = 0.02
R^2 = 0.19
Grade
a2 =0.3(0.09), β=0.31***
a_3 = -0.14(0.15), β=-0.09
a_4= -0.13(0.18), β= -0.07
a_5 = -0.30(0.19), β= -0.14
b2 =0.45(0.11), β=0.39***
b3 = -0.17(0.07), β=-0.24**
b4 =0.00(0.06), β=0.00
b5 = -0.03(0.05), β= -0.06
c'2 =0.08(0.1), β=0.07

Figure 10

Model summary information for the hypothesized mediation model portrayed in Figure 3

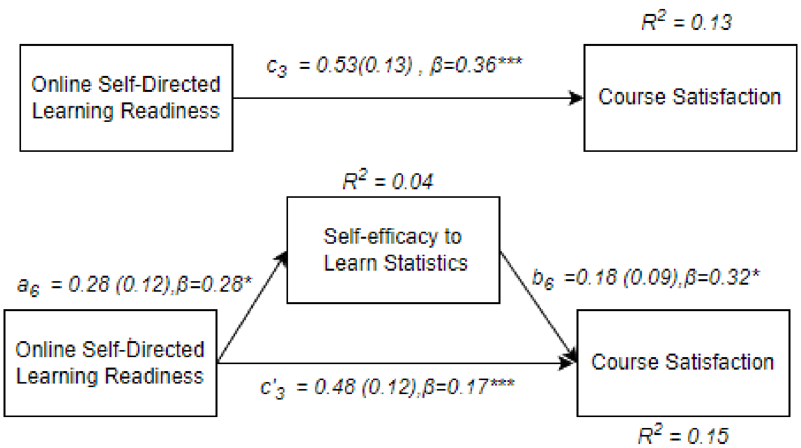
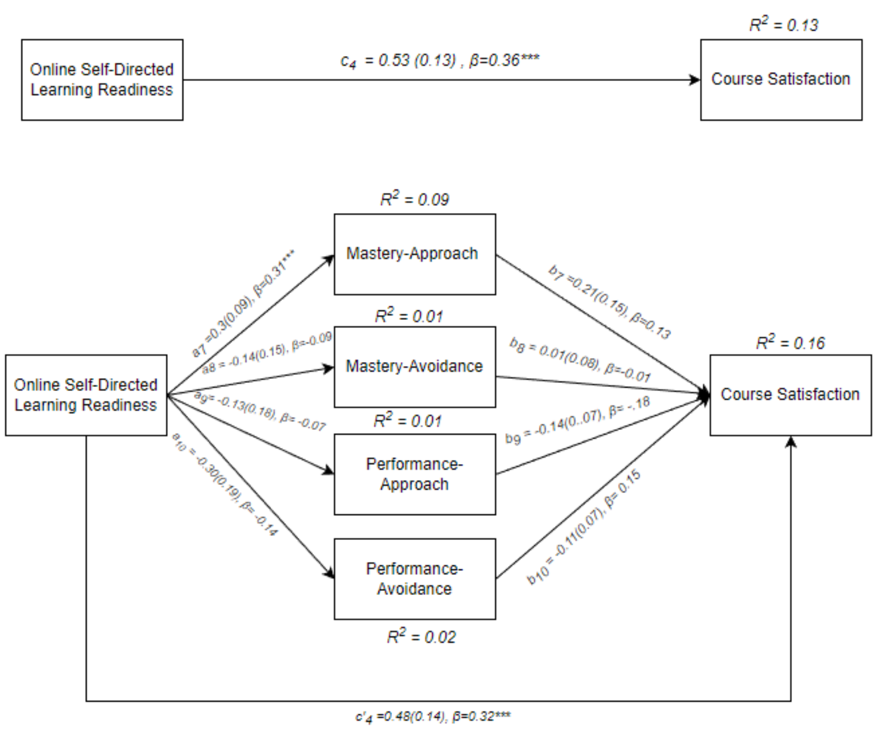


Figure 11

Model summary information for the hypothesized mediation model portrayed in Figure 4



Summary

The primary focus of this quantitative, cross-sectional correlation study was to investigate whether and to what extent OSDLR has an impact on academic outcomes measured by grade (cognitive learning outcome) and course satisfaction (affective learning outcome) through the potential mediators of SELS and each construct of 2x2 achievement goal orientation. The present study was conducted by analyzing the data collected from students enrolled in and studying at a large public university in the Southeast of the United States who had registered for at least one statistics course delivered online during the 2020 Fall semester. To answer the research questions of the current study, data was analyzed using OLS regression to estimate the hypothesized mediation model. In this model, the main interest was the indirect effects, which were representative of research questions that tested OSDLR as it relates to grade and course satisfaction through the potential mediators of SELS only ($a_1 \times b_1$; $a_6 \times b_6$) and each construct of 2x2 achievement goal orientation: MAP, MAV, PAP and PAV ($a_2 \times b_2$, + $a_3 \times b_3 + a_4 \times b_4 + a_5 \times b_5$; $a_7 \times b_7$, $a_8 \times b_8$, $a_9 \times b_9$, and $a_{10} \times b_{10}$).

This chapter provided the findings of the mediation model analyses. The results partially supported the research questions, thus suggesting that there was evidence of mediating pathways from OSDLR to academic outcomes measured by grade (cognitive learning outcomes) and course satisfaction (affective learning outcomes) through MAP.

In chapter 5, I will provide a comprehensive summary of the entire study, its limitations and conclusions, and its implications based on the findings of the mediation analysis.

Chapter 5 - Summary, Conclusions, Implications, Limitations, and Recommendations for Future Research

Overview

This chapter presents the study summary, conclusions based on the data analysis, implications of the findings, limitations, and results. Recommendations for future research are also described.

Problem Statement

The COVID-19 global pandemic has led to drastic changes in educational systems around the world. Students were forced to shift from physical to online classes in response to government restrictions on face-to-face instruction. These restrictions were considered critical to preventing the spread of COVID-19. Aguilera-Hermida (2020) explained that while numerous challenges accompanied these changes, these changes also created an awareness of the role and advantages of engaging in online learning. Therefore, even after the risk of virus spread was reduced, the popularity of online learning remained high. Bashir et al. (2021) reported that Aston University adopted a hybrid mode of course delivery (combining online and face-to-face courses) as a post-COVID solution that highlighted the popularity of online learning. A survey cited by Kelly (2021) established that 73% of students preferred studying fully online after the pandemic; however, only about 53% of faculty preferred teaching online.

In recent years, many statistics courses have also been transferred online, with studies such as that conducted by Ritzhaupt et al. (2020) revealing that students enrolled in the coursework experience less anxiety, making online instruction preferable to in-person learning. The popularity of online statistics courses post-pandemic has created a demand for understanding this modality of learning and how learners and educators can organize their courses effectively.

Further demand for understanding the learning modality has been created by studies such as those by Figueroa-Cañas and Sancho-Vinuesa (2020), which have reported that the dropout rate of online statistics courses is higher than that of traditional statistics courses. This is a significant concern because, even though most learners prefer online learning, this same online model has seen higher dropout rates. However, Knowles' self-directed learning theory has encouraged scholars to focus on self-efficacy to improve online statistics courses (Manning, 2007). Thus, the present study sought to explore the existing gap in the literature regarding the effects of self-efficacy, self-directed learning readiness (SDLR), and goal orientation on learning outcomes for learning statistics online.

Research Questions

1. What is the extent of the relationship between online self-directed learning readiness and grades mediated by self-efficacy to learn statistics and each construct of achievement goal orientations in an online statistic learning environment?

1.1 What is the extent of the relationship between online self-directed learning readiness and grades in an online statistic learning environment?

1.2 What is the extent of the relationship between online self-directed learning readiness and grades mediated by self-efficacy to learn statistics in an online statistic learning environment?

1.3 What is the extent of the relationship between online self-directed learning readiness and grades mediated by each construct of achievement goal orientations (MAP, MAV, PAP, PAV) in an online statistic learning environment?

2. What is the extent of the relationship between online self-directed learning readiness and course satisfaction mediated by self-efficacy to learn statistics and each construct of achievement goal orientations in an online statistic learning environment?

2.1 What is the extent of the relationship between online self-directed learning readiness and course satisfaction in an online statistic learning environment?

2.2 What is the extent of the relationship between online self-directed learning readiness and course satisfaction mediated by self-efficacy to learn statistics in an online statistic learning environment?

2.3 What is the extent of the relationship between online self-directed learning readiness and course satisfaction mediated by each construct of achievement goal orientations in an online statistic learning environment?

Study Overview

The increased demand for online learning in today's education system has caused scholars and educators to question how statistics coursework will be affected by the features of online teaching (Akabayashi et al., 2023). Thus, developing an understanding of self-directed, self-efficacy, and goal orientation theories is crucial to understanding such effects. Undoubtedly, online learning has drastically expanded learners' horizons by enabling them to not only save time but also access learning materials and resources without geographical barriers. As a result, the completion rate has increased as the number of online learning graduates increases. Nevertheless, the concept of the efficiency of online courses has laid the foundation for scholars to explore whether they are more effective than face-to-face learning (Kemp & Grieve, 2014).

Considering the growing demand for online learning, understanding the extent to which the outcomes of learning statistics online have been affected by self-directed learning readiness, self-efficacy, and goal orientation is crucial to promoting success among such classes (Chu & Tsai, 2009). The key focus of this study was to explore the literature gaps regarding the effects of self-directed learning readiness, self-efficacy, and goal orientation on learning outcomes for learning statistics online. While many studies on online learning struggle to examine the effectiveness of self-directed, goal-oriented, and self-efficacy theories in improving academic performance, this study examined the gap regarding learning outcomes for learning statistics online. To examine these gaps, this study utilized 2x2 achievement goal orientation, self-efficacy, and self-directed learning theory, which served as a road map for developing the arguments in this study.

Self-directed learning theory was used to demonstrate its effectiveness in enhancing self-efficacy in learners. This theory argues that individuals take initiative, with the help of others or on their own, to formulate goals, identify learning resources, and implement learning strategies (Charokar, 2022). Tekkol and Demirel's article argues that self-directed learning theory shifts the learning responsibility from educators or any external source to individuals (Tekkol & Demirel, 2018). Throughout the study, self-directed learning was used to investigate the extent to which self-directed learners take responsibility for their education and accept the independence that comes with focusing on meaningful topics. The theory was crucial in understanding knowledge acquisition, learner preparedness, and the extent to which this theoretical learning approach appears to be a pedagogical delivery that learners can benefit from in the changing world (Tekkol & Demirel, 2018). Moreover, it examined the extent to which learning can affect learners' academic performance, since the theory is regarded as a positive predictor of academic performance (Li et al., 2022). Hence, as a pedagogical strategy, self-directed learning facilitates understanding learners' needs in a rapidly globalizing, diversifying, and technologizing world

(Charokar, 2022). Furthermore, it was crucial to understand the relationship between mastery of concepts, motivation, and online statistics learners' performance.

As a primary element of Bandura's social-cognitive theory, self-efficacy tends to focus more on the role of motivation in academic achievement. This theory reviewed individuals' confidence and abilities to control their motivation, behavior, and external environments (Domenech-Betoret et al., 2017). The theory provided information on mastery experience and predicted students' academic achievements and performances. It allowed the researcher to recognize the need to achieve academic goals and superior grades and embrace new experiences. Furthermore, the theory was used to facilitate the study of mastery experiences, social modeling, social persuasion, and psychological responses (Bandura, 2012). By understanding the interaction between students' thoughts and the nature of the assigned tasks, the researcher was able to understand the relationship between self-efficacy and higher achievement levels (Iroegbu, 2015). Apart from being a predictor of academic success, the theory facilitates an understanding of how self-efficacy influences various learning areas. It allowed the researcher to explore the relationship between motivation and student performance and how self-efficacy improved learning statistics online. In addition to providing information on how to achieve successful statistical education and information, self-efficacy theory helped explore students' abilities to use symmetric variables. This theory was significant in understanding how statistical self-efficacy can contribute to improved performance.

Goal orientation theory is a social cognitive theory of achievement motivation. Unlike other motivational theories, goal orientation focuses on what stimulates learners to be more concerned with and engaged in learning (Wang et al., 2021). At the same time, the theory focuses on demonstrating why this theory is important to learners. The theory related to the current study facilitated an understanding of how students can improve their skills by concentrating on the learning process attained through effort. Furthermore, it facilitated an understanding of the role of mastery orientation in attaining academic goals (Sidebar & Shankar, 2022) and helped the researchers explore the role of performance-oriented learning in promoting student performance. Using goal orientation theory, the study managed to relate motivation to academic performance and the extent to which it supports a positive attitude toward performance-oriented goals. Generally, these theories were crucial in understanding how academic performance can be impacted. The relationship between this theory and the current study is that the theory determines the probability of success and the probability of attaining academic and professional goals. The theory provided the platform through which educators evaluated learners' initial core orientation (ability to master skills) and avoided failure or sought success. This was a critical area explored in this study, and the theory uncovered the extent to which learners became more concerned and engaged in learning.

The current study sought to create awareness and inform learners and tutors engaging in online statistics courses about how they can rely on self-directed learning readiness. The main objective of the study was to understand the effects of SDLR on grades and course satisfaction for online learning statistics through the mediating variables of self-efficacy and 2x2 achievement goal orientation. By understanding the potential mediator roles of SELS and AGO in learning statistics and OSDLR, the current study will have comprehensively investigated the relationship between OSDLR and grade outcomes and course satisfaction.

A quantitative research design explored the relationships between online self-directed learning readiness, self-efficacy to learn statistics, 2x2 achievement goal orientations, course satisfaction, and grades in online statistics course settings. To address the research questions, the study included a total of 168 students who participated in the survey. However, 47 participants were removed because of their high level of missing data. Therefore, only 121 participants were involved in this study. The Achievement Goal Questionnaire instrument evaluated AGOs computerized in the 2x2 goal framework. In addition, self-efficacy in learning statistics was a reliable instrument for measuring students' confidence and ability to learn statistics. Hung et al.'s (2010) article highlighted another instrument used in this study—an online SDLR used in the survey to evaluate online learning readiness. Such instruments were crucial in data analysis. Participants were those who enrolled as students at the university, were 19 years old or older and had registered for at least one statistics course delivered online during the 2020 fall semester. A cross-sectional and correlational study was used to collect data on relevant variables from different people, subjects, and phenomena.

Findings

The study's findings indicated that online self-directed learning readiness was positively associated with efficacy in learning statistics and grades. However, self-efficacy in learning statistics was not associated with grades. Moreover, the findings indicated that online self-directed learning readiness was positively related to MAP and that MAP was positively related to cognitive learning outcomes (grades). In addition, self-efficacy in learning statistics was positively related to satisfaction. Nonetheless, the indirect effect of self-efficacy in learning statistics and satisfaction was insignificant. It must be noted that only PAP was negatively related to course satisfaction, even if there was no significant indirect effect of self-efficacy.

Research Questions 1.1, 1.2 and 1.3 sought to investigate the effects of OSDLR on grades, cognitive learning outcomes, and the mediating effects of the association between OSDLR and grades through the mediators: SELS and each construct of 2x2 achievement goal orientations (MAP, MAV, PAP, and PAV from model 1-1 and 1-2.). The analysis revealed that OSDLR was directly associated with grades; however, there is no evidence of an association between SELS and grades. The result of the mediation model analysis did not support that SELS mediates the association between OSDLR and grades. Otherwise, in one of the 2x2 achievement goal orientations, only the MAP orientation was found to be a significant mediator of the association between OSDLR and grades.

Research Questions 2.1, 2.2 and 2.3 investigated the effects of OSDLR on course satisfaction, affective learning outcomes, and the mediating effects of the association between OSDLR and grades through the mediators of SELS and each construct of 2x2 achievement goal orientations (MAP, MAV, PAP, and PAV from models 2-1 and 2-2). The analysis revealed that OSDLR was related positively to SELS, and SELS was associated with affective learning outcomes (course satisfaction) when controlling for SDLR. However, this did not yield any significant indirect effect from the resampling method using 5,000 bootstrap samples applied to generate a 95% bias-corrected bootstrap confidence interval, which was found to be around zero. Therefore, this does not support the idea that SELS mediates the relationship between online self-directed learning readiness and affective learning outcomes (course satisfaction). The result analysis from model 2-2 showed that there is no evidence of a significant association between any of the constructs of 2x2 achievement goal orientations and course satisfaction.

Conclusions

The results of this study are divided into different models used in the analysis. The results indicated that some studies were consistent with the results of the current study, while others contradicted them. As demonstrated in the subsequent sections, some studies, such as Uus et al. (2022), support the findings of the current study that technology (such as the Internet) helps learners engage in self-directed learning. Previous research on the effects of self-directed learning readiness, self-efficacy, and goal orientation on learning outcomes for online statistics courses is limited. However, previously conducted studies such as that by Loeng (2020) demonstrated that self-efficacy, self-directed learning readiness, and goal orientation theories play a role in explaining online learners' performances in a different manner. As a pedagogical strategy, self-directed learning readiness is an excellent way of teaching students how to manage knowledge. The current study examined the extent to which self-directed learning readiness was related to self-efficacy in learning. It found a positive relationship between self-directed learning readiness and self-efficacy to learn statistics and satisfaction, respectively. Hence, it revealed that self-directed learners could identify learning requirements, create learning plans, and choose practical learning plans. Like previous studies, the current study revealed that technology empowered learners' abilities to engage in self-directed learning. In the following section, the conclusion regarding all variables in each model is first introduced, followed by the studies that support these findings and what these findings mean.

Research Questions 1.1 and 1.2

The results from this model indicate that online self-directed learning readiness (OSDLR) is positively related to grade, which is a cognitive learning outcome. The results also indicate that OSDLR is positively related to SELS. At the same time, the results did not provide evidence of the association between SELS and cognitive learning outcomes (grades). In other words, SELS is not a significant mediator between OSDLR and grade.

Existing research that was consistent with the findings of this study with regards to the relationship between OSDLR and grade as a learning outcome includes a study by Wei and Chou (2020), who found a positive relationship between OSDLR and student learning outcomes, such as grade. Tang et al. (2021) also established that the Internet, an important technology in facilitating OSDLR, plays a crucial role in strengthening OSDLR by positively influencing cognitive learning outcomes or grades.

Previous research on OSDLR and its relationship with learning outcomes was generally limited. Still, there was a plethora of literature on the relationship between SDLR and grades. For example, studies such as that by Örs (2018) argued that SDLR has a positive relationship with grades and that SDLR puts learners in a better position to comprehend their academic material and, thus, perform better. Shokar et al. (2002) also found a positive correlation between students' scores on the SDLR scale and their course grades.

In terms of the relationship between OSDLR and SELS, Tang et al. (2021) established a positive relationship between OSDLR and SELS that is consistent with the current study's findings. Tang et al. (2021) argued that motivation is key in OSDLR since it determines students' attitudes while learning online. Other studies, such as that by Yilmaz (2017), indicated that self-efficacy is a critical factor when discussing OSDLR since it enables the interaction between internal and external factors that enable students to achieve a certain degree of confidence to learn about a given concept, such as statistics. These results mean that students with higher levels of OSDLR achieve higher levels of self-efficacy, thereby creating pathways for them to interact with their teachers and peers. Other studies, such as that by Turan and Koç (2018) and Dong et al. (2021), investigated the relationship between self-efficacy and self-directed learning readiness. Both established a positive relationship between self-directed learning readiness and self-efficacy.

Some of the studies that contradict the findings of this study include those by Domenech-Betoret et al. (2017) and Betoret et al. (2014), which found a positive relationship between self-efficacy and grade. The sample comprises 797 Spanish secondary education students from 36 educational settings and three schools. The researchers argued that self-efficacy could be associated with motivation, better attitudes toward learning, good relationships and interactions with teachers and peers, and more confidence.

Studies such as the one conducted by Doménech-Betoret et al. (2017), postulate a relationship between self-efficacy, course satisfaction, performance, and expectancy-value beliefs. According to their findings, process expectations are connected to students' emotions during interactions with their teachers and play a significant role in determining satisfaction levels. However, this process can be influenced by students' self-efficacy and their expected performance in terms of grades. In other words, students with strong self-efficacy beliefs are more likely to envision successful outcomes, which guide their performance and provide them with the necessary support. As a result, these students tend to experience higher satisfaction with the learning process and achieve better performance.

The inconsistency between the findings of previous research and the current study regarding the relationship between self-efficacy, course satisfaction, and grades may be attributed to differences in sample characteristics, such as sample size, research context, study population, and the validity and reliability of the research instruments used in both cases.

Regarding the relationship between online self-directed learning readiness (OSDLR) and grades, both previous literature and the current study demonstrate a positive association. This implies that learners who possess the necessary attitudes, capabilities, and personality traits for online self-directed learning are more likely to achieve high academic performance. Furthermore, the results of this study suggest that such learners, who have the appropriate attitudes, capabilities, and personality characteristics for online self-directed learning, are also more likely to be confident in their ability to effectively learn statistical skills required for their statistics course.

Research Question 1.3

The results indicated that OSDLR is positively related to grades, as established in model 1-1. The results also established that OSDLR is positively related to MAP but shows no positive relationship with any other orientations (MAV, PAP and PAV). Moreover, MAP is positively related to grades; therefore, MAP is a significant mediator between the relationship between OSDLR and cognitive learning outcomes. It was also established that MAV is negatively related to grades and that neither PAP or PAV is significantly associated with grades.

The findings of the current study regarding the variables mentioned above are consistent with previous research. Studies cited in this study, such as those by Simamora and Mutiarawati (2021) and Keklik and Keklik (2013), indicate that the mastery approach (MAP) is the only significant mediator in the relationship between online self-directed learning readiness (OSDLR) and cognitive learning outcomes (grades). These studies show that MAP has a positive relationship with both OSDLR and grades, while the relationship between a mastery-avoidance approach (MAV) and grades is negative.

The results of this study suggest that learners who focus on developing competence-based learning, expanding their understanding, and improving their performance (or simply those who display a MAP orientation) are likely to achieve high academic performance. Furthermore, these findings imply that such students are more likely to possess the attitudes, capabilities, and personality characteristics necessary for online self-directed learning. Regarding the negative relationship between MAV and grades, the results suggest that learners who focus on avoiding the loss of knowledge or skills are likely to perform poorly academically. Additionally, whether learners strive to outperform others or demonstrate their competence does not impact their academic performance or their attitudes, capabilities, and personality characteristics necessary for online self-directed learning. Finally, whether learners focus on avoiding looking incompetent, making errors, or being outperformed by others does not affect their academic performance or their attitudes, capabilities, and personality characteristics necessary for online self-directed learning.

Research Questions 2.1 and 2.2

The results indicate a positive association between OSDLR and course satisfaction. They also show a positive association between self-efficacy for learning statistics (SELS) and course satisfaction. However, it was found that SELS did not serve as a significant mediator. These findings align with several previous studies, including those by Wei and Chou (2020) and Ariffin et al. (2020), who argue that OSDLR positively influences course satisfaction because it includes qualities such as self-confidence in using e-communication, student perception of learning delivery, and autonomy in learning participation, which are key components of course satisfaction. Ariffin et al. (2020) further note that OSDLR enhances student engagement in online courses, thereby increasing the likelihood of course satisfaction. Hoogerheide et al. (2018) and Hsia et al. (2016) also suggest that self-efficacy positively impacts overall course satisfaction as it improves learners' perception of the teaching model, particularly in terms of seeking high instructional value.

The results of this study indicate that OSDLR, as well as a learner's attitudes, capabilities, and personality characteristics necessary for online self-directed learning, play a significant role in determining students' satisfaction with their online statistics courses. Additionally, the confidence a student has in their ability to effectively learn statistical skills influences course satisfaction, but it does not affect their capabilities and personality characteristics necessary for self-directed learning in relation to course satisfaction.

Research Question 2.3

The results in this model show that none of the 2x2 achievement orientations were associated with course satisfaction. These results contradict most of the previous research. For example, studies such as that by Wolters (2004) argue that mastery structure and mastery orientation are directly associated with affective outcomes and course satisfaction. Butler (1987) found that achievement orientation can play a very important role in strengthening the ability of learners to master their coursework, which positively affects course satisfaction. Butler (1987) added that a mastery-goal orientation helps learners tackle complex tasks due to their intrinsic interest in learning and orientation toward the ultimate goal of learning, improving their skills, and increasing the chances of course satisfaction. Mega et al. (2014) argued that students with a mastery approach utilize cognitive strategies that enable them to comprehend their current subjects better and have the capacity to attain maximum skills and knowledge in a given course. According to Mega et al. (2014), course satisfaction among such students is often higher because learners are more likely to be satisfied in courses where they understand the content and have gained enough skills.

The results of this study imply that the patterns affecting a student's cognitive or emotional behavior regarding events do not affect their course satisfaction. There are some fundamental reasons why the current study's findings differ from previous research. They are, among others, the differences in sample characteristics and sample sizes, the differences in study populations, the fact that some previous studies investigated different subjects apart from statistics, and the fact that some previous studies investigated more than one subject.

Implications

Online learning has gained significant recognition and appreciation in educational institutions. However, studies specifically focused on learning statistics online are limited, as most research tends to concentrate on general online teaching and learning processes. Consequently, there is a lack of literature addressing the needs of online learners and the enhancement of learning outcomes in the context of online statistics learning (Salah Dogham et al., 2022). Given the challenges faced by online statistics learners, it is crucial to develop a deeper understanding of the impact of self-directed learning readiness, self-efficacy, and goal orientation on learning outcomes to enhance performance among these learners (Salah Dogham et al., 2022).

Mastery avoidance goal Orientation refers to an individual's focus on avoiding mistakes, failure, or the appearance of incompetence, rather than actively seeking to develop competence or master tasks (Lin et al., 2019). It suggests that the person's primary concern is to avoid looking incompetent or making errors, rather than pursuing growth or learning. The findings from the current study indicate that having a mastery avoidance goal orientation is associated with lower academic performance or poorer grades. Students who are primarily focused on avoiding mistakes or failure may not fully engage in the learning process, take risks, or invest the necessary effort to achieve high levels of understanding and performance. Given that mastery avoidance goal orientation is linked to lower grades, it is important for the instructor to promote mastery-approach goals (Benita, 2021). Encouraging students to focus on their personal growth, learning from mistakes, and seeking a deep understanding of statistical concepts can help counteract the negative effects of a mastery avoidance mindset. The instructor can provide examples of how mistakes and setbacks are valuable learning opportunities and emphasize the importance of effort and perseverance. Students with a mastery avoidance goal orientation may be more sensitive to criticism or fear of failure. Therefore, the instructor should create a supportive online learning environment that encourages risk-taking, emphasizes learning from mistakes, and provides constructive feedback. Offering opportunities for students to practice and apply statistical concepts in a safe and non-judgmental setting can help build their confidence and reduce anxiety related to making errors. Students with a mastery avoidance goal orientation may benefit from individualized support and motivation (Tuominen et al., 2012). The instructor can provide personalized feedback, guidance, and encouragement to help students overcome their fear of failure and develop a growth mindset. Recognizing and rewarding students' efforts, progress, and improvements can also help shift their focus from avoiding mistakes to embracing challenges and pursuing mastery.

Also, the instructor can assess students' goal orientations, including any signs of mastery avoidance, through surveys, self-reflection activities, or informal discussions. Identifying students who exhibit a mastery avoidance goal orientation can allow for targeted interventions and support. The instructor can engage in open and honest conversations about goal orientations, emphasizing the importance of a growth mindset and helping students reframe their perspectives on mistakes and failure.

From the results of the current study, encouraging students to adopt a mastery-approach goal orientation can be beneficial. By focusing on their personal growth, students are more likely to engage actively in the learning process, persist in the face of challenges, and strive for a deeper understanding of statistical concepts. The instructor can promote mastery goals by highlighting the importance of learning for its own sake, providing constructive feedback that supports improvement, and setting high but attainable expectations (Tuominen et al., 2012).

To recognize the significance of self-directed learning readiness, the instructor can design the course to foster independent learning skills. This can include incorporating self-paced learning modules, encouraging students to set their own learning goals, and providing resources and guidance for self-directed study. Promoting a supportive online learning environment that encourages active participation and collaboration can also enhance students' readiness for self-directed learning. Also, the instructor can monitor students' goal orientations throughout the course by using surveys or informal assessments to gauge their level of mastery-approach goal orientation. This information can help identify students who may need additional support in developing a mastery-focused mindset. Moreover, considering the connection between mastery-approach goal orientation and grades, the instructor can use this knowledge to provide targeted guidance and interventions to enhance students' academic performance.

Acknowledging the positive association between online self-directed learning readiness and self-efficacy to learn statistics, the instructor should foster an online learning environment that promotes and supports self-directed learning. This can include providing resources and tools for independent study, offering opportunities for students to set learning goals and monitor their progress, and promoting active engagement and collaboration among students (Liang et al., 2023). The instructor can also guide students in developing effective learning strategies and time management skills suited for online learning.

While self-efficacy to learn statistics is positively associated with course satisfaction, it does not mediate the relationship between course satisfaction and online self-directed learning readiness. This suggests that factors other than self-efficacy contribute to students' satisfaction with the course. The instructor should consider various aspects of the course experience, such as instructional design, course materials, instructor support, and engagement strategies, to ensure a positive and enriching learning environment. Collecting regular feedback from students and making necessary improvements based on their suggestions can also enhance course satisfaction.

Understanding the complex relationships between self-efficacy, course satisfaction, and online self-directed learning readiness, the instructor should adopt a holistic approach to support students' learning experiences. This involves addressing multiple dimensions, including building self-efficacy beliefs, fostering self-directed learning skills, and creating a satisfying course environment. By attending to these interrelated factors, the instructor can contribute to students' overall satisfaction, engagement, and success in the online statistics course.

Limitations

There were some limitations regarding the sample size for this study. The study relied on 168 participants, but 47 were removed because of high levels of missing data. Overall, only a valid sample of 121 participants was analyzed. This sample size is not large enough; hence, the researcher had to change the study's original design. Although Delice (2010) indicates that while the minimum sample size for quantitative research is 100, using a minimum sample in a study with such a large study population (by 2020, 7 million undergraduates were enrolled exclusively in online college courses, according to Reimers (2022)) is not sufficient. Additionally, Kock and Hadaya (2018) recommend that the best sample size for path analysis should be at least 20 times the number of parameters, and since this study had at least eight parameters, the best sample size would have been 160 participants.

Initially, it was planned to use SEM to demonstrate how latent variables were related and the dynamics of relations among every variable. However, due to the limited sample size, the study had to be divided into four different models. The reliability of the scale could have been improved if the study had a larger sample size. Additionally, it is important to note that this study did not include control variables due to the sample size and complexity of the models. Control variables are essential in any study as they help establish the correlation between dependent and independent variables. Therefore, this study was unable to establish a causal relationship between the variables of interest (York, 2018). Furthermore, the inclusion of both undergraduate and graduate students in the study may be seen as a limitation since the differences in grade and/or degree among students could have had a stronger impact on their self-efficacy skills. For instance, junior or senior students might have higher self-efficacy in learning statistics compared to freshmen. It is also important to consider potential factors such as gender and ethnicity in this study. Regarding the measurement of the mediation model, the initial plan was to measure the models in sequence. However, due to the nature of correlational research, which does not demonstrate causal relationships, testing the mediation models in sequence proved difficult. Additionally, some participants did not answer most parts of the survey, leading to the deletion of unanswered responses. This created a gap in explaining missing data, as deletion is not the best way to address this issue and may affect the reliability and validity of the study. Furthermore, the study relied on convenience sampling, which poses limitations as convenient samples may not fully represent the target population, thereby hindering generalization (Akabayashi et al., 2023). Therefore, the choice of sampling method affected the ability to generalize from the sample to the population of interest. Moreover, the study relied on self-reported questionnaires, increasing the likelihood of participant bias. The variables measured in the study required participants to express their opinions regarding goal orientation, self-efficacy, and self-directed learning theories. Since the study focused on online statistics learning settings, the generalizability of the results to other subjects and settings is questionable. The inclusion of numerous variables in the study also increased the potential for confounding variables. Additionally, some students reported their grades from multiple online statistics courses, which may have affected the reliability and validity of the data. Lastly, students may not have fully understood their achievement goal orientation.

Recommendations

Future studies should explore the effectiveness of self-directed learning, self-efficacy, and 2x2 achievement goal orientations (MAV, MAP, PAP, PAV) on outcomes for learning statistics online. In future studies, it would be valuable to explore influential factors such as learners' intrinsic motivation, learning goals, and attitudes toward the subject to further investigate their impact on the effectiveness of these theories in promoting positive affective and cognitive learning outcomes among online learners. To measure cognitive and affective learning outcomes, future studies should consider using an experimental research design. Additionally, it would be beneficial to compare the outcomes of online and face-to-face learning approaches to obtain reliable results. It should be noted that the current study lacked a control group, which is a limitation. Categorizing intervention and control groups in future studies would enhance the accuracy and validity of the data.

The study found a positive association between online self-directed learning readiness, self-efficacy in learning statistics, and grades. Additionally, online self-directed learning readiness was positively related to MAP, which, in turn, was positively related to grades, while MAV was negatively related to grades. Furthermore, self-directed learning readiness was positively related to self-efficacy in learning statistics and satisfaction, and self-efficacy in learning statistics was positively related to satisfaction. Many factors can influence academic performance among learners, including stress, satisfaction, and motivation. Therefore, future studies should explore how these influences affect the extent to which the mentioned theories impact performance among online learners. Such studies could provide a deeper understanding of the factors affecting academic performance and offer potential solutions to issues affecting the effectiveness of online learning.

Moreover, the current study relied on a survey method to collect data. In future studies, it would be valuable to utilize mixed methods research design that involves combining quantitative research design approaches and qualitative studies, such as observation, interviews, focus groups, and group discussions. These approaches would help gain a deeper understanding of the effects of self-directed learning, self-efficacy, and goal orientation on learning outcomes for online statistics learning. Additionally, follow-up studies should aim to clarify the factors that influence learners' performance and how they impact the success of self-directed learning, self-efficacy, and goal orientation in promoting the effectiveness of online statistics learning.

These recommendations have the potential to benefit not only online statistics learning but also online learning in general. With an increasing number of educational institutions adopting online learning, these recommendations may contribute to the improvement and effectiveness of the online learning approach. Furthermore, as policies regarding online learning continue to evolve, the recommendations presented in this study can serve as a foundation for shaping future online learning policies. They can inform and guide decision-making processes within educational institutions' administrations.

Lastly, online learning is a unique approach. This study takes an important step in addressing gaps in understanding the effects of self-directed learning readiness, self-efficacy, and goal orientation on learning outcomes for online statistics learning. Moreover, it highlights the significance of improving academic performance among online learners. Therefore, this study contributes to the existing literature in this field and extends the application of these theories to shaping academic performance. Additionally, it suggests practical strategies that higher education institutions, faculty members, and other education stakeholders can use to support student achievements.

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Appendix A

The Online Survey

Default Question Block

INFORMATION LETTER
for a Research Study entitled
"Relations of Online readiness, Academic procrastination, Achievement goal theory, learning interaction and online statistics learning outcomes"

You are invited to participate in a research study to investigate relations of online readiness, academic procrastination, statistical self-efficacy, goal-approach orientation, learning interaction and learning outcomes in online statistics learning settings. The study is being conducted by Sangah (Sunny) Lee, and Hyeon Jean Yoo, Ph.D student in Department of Educational Foundations, Leadership and Technology at Auburn University under the direction of Dr. Chih-hsuan Wang, a professor of the Department of Educational Foundations, Leadership, and Technology at Auburn University. You are invited to participate because you over 18 years old and who have been taking statistics course(s) offered from Department of Educational Foundations, Leadership and/or Technology and Department of Mathematics and Statistics at Auburn University in Fall semester 2020.

What will be involved if you participate? Your participation is completely voluntary. If you decide to participate in this research study, you will be asked to click the **"NEXT"** button if you consent to participate in the survey. Your total time commitment will be approximately 20 minutes.

Are there any risks or discomforts? There is no known risk or discomfort associated with this survey. The survey questions focus on your learning experiences in taking online statistics courses.

Will you receive compensation for participating? To thank you for your time you will be entered into a random drawing to win one of the ten $30 Amazon e-Gift Card at the end of the survey. You will be asked to provide your information if you wish to be entered in a drawing to receive a gift certificate. Your information will not be associated with your survey responses.

If you change your mind about participating, you can withdraw at any time by closing your browser. If you choose to withdraw, your data can be withdrawn as long as it is identifiable. Once you've submitted anonymous data, it cannot be withdrawn since it will be unidentifiable. Your decision about whether or not to participate or to stop participating will not jeopardize your future relations with Auburn University, the Department of Educational Foundations, Leadership, and Technology.

Any data obtained in connection with this study will remain anonymous. We will protect your privacy and the data you provide by password protected only via Horizon Auburn VPN software. Information collected through your participation may be published in a professional journal, and/or presented at a professional conference.

If you have questions about this study, please contact Sangah (Sunny) Lee at szl0146@auburn.edu, Hyeon Jean Yoo at hjy0002@auburn.edu or Dr. Chih-hsuan Wang at wangchi@auburn.edu.

If you have questions about your rights as a research participant, you may contact the Auburn University Office of Research Compliance or the Institutional Review Board by phone (334) 844-5966 or e-mail at IRBadmin@auburn.edu or IRBChair@auburn.edu.

Demographics

What is your gender?

- Male

- Female
- Prefer not to say

What is your age?

What is your ethnicity?

- Asian
- African-American
- White/Caucasian
- Hispanic/Latino
- Hawaiian/Pacific Islander
- Other. Please specify

Are you an international student or domestic student?

- International student
- Domestic student

Are you currently taking the online course in the States or in your home country?

- in the United States
- in my home country

Have you taken online courses before?

- Yes
- No

What is your major area? *(STEM-related major indicates that the majors in science, technology, engineering and mathematics, including agriculture, medical and health majors)*

- STEM
- Non-STEM

What is your major?

Which degree level of school are you registered in Fall 2020?

- Undergraduate
- Master's
- PhD

Which Department did you take statistics course from in Fall 2020?

- EFLT (Department of Educational Foundations, Leadership and Technology; e.g. ERMAXXXX..)
- MATH/STAT (Department of Mathematics and Statistics; e.g. STATXXXX)

Think about ONE of the statistical courses you are taking in Fall 2020.
What is the Course Number (e.g., STAT XXXX or ERMA XXXX)?

What is your expected final grade of the course you specified above? (Based on the grade from class activities, participation, Midterm or homework, and so on.)

A	B	C	D	F
O	O	O	O	O

Online Readiness

The following statements will help us understand your **online learning readiness**. Using the scale below (from strongly disagree to strongly agree), please indicate to what extent each of the following items corresponds to you.

All of your responses will be kept anonymous and confidential. There are no right or wrong responses, so please be open and honest.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I feel confident in performing basic functions of Microsoft Office programs (MSWord, MS Excel, MS Power Point)	O	O	O	O	O
I feel confident in my knowledge and skills of how to manage software for online learning	O	O	O	O	O
I feel confident in using the Internet to find information	O	O	O	O	O
I carry out my own study plan while learning online	O	O	O	O	O
I seek assistance when facing learning problems	O	O	O	O	O
I manage my time well while learning online	O	O	O	O	O
I set up my online learning goals	O	O	O	O	O
I have a high expectation for my learning performance	O	O	O	O	O
I can direct my own learning progress while learning online	O	O	O	O	O
I am not distracted by other online activities (WhatsApp, Insta, FB) while learning online	O	O	O	O	O
I repeated the online learning materials based on my needs	O	O	O	O	O
I am open to new ideas when learning online	O	O	O	O	O
I have the motivation to do online learning	O	O	O	O	O

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
While learning online, I improve from my previous mistakes	○	○	○	○	○
I like to share my ideas with ideas others while learning online	○	○	○	○	○
I feel confident in using online tools to communicate with others	○	○	○	○	○
I express my thoughts through online text messages/ posting comments	○	○	○	○	○
I post questions in online discussion	○	○	○	○	○

Procrastination

The following questions assess your **habits and routines** as a student. Please answer the following as they apply to yourself. how much do you, yourself agree to the following statement?

There are no right or wrong responses, so please be open and honest.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
1. I usually allocate time to review and proofread my work.	○	○	○	○	○
2. I put off projects until the last minute.	○	○	○	○	○
3. I have found myself waiting until the day before to start a big project.	○	○	○	○	○
4. I know I should work on schoolwork, but I just don't do it.	○	○	○	○	○

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
5. When working on schoolwork, I usually get distracted by other things.	O	O	O	O	O
6. I waste a lot of time on unimportant things.	O	O	O	O	O
7. I get distracted by other, more fun, things when I am supposed to work on schoolwork.	O	O	O	O	O
8. I concentrate on schoolwork instead of other distractions.	O	O	O	O	O
9. I can't focus on schoolwork or projects for more than an hour until I get distracted.	O	O	O	O	O
10. My attention span for schoolwork is very short.	O	O	O	O	O
11. Tests are meant to be studied for just the night before.	O	O	O	O	O
12. I feel prepared well in advance for most tests.	O	O	O	O	O
13. "Cramming" and last-minute studying is the best way that I study for a big test.	O	O	O	O	O
14. I allocate time so I don't have to "cram" at the end of the semester.	O	O	O	O	O
15. I only study the night before exams.	O	O	O	O	O
16. If an assignment is due at midnight, I will work on it until 11:59.	O	O	O	O	O
17. When given an assignment, I usually put it away and forget about it until it is almost due.	O	O	O	O	O

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
18. Friends usually distract me from schoolwork.	○	○	○	○	○
19. I find myself talking to friends or family instead of working on school work.	○	○	○	○	○
20. On the weekends, I make plans to do homework and projects, but I get distracted and hang out with friends.	○	○	○	○	○
21. I tend to put off things for the next day.	○	○	○	○	○
22. I don't spend much time studying school material until the end of the semester.	○	○	○	○	○
23. I frequently find myself putting important deadlines off.	○	○	○	○	○
24. If I don't understand something, I'll usually wait until the night before a test to figure it out	○	○	○	○	○
25. I read the textbook and look over notes before coming to class and listening to a lecture or teacher	○	○	○	○	○

Achievement Goal

The following statements represent **types of goals** that you may or may not have for this class.
Using the scale to the right of each statement, select the answer that best describes you.
All of your responses will be kept anonymous and confidential. There are no right or wrong responses, so please be open and honest.

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, find 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
It is important to me to perform as well as I possibly can.	○	○	○	○	○	○	○
I want to perform as well as it is possible for me to perform.	○	○	○	○	○	○	○
It is important for me to master all aspects of my performance.	○	○	○	○	○	○	○
I worry that I may not perform as well as I possibly can.	○	○	○	○	○	○	○
Sometimes I'm afraid that I may not perform as well as I'd like.	○	○	○	○	○	○	○
I'm often concerned that I may not perform as well as I can perform.	○	○	○	○	○	○	○
It is important to me to do well compared to others.	○	○	○	○	○	○	○
It is important for me to perform better than others.	○	○	○	○	○	○	○
My goal is to do better than most other performers.	○	○	○	○	○	○	○
I just want to avoid performing worse than others.	○	○	○	○	○	○	○
My goal is to avoid performing worse than everyone else.	○	○	○	○	○	○	○
It is important for me to avoid being one of the worst performers in the group.	○	○	○	○	○	○	○

Stat SE

The following statement relate to your **confidence** in completing the following tasks successfully. Please answer the following as they apply to yourself.

The item scale has 6 possible responses: (1) = no confidence et all, (2) = a little confidence, (3) = a fair amount of confidence, (4) much confidence, (5) = very much confidence, (6) = complete confidence.

	No confidence et all (1)	A little confidence (2)	A fair amount of confidence (3)	Much confidence (4)	Very much confidence (5)	Complete confidence (6)
1.Identify the scale of measurement for a variable.	○	○	○	○	○	○
2.Interpret the probability value(p-value) from a statistical procedure.	○	○	○	○	○	○
3.Identify if a distribution is skewed when given the values of three measures of central tendency.	○	○	○	○	○	○
4.Select the correct statistical procedure to be used to answer a research question.	○	○	○	○	○	○
5.Interpret the results of a statistical procedure in terms of the research question.	○	○	○	○	○	○
6.Identify the factors that influence power.	○	○	○	○	○	○
7.Explain what the value of the standard deviation means in terms of the variable being measured.	○	○	○	○	○	○

The following statement relate to your **confidence** in completing the following tasks successfully. Please answer the following as they apply to yourself.

The item scale has 6 possible responses: (1) = no confidence et all, (2) = a little confidence, (3) = a fair amount of confidence, (4) much confidence, (5) = very much confidence, (6) = complete confidence.

	No confidence et all (1)	A little confidence (2)	A fair amount of confidence (3)	Much confidence (4)	Very much confidence (5)	Complete confidence (6)
8.Distinguish between a Type 1 error and a Type 2 error in hypothesis testing.	○	○	○	○	○	○
9.Explain what the numeric value of the standard error is measuring.	○	○	○	○	○	○
10.Distinguish between the objectives of descriptive versus inferential statistical procedures.	○	○	○	○	○	○
11.Distinguish between the information given by the three measures of central tendency.	○	○	○	○	○	○
12.Distinguish between a population parameter and a sample statistic.	○	○	○	○	○	○
13.Identify when the mean, median, and mode should be used as a measure of central tendency.	○	○	○	○	○	○
14.Explain the difference between a sampling distribution and a population distribution.	○	○	○	○	○	○

Interaction

The following statements will help us understand the **type of interaction** you had in your class.
Using the scale below, indicate to what extent each of the following items presently corresponds to one of the interaction you had in your class.

	No confidence 1	2	3	4	5	6	7	8	Total Confidence 9
30. Selecting reliable and valid instruments	○	○	○	○	○	○	○	○	○
31. Writing statistical computer programs	○	○	○	○	○	○	○	○	○
32. Getting money to help pay for research	○	○	○	○	○	○	○	○	○
33. Operationalizing variables of interest	○	○	○	○	○	○	○	○	○

Satisfaction

The following questions relates to your **satisfaction** with the course you had. Using the scale to the right of each statement, select the answer that best describes you.

There is no right or wrong answer, just respond as best you can.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Overall, I am satisfied with this class.	○	○	○	○	○
This course contributed to my educational development.	○	○	○	○	○
This course contributed to my professional development.	○	○	○	○	○
I am satisfied with the level of interaction that happened in this course.	○	○	○	○	○
In the future, I would be willing to take a fully online course again.	○	○	○	○	○

Gift

Do you want to be entered in a drawing to receive a gift certificate?

Appendix B

Information Letter of the Online Survey for the Study

AUBURN UNIVERSITY

COLLEGE OF EDUCATION

EDUCATIONAL FOUNDATIONS, LEADERSHIP AND TECHNOLOGY

(NOTE: DO NOT AGREE TO PARTICIPATE UNLESS IRB APPROVAL INFORMATION WITH CURRENT DATES HAS BEEN ADDED TO THIS DOCUMENT.)

INFORMATION LETTER
for a Research Study entitled
"Relations of Online readiness, Academic procrastination, Achievement goal theory, learning interaction and online statistics learning outcomes"

You are invited to participate in a research study to investigate relations of online readiness, procrastination, learning factors and learning outcomes in online statistics learning settings. The study is being conducted by Sangah (Sunny) Lee, and Hyeon Jean Yoo, Ph.D students in Department of Educational Foundations, Leadership and Technology at Auburn University under the direction of Dr. Chih-hsuan Wang, a professor of the Department of Educational Foundations, Leadership, and Technology at Auburn University. You are invited to participate because you over 18 years old and who have been taking statistics course(s) offered from Department of Educational Foundations, Leadership and/or Technology and Department of Mathematics and Statistics at Auburn University in Fall semester 2020.

What will be involved if you participate? Your participation is completely voluntary. If you decide to participate in this research study, you will be asked to take an anonymous online survey through Qualtrics and click "NEXT" button if you consent to participate in the survey. Your total time commitment will be approximately 20 minutes.

Are there any risks or discomforts? There is no known risk or discomfort associated with this survey. The survey questions focus on your learning experiences in taking online statistics courses.

Will you receive compensation for participating? To thank you for your time you will be entered into a random drawing to win one of the ten $30 Amazon e-Gift Card at the end of the survey. You will be asked to provide your information if you wish to be entered in a drawing to receive a gift certificate. Your information will not be associated with your survey responses.

 Version Date (date document created): ___11/09/2020__

The Auburn University Institutional Review Board has approved this Document for use from 11/05/2020 to ----------
Protocol # 20-535 EX 2011

If you change your mind about participating, you can withdraw at any time by closing your browser. Once you've submitted anonymous data, it cannot be withdrawn since it will be unidentifiable.   Your decision about whether or not to participate or to stop participating will not jeopardize your future relations with Auburn University, the Department of Educational Foundations, Leadership, and Technology.

Any data obtained in connection with this study will remain anonymous. We will protect your privacy and the data you provide by password protected only via Horizon Auburn VPN software. Information collected through your participation may be published in a professional journal, and/or presented at a professional conference.

If you have questions about this study, please contact Sangah (Sunny) Lee at szl0146@auburn.edu, Hyeon Jean Yoo at hjy0002@auburn.edu or Dr. Chih-hsuan Wang at wangchi@auburn.edu.

If you have questions about your rights as a research participant, you may contact the Auburn University Office of Research Compliance or the Institutional Review Board by phone (334) 844-5966 or e-mail at IRBadmin@auburn.edu or IRBChair@auburn.edu.

HAVING READ THE INFORMATION ABOVE, YOU MUST DECIDE IF YOU WANT TO PARTICIPATE IN THIS RESEARCH PROJECT. IF YOU DECIDE TO PARTICIPATE, PLEASE CLICK ON THE LINK BELOW.
YOU MAY PRINT A COPY OF THIS LETTER TO KEEP.

Sangah (Sunny) Lee   11/16/2020
Investigator   Date

Chih-hsuan Wang   11/16/2020
Faculty Advisor   Date

The Auburn University Institutional Review Board has approved this Document for use from 11/05/2020 to ----------- Protocol # 20-535 EX 2011

Hyeon Jean Yoo   11/16/2020
Co-Investigator   Date

The Auburn University Institutional Review Board has approved this document for use from _________ to ________. Protocol #_______

https://auburn.qualtrics.com/jfe/form/SV_cRV9rfOHqmcsDSB

Version Date (date document created): ___11/09/2020__

2 of 2

Appendix C

Initial E-mail Invitation

E-MAIL INVITATION FOR ON-LINE SURVEY

Dear valued students,

My name is Sangh (Sunny) Lee and I am a graduate student in the Department of Educational Foundations, Leadership and Technology and Department of Mathematics and Statistics at Auburn University. I would like to invite you to participate in my research study to examine the "Relations of Online readiness, Academic procrastination, Achievement goal theory, learning interaction and online statistics learning outcomes." Because you are over 18 years old and who have been taking statistics course(s) offered from Department of Educational Foundations, Leadership and Technology and Department of Mathematics and Statistics at Auburn University in Fall semester 2020, I am inviting you to participate in this research study by completing the attached surveys.

In this study, you will be asked to complete an electronic survey. Your participation in this study is completely voluntary and you are free to withdraw your participation from this study at any time. The following questionnaire will require approximately 20 minutes to complete. Participants may win $30 Amazon Gift Card and those who entirely complete the survey would be part of the draw to win the gift card.

This survey has been approved by the Institutional Review Board of Auburn University. There are no risks associated with participating in this study. The survey collects no identifying information of any respondent. All of the response in the survey will be recorded anonymously.

If you decide to participate in this research study, please click the link below to go the survey and then you will be asked to click "NEXT" button if you consent to participate in the survey.

https://auburn.qualtrics.com/jfe/form/SV_cRV9rfOHqmcsDSB

Thank you for taking the time to assist me in my educational endeavors. The data collected will provide useful information regarding. If you would like a summary copy of this study, please complete and detach the Request for Information Form and return it to me in a separate envelope. Completion and return of the questionnaire will indicate your willingness to participate in this study. If you require additional information or have questions, please contact me at the email address listed below.

If you would like to know more information about this study, an information letter is attached to this email. If you decide to participate after reading the letter, you can access the survey from a link below and

If you have any questions, please contact me at szl0146@aburun.edu or my advisor, Dr. Chih-hsuan Wang, at wangchi@auburn.edu.

Thank you for your consideration,
/sign/

The Auburn University Institutional
Review Board has approved this
Document for use from
11/05/2020 to ------------
Protocol # 20-535 EX 2011

Appendix D

Approved Email from Office of Research Compliance of Auburn University

Lee Approval Exempt Protocol #20-535 EX 2011, "Relations of Online Readiness, Academic Procrastination, Achievement Goal Theory, Learning Interaction, Self-Efficacy and Online Statistics Learning Outcomes"

IRB Administration <irbadmin@auburn.edu>

Wed 12/2/2020 8:13 AM

To: Sunny Lee <szl0146@auburn.edu>

Cc: Chih-hsuan Wang <wangchi@auburn.edu>;James Satterfield <jws0089@auburn.edu>

2 attachments (4 MB)

Investigators Responsibilities rev 1-2011.docx; Lee 20-535 EX 2011 Revisions 2.pdf;

Use IRBsubmit@auburn.edu for protocol related submissions and IRBadmin@auburn.edu for questions and information.
The IRB only accepts forms posted at https://cws.auburn.edu/vpr/compliance/humansubjects/?Forms and submitted electronically.

Dear Sangah,

Your protocol titled "Relations of Online Readiness, Academic Procrastination, Achievement Goal Theory, Learning Interaction, Self-Efficacy and Online Statistics Learning Outcomes" was approved by the AU IRB as "Exempt" under federal regulation 45 CFR 46.101(b)(1,2).

Official notice:
This e-mail serves as notice the protocol has been approved. By accepting this approval, you also accept your responsibilities associated with this approval. Details of your responsibilities are attached. Please print and retain.

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Information Letter:
A copy of your approved protocol is attached. However you still need *to add the following IRB approval information to your information letter(s):* **"The Auburn University Institutional Review Board has approved this document for use from November 5, 2020 to --------- Protocol #20-535 EX 2011, Lee.**

You must use the updated document(s) to consent participants.

Expiration:
Continuing review of this Exempt protocol is not required; however, all modification/revisions to the approved protocol must be reviewed and approved by the IRB.

When you have completed all research activities, have no plans to collect additional data and have destroyed all identifiable information as approved by the IRB, notify Office of the IRB via e-mail. A final report is **not** required for Exempt protocols.

Best wishes for success with your research!

IRB Admin
Office of Research Compliance
Auburn University
115 Ramsay Hall
Auburn, AL 36849