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Motivation and Statistics Anxiety Among Adult Online Learners: The Mediating Role of Self-Regulated Learning

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Dissertation Submitted in Partial Fulfillment

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Abstract

Students who experience statistics anxiety have reported struggling with academic performance, an increase in academic dishonesty, and an aversion to careers or majors that are perceived to rely on statistical skills. Research has suggested that statistics anxiety is related to lower levels of motivation; however, it remains unknown if, or to what extent, self-regulated learning skills, including management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking may play a role in the relationship between motivation and statistics anxiety. This research study relies on the theoretical foundation of social cognitive theory, which proposes that statistics anxiety is a result of the reciprocal relationship between personal, cognitive, behavioral, and environmental influences. The purpose of this quantitative study was to explore the extent to which self-regulated learning strategies mediate the relationship between motivation and statistics anxiety in online higher education students. In this correlational research study, a mediation analysis with multiple linear regressions was used to analyze data collected from an online survey of 158 online graduate students. Most notably, management of time and effort mediated the relationship and reduced statistics anxiety for the sample. Learning strategies that were identified to mediate the relationship have implications for positive social change by influencing the design of statistics curriculum education to reduce statistics anxiety.

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Dedication

I dedicate this to my son, who inspires me daily. Tyler, you live your life with such courage, kindness, and confidence. All the other achievements in my life pale in comparison with the ultimate privilege of being your mom.

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I would like to thank my friends and colleagues who have pushed me, encouraged me, and cheered me through this journey.

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Chapter 1: Introduction to the Study

Introduction

Statistical literacy and quantitative reasoning are crucial 21st century skills desired by employers across industries (Rosen, 2003). In addition to workforce skills, the nature of democracy requires informed citizens with statistical literacy to quickly and critically evaluate a vast amount of information distributed through various mediums (Eshet et al., 2021; MacArthur, 2020; Steinberger et al., 2021). However, in the higher education environment in which students ought to be developing their statistical literacy, students report high levels of anxiety in statistics courses (Cui et al., 2019; Johannssen et al., 2021; Yoon & Lee, 2022). Students with statistics anxiety perceive statistics as having little value (Songsore & White, 2018), avoid careers that are associated with math or statistics (Bourne & Nesbit, 2018), and struggle with performance in statistics courses (DeVaney, 2010). Non-traditional students also reportedly struggle more than their traditional counterparts (Jameson & Fusco, 2014; Ryan & Fitzmaurice, 2017).

Statistics anxiety is the fear or apprehension an individual experiences when collecting, analyzing, or interpreting statistical information (Cruise et al., 1985). Research suggests that no one is immune from this anxiety, which impacts individuals of all ages, genders, and education levels (Barroso et al., 2021; Cui et al., 2019). The impact of statistics anxiety includes both academic and non-academic consequences, but research suggests that statistics anxiety may impact academic performance in undergraduate and graduate students (Zekeri et al., 2019; Zimmerman & Johnson, 2017). In addition to academic consequences, students who report statistics anxiety may also be more likely to engage in academic dishonesty or other ethical violations within the classroom (Eshet et al., 2021; Steinberger et al., 2021). Finally, statistics anxiety has been associated with negative attitudes towards statistics (Sandoz et al., 2017). These negative perceptions may cause some students to pursue majors and career fields that they perceive to require less statistical material (Beilock & Maloney, 2015; Songsore & White, 2018).

To resolve statistics anxiety for students, it is crucial to identify the contributing factors that cause anxiety. By identifying the variables that may contribute to students developing statistics anxiety, online institutions may be able to address these issues within the design of their online statistics courses. When students are no longer burdened with statistics anxiety, they may perform better in their statistics courses, increase their quantitative literacy, and follow STEM career paths.

The study sought to determine the extent to which self-regulated learning strategies, specifically management of time and effort, simple or complex cognitive strategy use, contact with others, and academic thinking mediate the relationship between motivation and statistics anxiety in graduate students completing their program online. The results of this study add value to the field by identifying behavioral strategies that reduce statistics anxiety and can be integrated into the statistics curriculum in higher education.

This chapter will summarize the current state of the literature on statistics anxiety, identify the problem or gap that this study sought to resolve, and articulate the purpose and research question that guided the study. Also, I will discuss the theoretical foundation that provides a framework for the study. Finally, I will articulate the study's operational definitions, assumptions, scope, and limitations.

Background

Online graduate students are considered non-traditional students. They are generally older, typically 24 years old or older, and are more likely to work full-time, have a partner or children, and have different financial considerations than traditional, on-campus students (National Center for Education Statistics, n.d.). Non-traditional students report higher levels of anxiety and lower self-efficacy levels than traditional students (Jameson & Fusco, 2014; Ryan & Fitzmaurice, 2017). Their grades are also more likely to suffer as non-traditional students succeed in statistics courses at lower rates than traditional students (Hedges, 2017). Research has explored the relationship of certain predictive variables or antecedents of statistics anxiety, such as motivation, self-efficacy, goal orientation, and self-regulated learning strategies (Cui et al., 2019).

Cruise et al. (1985) were the first to differentiate statistics anxiety from math anxiety. Whereas math anxiety is associated with computation and math reasoning skills, statistics anxiety also includes fear or apprehension regarding the interpretation and recognition of statistical material (Bourne, 2018). Paechter et al. (2017) explain that statistics anxiety is more closely related to verbal reasoning skills than mathematical skills. Statistics anxiety is also domain-specific anxiety, which differentiates it from general anxiety (Ramos Salazar, 2018).

The consequences of statistics anxiety include both academic performance and non-performance issues. Research has suggested that students who report higher levels of statistics anxiety have lower success rates in statistics courses compared to those students with lower levels of anxiety (Paechter et al., 2017; Zekeri et al., 2019; Zimmerman & Johnson, 2017). In addition to potential performance concerns, students who report statistics anxiety also report a higher likelihood of engaging in academic dishonesty (Eshet et al., 2021; Steinberger et al., 2021). Students with statistics anxiety are more likely to cheat or plagiarize than students without reported statistics anxiety.

Whereas research has demonstrated several potential consequences of statistics anxiety, the exact cause of statistics anxiety has not yet been determined. Research has indicated several potential relationships with variables such as gender (Ediriossoriya & Lipscomb, 2021) and age (Heretick & Tanguma, 2021). In their review, Cui et al. (2019) categorize the antecedents of statistics anxiety as situational, dispositional, and cognitive. Examples of situational factors include the classroom or learning environment. Research in this area has explored the potential influence of online education and instructor presence. Additional environmental influences include family support and additional academic support.

Research on cognitive elements of statistics anxiety focuses on aspects of cognitive processing, using fMRI and other techniques to explore the biological activity in the brain that may explain the root cause of statistics anxiety. Findings in this area have identified potential activity or activation in areas such as the amygdala that may explain the source of statistics anxiety (Pizzie et al., 2020). Examples of dispositional factors include individual personality, attitude, and motivation. A considerable amount of research has focused on this area. The dominant research design is correlational and has identified variables related to statistics anxiety, including motivation, achievement orientation, personality style, time management, self-regulated learning strategies, self-efficacy, and prior experience. However, few research studies extend this design and explore potential mediating factors that may explain the relationship between a dispositional variable and statistics anxiety.

This study is needed because a gap remains within the research about the potential mediating variables that explain statistics anxiety. Research has amassed quite a list of situational and dispositional factors that relate to statistics anxiety; however, underlying causal mechanisms have yet to be reported. This study adds value to the field by identifying the potential mediating effect of self-regulated learning strategies, including management of time and effort, simple and complex cognitive strategy use, contact with others, and academic thinking.

Problem Statement

Research in education and psychology has yet to determine precisely how statistics anxiety is caused. Without this clear understanding of the underlying mechanisms that precipitate this domain-specific anxiety, research has been unable to identify evidence-based strategies to mitigate the potential adverse side effects of statistics anxiety (Hegman & Elmi, 2021, Zimmerman & Austin, 2018). As previously stated, statistics anxiety is often bred from, or directly results, in a lower perceived value of statistics (Bourne and Nesbit, 2018, Songsore & White, 2018). This negative view of statistics leads to fewer individuals pursuing career fields that rely on collecting and interpreting statistical data (González et al., 2016). In addition, a negative attitude toward statistics and general anxiety associated with statistics are likely to undermine students' statistical literacy. Low statistical literacy directly impacts the students’ ability to critically evaluate information presented in educational settings, business environments, and even news outlets.

Recent research regarding statistics anxiety has identified certain predictive relationships, including personality traits (Chew & Dillon, 2014; Steinberger et al., 2021), gender (Condron et al., 2018; Edirisooriya & Lipscomb, 2021; Hedges, 2017; MacArthur, 2020; Ralston et al., 2016; Salehi et al., 2019; Zekeri et al., 2019), math experience or ability (Faber & Drexler, 2019; Khasawneh et al., 2021; Ralston, 2020), and self-efficacy (Abdous, 2019; Hoegler & Nelson, 2018; Palestro & Jameson., 2020; Ramos Salazar, 2018). However, the research remains unclear on the exact mechanisms that cause the direct effect between the predictive variables and statistics anxiety. In addition, research has not explored how these predictive variables may mediate one another regarding the relationship with statistics anxiety in the online learning environment. A study by Leenknecht et al. (2019) found that deeper cognitive learning strategies mediate the relationship between motivation and the student’s likelihood to seek feedback. These results suggest that self-regulated learning strategies may play a role in students’ motivation and behavior; however, there remains a gap in the literature exploring the role of self-regulated learning strategies on the relationship between motivation and statistics anxiety.

Purpose of the Study

The purpose of this quantitative study was to explore the extent to which self-regulated learning strategies mediate the relationship between motivation and statistics anxiety in online higher education students. The independent variable was motivation, measured using the scores from the Motivated Strategies for Learning Questionnaire (MSLQ) subscales of intrinsic goal orientation, task value, and self-efficacy for learning and performance. The dependent variable was statistics anxiety, which was measured using the Statistics Anxiety Rating Scale (STARS). The mediator variables are five specific self-regulated strategies for learning, which are represented by the scores on the subscales from the Part B of the MSLQ (B), including management of time and effort, simple cognitive strategy use, complex cognitive strategy use, contacts with others, and academic thinking.

Research Questions and Hypotheses

RQ1: To what extent do self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) mediate the relationship between intrinsic goal orientation and statistics anxiety in adult students in online learning environments?

RQ2: To what extent do self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) mediate the relationship between self-efficacy and statistics anxiety in adult students in online learning environments?

$H2_0$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do not significantly mediate the relationship between self-efficacy and statistics anxiety in adult students in online learning environments.

$H2_1$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do significantly mediate the relationship between self-efficacy and statistics anxiety in adult students in online learning environments.

RQ3: To what extent do self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) mediate the relationship between task value and statistics anxiety in adult students in online learning environments?

$H3_0$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do not significantly mediate the relationship between task value and statistics anxiety in adult students in online learning environments.

$H3_1$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do significantly mediate the relationship between task value and statistics anxiety in adult students in online learning environments.

Theoretical Framework

The theoretical framework that supports this research is social cognitive theory (SCT) (Bandura, 1978). SCT explains individual behavior as the product of both internal psychological forces and external environmental influences (Bandura, 1991). A fundamental construct of SCT is reciprocal determinism, which highlights the reinforcing effects of cognitive, behavioral, and environmental influences. As opposed to theories of behaviorism, SCT proposes that an individual is an active agent in shaping their behavior. This principle is known as self-regulation, which refers to an individual's active involvement in their learning, including cognitive, motivational, and behavioral engagement (Zimmerman, 1989). This theory provides the framework to explore possible cognitive, behavioral, or environmental variables that may influence statistics anxiety in adult online students. The framework of SCT relates to the research question, which explores how cognitive and behavioral variables influence the response of statistics anxiety.

As I will review in more detail in Chapter 2, research regarding statistics anxiety has focused on one, or perhaps two, of the areas of self-regulation at a time. Whereas other research studies on the phenomenon of statistics anxiety have explored individual elements of self-regulated learning, I proposed a mediating model to explore the causal effect of specific self-regulated learning strategies on the relationship between motivation and statistics anxiety. This allowed me to expand on research focused on the personal factors of motivation, self-efficacy, and task value by incorporating other areas of self-regulation, including cognition and behavioral strategies that may influence the relationship with statistics anxiety.

Nature of the Study

The nature of this quantitative study was a correlational mediating model exploring the influence of self-regulated learning strategies, specifically management of time and effort, complex and simple cognitive strategy use, contact with others, and academic thinking, between the relationship between motivation and statistics anxiety. This approach aimed to identify the effect these self-regulated learning strategies have on motivation and statistics anxiety in adult students in online higher education. Identifying causal mechanisms can be challenging because there are often multiple variables that contribute to the state of anxiety; however, mediation analysis is one research design that provides a method for examining the effect or contribution of a third variable (Hayes, 2009). The independent variable was motivation and the dependent variable was statistics anxiety. The mediating variable was self-regulated learning strategies, including management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking. A correlational design is also the most appropriate design when the nature of the research question is to explore a relationship between variables. An experimental approach, which involves the manipulation of the independent variable, is not a fit because it would not be appropriate or ethical to alter the students' level of motivation. In addition, a qualitative study would not be a match for this question as there was no intent to gather data regarding participants' subjective experiences, narratives, or perspectives through interviews or observations. Therefore, a non-experimental correlational design was the most appropriate research design. (Hayes, 2009).

I employed a convenience sample to gather data from participants by posting an advertisement on social media sites such as Facebook and LinkedIn. The advertisement included a brief overview of the project and participant efforts and a link to the questionnaire, which consisted of informed consent, demographic questions, and a survey with questions from validated instruments. Motivation was measured using three subscales of the motivation scale from the MSLQ, including intrinsic goal orientation, task value, and self-efficacy for learning and performance (Pintrich et al., 1991). Learning strategies were measured using the MSLQ-B (Meijs et al., 2019). The MSLQ-B includes five subscales: management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking. Statistics anxiety was measured using the STARS (Cruise et al., 1985). The STARS includes five subscales: test and class anxiety, interpretation anxiety, worth of statistics, computational self-concept, fear of statistics teachers, and fear of asking for help. Data was analyzed using a series of linear regressions through the PROCESS macro available in the data analytics program Statistical Package for Social Sciences (SPSS) (Hayes, 2009), and through percentile-based bootstrapping the confidence interval was set at 95%.

Definitions

The following terms are used throughout this research study:

Academic thinking: The critical thinking and critical reading strategies that a student employs in their academic courses to connect new course content with prior knowledge (Meijs et al., 2019)

Adult student: The adult student, also known as a non-traditional student, meets at least one of the following criteria: generally older than 24 years old, works more than 30 hours per week, has a family or other dependents, relies on financial aid, and is more likely to have a non-traditional path to college entrance such as a GED (National Center for Education Statistics, 2019).

Complex cognitive strategy use: Self-regulated learning strategies such as elaboration and organization, are related to deeper learning (Meijs et al., 2019).

Computational self-concept: An individual's perception of their ability to perform mathematical computations necessary in statistical analysis (Cruise et al., 1985).

Contacts with others: Reaching out to peers or professors for support or with questions (Meijs et al., 2019). This interaction looks different in online education as compared to traditional face-to-face learning environments. Adult students in online learning environments report they are less like to reach out to others (Meijs et al., 2019).

Control beliefs: The belief that the outcome is dependent on the effort one puts into the learning activity, and not external factors such as a teacher (Pintrich et al., 1991).

Extrinsic goal orientation: The student's goals for the learning activity are externally motivated, including performance, grades, or comparing themselves to other students (Pintrich et al., 1991).

Fear of asking for help: Anxiety associated with reaching out to others for help in understanding statistics material (Cruise et al., 1985).

Fear of statistics teachers: Anxiety is associated with the student's perception of statistics teachers, particularly a perceived lack of empathy and rapport (Cruise et al., 1985).

Interpretation anxiety: Anxiety is associated with the interpretation of statistical content, specifically identifying the appropriate statistical tests to perform and interpreting the conclusions in a real-world and meaningful way (Cruise et al., 1985).

Intrinsic goal orientation: The student's goals for the learning activity are internally motivated by a number of things, including content mastery, curiosity, and challenge (Pintrich et al., 1991).

Management of time and effort: Strategies the adult student uses to prioritize competing priorities such as work, family, and school, as well as the moderation of energy to study (Meijs et al., 2019).

Motivation: "The processes that instigate and sustain goal-directed activities [… specifically] internal (personal) processes that manifest themselves overtly in goal-directed actions" (Schunk & DiBenedetto, 2020, p. 1).

Self-efficacy for learning and performance: An individual's perception of their ability to succeed at a learning task (Pintrich et al., 1991).

Self-regulated learning strategies: "Learning strategies that can be used during studying are cognitive information processing strategies, active study strategies, support strategies, and metacognitive strategies…reflect actions learners undertake to make their learning more effective and to facilitate their knowledge acquisition and comprehension" (Meijs et al., 2019, p. 1).

Simple cognitive strategy use: Basic or surface learning strategies such as rehearsal or recitation by which the information is memorized but is not associated with prior knowledge, and therefore is not likely to be transferred to long-term memory (Meijs et al., 2019).

Statistics anxiety: "The feelings of anxiety encountered when taking a statistics course or when doing statistical analyses; that is, gathering, processing and interpreting data" (Cruise et al., 1985, p. 92).

Task value: The perception that the task itself is valuable and worthwhile (Pintrich et al., 1991).

*Test and class anxiety: "*Anxiety when enrolling in, doing course work or taking an exam in a statistics course" (Cruise et al., 1985, p. 93).

Test anxiety: A student's worry or fear about taking a test may negatively impact their performance on the test (Pintrich et al., 1991).

Worth of statistics: A student's negative attitude about the relevance of statistics in everyday life or in their professional role (Cruise et al., 1985).

Assumptions

The first assumption was that the participants were truthful and honest in their responses to the self-report tools. The information gathered from self-report instruments is only as good as the ability to have accurate self-perceptions on the part of the participants. This has been a challenge in motivational science research, which largely relies on self-report measures (Cook & Artino, 2016). An alternative method to gather data on the variables of motivation and learning strategies would be observation; however, this approach presents other significant limitations, including time, cost, and reliability. Cook and Artino (2016) recommend researchers use self-report instruments that align with the research question and measure theoretically aligned outcomes. The extensive literature on my proposed instruments, MSLQ and STARS, helped reduce the risks of a misaligned self-report measure.

The second assumption was that the statistical model selected was appropriate to the research design. Hayes (2022) explains the mediating model as an exploration to uncover the underlying mechanisms that influence an existing relationship; however, the assumptions of the mediating model require that a theoretical relationship exists between the independent and dependent variables. There is support in the literature for a relationship between decreased motivation and statistics anxiety (Lavasani et al., 2014; Lou et al., 2021, Neroni et al., 2018).

Scope and Delimitations

The scope of this study was limited to individual factors such as motivation, self-regulated learning strategies and statistics anxiety. This research study did not explore samples of specific classes or institutions. This research study also did not explore potential external variables such as instructor presence or rapport, the academic rigor of the statistics curriculum, or a comparison between face-to-face and online students. The boundary of this study was the exploration of individual dispositional variables. Also, this study did not explore potential results of statistics anxiety, including academic performance, academic integrity, or academic persistence. Whereas these are important consequences to consider, they were not within the scope of this research problem and were out of scope for this research study.

Finally, the scope of this research study was focused on the population of online graduate students. Although it is clear from the research that statistics anxiety may be present across multiple student populations, this research study focused on online graduate students. Online graduate students are more likely to have taken more statistics courses than undergraduate courses, which likely yields more experience with statistics from which the participants may draw while completing the survey.

Limitations

The first potential limitation was the instruments used to gather data. The internal and construct validity of the study would be compromised if the instruments are not reliable and valid. The MSLQ has been extensively used in the literature with higher education students. The validity, as reported by Cronbach's alpha, is regularly in the medium to high range (Khampirat, 2021; Maun et al., 2020; Meijs et al., 2019; Neroni et al., 2019). The STARS is the most common instrument used to measure statistics anxiety, and confirmatory factor analysis and reviews of reliability and validity also report medium to high Cronbach's alpha results (Chew et al., 2018; DeVaney, 2016; Frey-Clark et al., 2019; Nesbit & Bourne, 2018; Nielsen & Kreiner, 2018).

The second potential limitation in this study was the presence of confounding variables. This study did not isolate all potential confounding variables that may play a role in the relationship between motivation and statistics anxiety. Whereas this research study focused on the role of self-regulated learning strategies, it is conceivable that there may be additional mediating variables that have an indirect or direct effect on this relationship. One strategy to mitigate this threat was to gather data regarding individual factors that may play a role, including education level, gender identity, age, and the number of statistics courses taken. This allowed me to control for these variables when analyzing the data.

The third potential limitation was researcher bias. As a practitioner in higher education, I recognized I have a natural bias that accepts statistics anxiety as a true construct. This has the possibility to negatively influence the interpretation of the results, which ultimately impacts the generalizability of the research study; however, the nature and design of this study were not to validate the reality of statistics anxiety, but rather to explore additional mediating factors that may also attribute to online graduate students' self-reported levels of anxiety.

Significance of the Study

The significance of the study to advance knowledge in this discipline was to identify the role that self-regulated learning strategies may play in statistics anxiety among online graduate students. The research design may begin to highlight potential causal mechanisms that may explain the presence of statistics anxiety. Understanding the causal mechanisms will allow educators to design strategies to reduce or mitigate statistics anxiety.

This study was also significant in understanding certain malleable cognitive and behavioral factors that play a role in statistics anxiety will allow educators to design and integrate interventions into the course curriculum that may positively affect statistics anxiety. This study aimed to identify specific, self-regulated learning strategies that may increase motivation and decrease statistics anxiety in adults enrolled in online higher education programs. Incorporating these strategies in higher education statistics courses may increase the success and confidence of adult students in online programs.

This study has potential implications for positive social change by leading to increased success in statistics courses, increasing quantitative literacy, and creating critical consumers of research. Students with lower statistics anxiety are more willing to engage in statistical interpretation in their professional and personal lives (Sandoz et al., 2017). Finally, reducing statistics anxiety in adult students may encourage more students to pursue STEM fields, increasing the workforce in areas such as psychology, engineering, cybersecurity, and more.

Summary

The purpose of this chapter was to outline the research problem and purpose for the proposed research study. Statistics anxiety has been noted in the research to be a concern for students in higher education. Fear and apprehension of statistical data and interpretation results in decreased willingness to engage with statistics and a lower perception of the value of statistics. The result of this is an aversion to anything to do with statistics, including critically evaluating data and research studies, as well as an aversion to career fields that rely on statistics. Prior research has indicated a relationship between decreased motivation and statistics anxiety. The purpose of this research study was to explore the role of self-regulated learning strategies, including management of time and effort, complex and simple cognitive strategy use, contact with others, and academic thinking on the relationship between motivation and statistics anxiety.

In this chapter, I also discussed the nature of the study, assumptions that may impact the generalizability of the study, potential limitations and mitigation strategies, and defined the scope of the research study. In Chapter 2, I will discuss the theoretical framework that supports this research study. I will also provide a literature review of this study's key variables, including motivation, statistics anxiety, and self-regulated learning strategies.

Chapter 2: Literature Review

Introduction

For decades, researchers in education and psychology have explored the phenomenon of statistics anxiety. Researchers and practitioners alike have witnessed the fear, anxiety, trepidation, and apprehension of students caused by statistics, particularly those in social sciences such as education, psychology, and sociology (Puklek & Cukon, 2020). The purpose of this quantitative study is to explore the extent to which self-regulated learning strategies mediate the relationship between motivation and statistics anxiety in online higher education students.

Statistics anxiety is defined as "the feelings of anxiety encountered when taking a statistics course or when doing statistical analyses; that is, gathering, processing and interpreting data" (Cruise et al., 1985, p. 92). The root cause of statistics anxiety is layered and multi-faceted, but research has indicated that variables such as gender, instructor presence, motivation, and self-concept play an important role in developing statistics anxiety. In this chapter, I present a literature search strategy, theoretical foundation, and a literature review of key variables in statistics anxiety.

Literature Search Strategy

The literature search strategy leveraged several scholarly databases, including Education Source, APA PsycInfo, ScienceDirect, and SAGE databases. The search was limited to peer-reviewed scholarly journals. The keywords used for primary searches included *statistics anxiety* (1,471 results), *statistics anxiety* and *college* or *university* or *higher education* or *post-secondary education* (1,017 results), and the previous keywords combined with *adult learners* or *adult students* or *non-traditional* students or *nontraditional students* (5 results). I further refined the search criteria by using variations of the previous keywords and additional search terms such as *self-regulation, learning strategies,* and *anxiety*. Search results were narrowed by focusing on results from 2016 to 2021. Most of the sources utilized in the literature review were between these years, with the exception of seminal works on relevant theories and foundational research on key variables.

Theoretical Foundation

Social Cognitive Theory

Social cognitive theory (SCT) has been applied in many areas of education and psychology. Bandura (1978), a pioneer of SCT, conceptualized that human behavior is the result of cognitive, behavioral, and environmental influences. SCT was developed in the 1970s as a response to the theories of behaviorism that were popular at that time. Behaviorist theories posit that behavior is the product of various reinforcements and rewards. Bandura saw behaviorist theories as flawed because their principles positioned the individual as a helpless reactive organism shaped only by reinforcements (Cook & Artino, 2016). Bandura acknowledged that the environment is an influential factor in human behavior; however, he asserted that how an individual thinks (cognition) influences how they perceive their environment and how they act as a result (behavior) (Cook & Artino, 2016). The purpose of this research study is to explore how certain cognitive and behavioral strategies may influence statistics anxiety in online graduate students. This makes SCT a logical choice for this research study.

Reciprocal Determinism

One of the key constructs of SCT is the principle of reciprocal determinism, also referred to as reciprocal causation or triarchic causality. According to Bandura (1978), human behavior can best be explained by the confluence of cognitive (or personal, behavioral, and environmental influences. These three distinct areas of influence create a cyclical reinforcement structure such that they each exert influence over one another. They cannot operate in isolation; rather, human behavior is the sum of all these individual parts (Bandura, 1978). In a succinct summary by the founding scholar, Bandura (2018) explained, “Social cognitive theory acknowledges that human behavior is socially situated, discriminatively contextualized, and conditionally manifested” (p. 134). When statistics anxiety is viewed through the lens of SCT, it is situated as a personal factor and as such, has an influence over a student’s behaviors both in and out of the classroom. Their anxiety influences their behaviors just as much as their behaviors may influence their anxiety. Jameson (2020) used SCT as the framework for their qualitative inquiry, which explored the impact of math anxiety on five female adult students. Their analysis revealed that the environmental support the student received from teachers or family members positively influenced their math anxiety, whereas the student’s perceptions of their own math abilities negatively influenced their math anxiety. This evaluation of personal ability, known as self-efficacy, is another core tenant of SCT.

Self-Efficacy

Bandura asserted that individuals' actions are a direct result of how they perceive their environment and their thoughts regarding that environment. A crucial part of Bandura's theory is the individual perception of one's ability to succeed. Bandura developed the term self-efficacy, which is "the belief in one's capabilities to organize and execute desired actions and to successfully produce desired results" (Drysdale & McBeath, 2018, p. 480). Self-efficacy is highly correlated with motivation because the higher someone's perceived ability in a task, the more effort and interest they put in attaining goals or activities related to the task (Bandura, 1989). Palestro and Jameson (2020) applied SCT to their research on math anxiety and found that domain-specific self-efficacy influenced the relationship between anxiety and performance. An individual's level of self-efficacy influences the specific strategies or behaviors that an individual deploys (Schunk & DiBenedetto, 2020). These strategies are referred to as self-regulating strategies; and when viewed in an academic context, they are referred to as self-regulated learning strategies.

Self-Regulated Learning

Zimmerman's (1989) approach to self-regulated learning, the extent to which a student is metacognitively, motivationally, and beahviorally engaged or active in their learning, was derived from SCT (Panadaro, 2017; Pintrich, 2000; Schunk & DiBenedetto, 2020; Zimmerman, 1989). This concept aligns philosophically with the guiding principles of SCT in that individuals are not helpless victims of their environment but, instead, play a role in shaping their outcomes (Cook & Artino, 2016). Zimmerman (1989) proposed that a student's degree of self-regulated learning is the result of the triadic influences of personal, behavioral, and environmental factors. Zimmerman's conceptual framework operationalized SCT and highlighted the importance of motivation as a driving force in learning (Cook & Artino, 2016; Schunk & DiBenedetto, 2020). Given the reciprocal nature of these factors and how closely related they are, research rooted in the social cognitive lens of self-regulated learning should examine them together and not in isolation (Kim et al., 2020).

There has been considerable research in cognitive psychology to explore how motivation and self-regulated learning influence academic outcomes. Baloglu et al. (2017) explored the relationship between motivational beliefs and statistics anxiety in undergraduate students. Drawing from goal orientation theory and expectancy-value theory, the authors identify several latent variables representing motivational beliefs, including intrinsic goal orientation, extrinsic goal orientation, task value, control of beliefs, and self-efficacy. Several constructs pointed to statistics anxiety, including the worth of statistics, interpretation anxiety, test/class anxiety, computational self-concept, and fear of asking for help. Data was collected from 305 traditional university students in Turkey using the STARS and the MSLQ. A canonical correlation analysis was used to analyze the six statistics anxiety subscales and their relationship to the motivational belief variables. The results suggest that students with higher task values report lower levels of statistics anxiety. Students who perceive statistics to be valuable and useful are more likely to have a favorable view of statistics, and therefore, have lower anxiety when working with statistics in class or professional settings.

Although research has focused on how motivation enhances or alters the selected self-regulated learning strategies a student may deploy, very little research was found that explores how self-regulated learning strategies may alter motivation (Pintrich, 2003). The goal of this research study is to build on the theory of SCT by exploring this gap in the literature. Students who are highly motivated will select effective self-regulatory behavioral strategies, which in turn, will likely increase the student's motivation (Bartels et al., 2017; Schunk & DiBenedetto, 2020). Understanding the specific strategies that students might use to succeed in statistics education would assist educators to devise a curriculum to incorporate these strategies (Raza et al., 2021). Understanding the relationships between motivation, self-regulated learning, and statistics anxiety may be a key to identifying strategies that will help online students overcome the unique barriers they face, including technology complications and competing priorities (Bruso et al., 2020). Strategies that help students decrease their statistics anxiety may lead to higher levels of success in statistics courses, leading overall to a decrease in avoidance of general quantitative subject areas.

Literature Review

Statistics Anxiety

As stated previously, statistics anxiety has been defined as the fear, worry, or otherwise negative reaction a student has when confronted with statistical data, including identification, computation, and interpretation (Cruise et al., 1985). According to SCT, the negative reactions associated with anxiety are likely to undermine self-efficacy, which decreases motivation and inhibits learning (Bandura, 1989). The theoretical assumption is that these negative feelings classified here as statistics anxiety interfere with student learning, thus resulting in academic and non-academic consequences (Cui et al., 2019; Puklek & Cukon, 2020).

Whereas it is quite similar to feelings of math anxiety, the concept of statistics anxiety may be broader (Barroso & Ganley, 2021; Cruise et al., 1985; Paechter, 2017). Math anxiety focuses on the computational aspects of the core arithmetic functions; however, statistics anxiety encompasses both the mathematical component and interpretation of the data (Puklek & Cukon, 2020). The impact of statistics anxiety may include negative feelings, academic difficulties, and potential avoidance of all subjects or topics associated with statistics.

Consequences of Statistics Anxiety

Online students report higher levels of anxiety than their face-to-face counterparts (DeVaney, 2010; Hedges, 2017; Zimmerman & Austin, 2018). Students enrolled in online learning environments are often considered adult or nontraditional students (Morin et al., 2019). These students are often enrolled part-time, and many have full-time jobs, families, and financial burdens (Cotton et al., 2017). These additional constraints present barriers for adult students to be successful in higher education (Ellis, 2019; Ellis, 2020; Osam et al., 2017). The research that focuses specifically on adult online students with statistics anxiety is limited; however, Heretick and Tanguma (2020) explored the difference in attitudes and anxieties regarding statistics based on age. They focus on nontraditional students and divide them into two age groups: younger students (ages 26 to 49 years old) and older students (50 years or older). Data is collected using the Attitudes Toward Research (ATR) scale and the STARS. There are five subscales on the ATR that focus on attitudes and anxieties. There are six subscales on the STARS that also assess attitudes and anxieties. These instruments, along with a demographic questionnaire, were administered to 92 students. The sample included undergraduate, graduate, and doctorate students, as well as online, face-to-face, or a combination of class delivery methods. The sample also had a range of prior research experience. This is important to note because it indicates a slightly different sample than what is often used in statistics anxiety research, which skews younger and is more often undergraduate students. Using the data from the STARS, the younger group reported statistically significant higher levels of anxiety and lower levels of positive attitudes toward statistics. Compared to the data gathered from the ATR scale, the older students had more positive attitudes towards research. Additional research is necessary to understand these differences further.

The selection of positive study strategies may also temper adult students' anxiety. Wong and Chiu (2019) interviewed 30 high-achieving, non-traditional students in higher education programs that experience an increase in barriers and obstacles compared to other students, and yet still receive high academic marks. Using a social constructionist framework, the authors explored personal and academic identity construction. They conducted interviews with each of the participants. They identified several themes from their analysis, including the selection and implementation of successful study strategies. The authors concluded that self-regulated learning strategies were a key differentiator for high-achieving nontraditional students in online education.

In addition to persistence, research in this area has been split regarding the impact of statistics anxiety on overall academic performance. Several research studies have suggested that there is a relationship between statistics anxiety and academic success. In a meta-analysis of 49 articles studying math anxiety in all ages, Zhang et al. (2019) reported the overall mean effect size was -0.3, which suggests that students with math anxiety do have poorer math performance; however, the effect size is small. This is supported by other research studies that have found little to no impact on course performance (Bourne, 2018; MacArthur, 2020; Paechter et al., 2017).

Zimmerman and Johnson (2017) studied 353 undergraduate students and gathered dating using the Goals and Outcomes Associated with learning Statistics (GOALS) and the STARS. Using a MANOVA, they found no statistically significant difference on any of the STARS subscales between the students who did and did not successfully complete the course. In their review of the literature, Ralston et al. (2016) agreed that the consensus on the effect of statistics anxiety on academic performance is inconclusive; they further argued that perhaps an appropriate degree of statistics anxiety may improve academic performance. MacArthur (2020) conducted a pre-and post-test analysis on 113 university students and found that any change in statistics anxiety was not a predictor of their overall exam performance. MacArthur (2020) cautioned against over diagnosing statistics anxiety and encouraged researchers to identify risk factors that contribute to performance. In a path analysis with 72 undergraduate psychology students, Hoegler and Nelson (2017) found no direct effect of statistics anxiety on exam performance; however, they did find that statistics anxiety had an indirect effect on performance by way of its influence on self-efficacy. Whereas the research is inconclusive regarding the clear negative impact of statistics anxiety on academic success, research suggests that statistics anxiety may have other non-academic consequences.

Although the research on academic consequences remains unclear, statistics anxiety introduces additional pressure that may negatively impact students' decision-making (Eshet et al., 2021). Increased anxiety has been attributed to an elevation of unethical academic behavior (Eshet et al., 2021). Steinberger et al. (2021) found that students suffering from statistics anxiety, combined with the added pressure from COVID-19, were more likely to engage in unethical behavior in the classroom. Students in classes that immediately shifted to online delivery in the wake of the COVID pandemic experienced higher levels of anxiety and a higher propensity towards unethical academic behaviors (Steinberger et al., 2021). In addition to the evidence of non-academic consequences, these findings present evidence that environmental influences contribute to statistics anxiety, which is consistent with SCT and reciprocal determinism.

Finally, statistics anxiety and negative attitudes about statistics may discourage students from entering STEM majors and careers (Beilock & Maloney, 2015). Bourne and Nesbit (2018) surveyed 41 high-school seniors and found that students with higher levels of statistics anxiety were less likely to pursue psychology as their major. Their hierarchical logistic regression identified that a favorable view of the worth of statistics was a statistically significant predictor of a student's intention to pursue a major in psychology (Bourne and Nesbit, 2018). Students in social majors, such as teaching, psychology, and sociology, report higher levels of statistics anxiety than students in STEM programs (González et al., 2016). The consequence of statistics anxiety and low confidence may cause students to think they will not be successful in majors or career fields that require statistics.

Causes of Statistics Anxiety

In a literature review focused on statistics anxiety, Cui et al. (2019) classified the potential causes of statistics anxiety into three themes: situational, dispositional, and cognitive. These three areas can also be related to the three areas of influence in SCT. Situational antecedents are environmental influences such as course delivery and instructor influence. Dispositional themes include individual attitudes such as motivation, experience, and self-efficacy. The cognitive category of antecedents, which Bandura might classify as behavioral, includes individual behaviors, choices, or actions that a student makes as an agent in their learning. The following sections of this literature review will focus on detailing the relevant research in each of these three areas.

Situational Antecedents

The classroom setting is a key environmental factor that influences students' levels of anxiety. Students in online statistics courses have been found to withdraw at a higher rate compared to face-to-face students. In a quasi-experimental study, Hedges (2017) explored the difference in student performance and anxiety in students enrolled in face-to-face and online statistics courses. The author also explored variability in gender, class status, and program of study. The dependent variables were persistence, performance, and anxiety. Persistence includes students who officially withdraw from the course and unofficially withdraw by nonparticipation. Performance was measured using points earned out of a possible 60 possible points during the course, broken down by homework points, quiz points, and exam points. Statistics anxiety was measured using five of the six subscales of the STARS instrument. The study included a sample of 152 undergraduate students (71 online students, 71 face-to-face students). A statistically significant difference was identified in withdrawal rates, suggesting that online students have lower persistence than face-to-face students. A statistically significant difference was found in homework points earned by the delivery method, suggesting that online students performed better in the course than face-to-face students. There was no significant difference in quiz and exam points earned. The Test & Class Anxiety subscale of the STARS instrument provided the most interesting findings. There was a statistically significant difference between anxiety levels, suggesting that online students were 16% more anxious than face-to-face students.

Additional research suggests that online students may report higher levels of statistics anxiety than face-to-face students at the beginning of the course, but after the course, online students report lower levels of anxiety compared to their traditional counterparts (DeVaney, 2010; Frey-Clark et al., 2019). Zimmerman and Austin (2018) sampled over 1,000 students in online and face-to-face introductory statistics courses and found that online students had lower levels of anxiety and a higher perception of the worth of statistics after the course. However, they concluded that it was difficult to determine whether the variation in anxiety levels could be attributed to differences in the students' anxiety or influenced by the difference in course delivery. Hoffman and Elmi (2021) were able to control for the variability of the instructor influence by comparing online and face-to-face sections taught by the same professor. They suggest that there is little difference in performance between the two learning environments.

The role of the instructor has received significant attention in the research (Dunn, 2014; MacPherson, 2016; Rothes et al., 2017; Tonsing, 2018; Waples, 2016). The instructor's teaching style can impact a student's attitude and anxiety around statistics (Jameson, 2020). Instructors who report a positive attitude toward teaching also create positive classroom environments that are supportive of learning (Xu et al., 2021). Instructors who develop strong emotional rapport with their students (Waples, 2016) and those who emphasize the practical application of statistics in everyday life (Xu et al., 2021) have the greatest impact on their students' success and anxiety. Condron et al.

(2020) recommended that teachers openly discuss the sources of statistics anxiety and purposefully work to build their student's confidence in their statistical abilities.

In addition to teaching style, curriculum design may also influence statistics anxiety. Several theories have been applied in statistics courses to improve success and retention in higher education, including social-constructivism (Rock et al., 2016), active learning (Rock et al., 2016; Allen & Baughman, 2016), and cognitive learning theory (Alpay et al., 2017). Alpay et al. (2017) applied cognitive learning theory and cognitive theory of multimedia learning to their course design. The results of their curriculum intervention are impressive; in their comparative analysis, they found that students in the redesigned course receiving a passing grade (that is, an A, B, or C) went up by 9.2%. Course attrition rates were also dramatically reduced, 26.3% before the intervention and 15.21% after the course redesign. Finally, while historically, online students have higher attrition rates than face-to-face students, they found that their course intervention brought the online attrition rate up to a comparable level with face-to-face students; 15.76% for online sections compared to 16.94% for face-to-face sections. Additional curriculum interventions include project-based learning (Nazarro, 2020), collecting and using real-world data in class (Allen & Baughman, 2016; Lindner, 2012), game-based education (Shaker et al., 2021, Smith, 2017; Zhang & Yu, 2022), and implementing growth mindset interventions (Smith & Capuzzi, 2019; Sockol et al., 2021). Although these approaches appear promising, the evidence is limited in these studies to single courses and may be difficult to generalize to all statistics classrooms. The research does seem to suggest that students who are exposed to learning strategies as part of the instruction increase their learning (Gutierrez de Blume, 2021; Mann & Willans, 2020). Valle et al. (2021) explored the use of a specific intervention designed to increase learner motivation and task value. The results of the intervention did not show a statistically significant improvement in improving motivation or course success. However, the course design did show a decrease in anxiety levels for the students suggesting that exposing students to content that highlights the worth and importance of statistics may help reduce their anxiety (Valle et al., 2021).

Dispositional Antecedents

Statistics anxiety presents a dispositional barrier for adult students that may impact their retention and success (Zimmerman & Johnson, 2017). Dispositional barriers include individual traits, attitudes, and motivations. Some of these traits, such as motivation and self-efficacy, are malleable and open to intervention. However, others, such as gender and personality type, are fixed traits. Gender has been one of the most common traits identified in the research that relates to students' level of statistics anxiety. There is consensus within the research that students identifying as female report higher levels of statistics anxiety compared to students who identify as male (Condron et al., 2018; Edirisooriya & Lipscomb, 2021; Hedges, 2017; MacArthur, 2020; Ralston et al., 2016; Salehi et al., 2019; Zekeri et al., 2019). A possible explanation is that culture may stereotype men as being better at math, which influences the female perception of their competence in math (Condron et al., 2018; Ramos Salazar, 2018).

An additional factor that may influence statistics anxiety is the students' fear of asking for help. High-achieving adult students expressed fear or apprehension about reaching out to peers or formal academic support for help. They expressed a fear of being seen as less than or inferior to their peers (Wong & Chiu, 2019). Bebermeier et al. (2020) found that students with higher confidence in math abilities were less likely to reach out to academic support services. Online students are typically older than on-campus students, and research suggests that age may be a protective factor when it comes to asking for help. According to Zimmerman and Austin (2018), online students in their study reported less anxiety about asking for help and a more positive view of statistics compared to traditional counterparts. Heretick and Tanguma (2021) also found that students over the age of 50 generally had lower anxiety levels than younger students. In addition to lower levels of anxiety, adult learners may also have more favorable attitudes towards statistics. This may be due to their broader life experience and their appreciation for the practical application of statistics (Zimmerman & Austin, 2018).

Individual personality type has been identified as a dispositional antecedent to statistics anxiety. The Five-Factor Model of personality (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) has been applied in research to identify specific traits that may contribute to or alleviate statistics anxiety. Research suggests that students with higher levels of Neuroticism or emotional instability report higher levels of statistics anxiety (Chew & Dillon, 2014; Steinberger et al., 2021). Steinberger et al. (2021) identified that higher levels of Extraversion were positively correlated with statistics anxiety, including interpretation anxiety, test and class anxiety, and fear of asking for help for students in online sections of their statistics courses. However, Chew and Dillon (2014) did not find statistically significant correlations between these variables. Openness to Experiences was found by both Steinberger et al. (2021) and Chew and Dillon (2014) to be moderately predictive of statistics anxiety. The theoretical assumption is that students with higher degrees of openness are open and willing to embrace new challenges and experiences; therefore, they may see statistics as a new frontier and worth their energy to explore. Student feedback supports this assumption. Allen et al. (2016) conducted a qualitative exploration with nine undergraduate psychology students, and one of the main findings was that students recognized the subject matter was challenging but important.

In addition to personality traits, themes such as gender, self-concept, and mathematical ability have been tied to statistics anxiety (Khasawneh et al., 2021). Prior math experience has been tied to statistics anxiety (Faber & Drexler, 2019; Ralston, 2020). The amount of time since their last math class is a source of anxiety for many adult students (Jameson, 2020; Jameson & Fusco, 2014). These factors are included in an individual's self-evaluation, which is used to judge their performance. This self-evaluation alters their self-efficacy and therefore decreases their overall motivation to pursue additional learning in that subject (Bandura, 1989; Faber & Drexler, 2019; Jameson, 2020). However, Bourne and Nesbit (2018) found that computational self-concept was not a strong predictor of statistics anxiety and did not significantly alter students' decision to major in psychology. The authors hypothesized that perhaps the students in their sample had higher levels of motivation, which served as a mediating variable that counteracted their negative self-concept (Bourne & Nesbit, 2018).

Motivation. Motivation is considered an internal process that drives individuals to reach their goals (Schunk & DiBenedetto, 2020). Motivation includes both goal-directed actions as well as individual perceptions regarding the importance or relevance of a task. Intrinsic motivation has been correlated with lower levels of anxiety (Lavasani et al., 2014). Lavasani et al. (2014) applied achievement goal theory to explore statistics anxiety and reported that students with a mastery goal approach, that is, their goal was to understand and gain mastery over the concept of statistics, reported lower levels of anxiety. They also reported that intrinsic motivation indirectly affected the relationship between mastery goals and statistics anxiety (Lavasani et al., 2014). Lou et al. (2021) found that online students' willingness to learn was largely influenced by intrinsic motivation and less influenced by extrinsic factors. The online students whose basic psychological needs were met were more likely to continue with their studies. This indicates that intrinsic needs played a large role in the students' motivation and ongoing self-regulated learning.

Students with higher intrinsic goal orientation are more likely to report increased levels of self-efficacy and more likely to use deeper learning strategies (Drysdale & McBeath, 2018). Neroni et al. (2018) explored goal orientation and academic performance in over 1,000 adult online students. The results of their research were that students with a performance approach, that is, an outcome that is focused on performing better than others had greater academic performance (Neroni et al., 2018). Leenknecht et al. (2019) offered additional research that helps to expand these findings. Their study discovered that deeper learning strategies were found to mediate the relationship between the students' motivation and their feedback-seeking behavior. This points to the possible influence of self-regulated learning strategies as a possible mediator between motivation and statistics anxiety.

Task value is a specific component in motivational science, and it refers to the subjective value that an individual places on a given task. The value an individual assigns to a task is influenced by four components: the intrinsic value (the internal interest or pleasure in the task), the attainment value (what they will get from the task), the utility value (how useful the task is to them or their needs), and the cost (the psychological, emotional, and physical output required for the task) (Eccles & Wigfield, 2020). Task value has been correlated with the degree of worth a student perceives in statistics (Bourne, 2018) and lower statistics anxiety (Baloglu et al., 2017). Students who report a higher degree of importance and willingness to study statistics are less likely to report statistics anxiety (Sandoz et al., 2017). In a qualitative analysis of discussion boards in an online introductory statistics course, Songsore and While (2018) explored the areas in which students felt that statistics was the most useful. They identified three main areas of statistical application through the students' discussion: practical life skills, discipline-specific, and career-specific (Songsore & While, 2018). The most in-depth discussions were around the practical application that statistics has in everyday life. This suggests that students saw the value and worth of studying statistics.

Self-efficacy. Self-efficacy is a significant predictor of academic performance. Even more than general self-efficacy, domain-specific self-efficacy plays a strong role in predicting anxiety and performance (Palestro & Jameson., 2020; Ramos Salazar, 2018). Students who feel more confident in their statistical abilities report lower levels of anxiety (Abdous, 2019; Ralston, 2020). Hoegler and Nelson (2018) compared the influence of a student's prior GPA against their level of general self-efficacy. They found that self-efficacy was a much stronger predictor of performance on a final exam. Self-efficacy accounted for 21% of the variability in exam performance, whereas prior GPA accounted for only 7.1% (Hoegler & Nelson, 2018). The authors also found that statistics anxiety had an indirect effect on exam performance by way of the influence on self-efficacy (Hoegler & Nelson, 2018). It also appears that higher self-efficacy encourages positive attitudes toward statistics which decreases statistics anxiety (Baloglu et al., 2017). This suggests a connection between self-efficacy and statistics anxiety.

In a correlational study, Palestro and Jameson (2020) attempted to distinguish between general emotional self-efficacy and domain-specific math self-efficacy. They also set out to identify if general or domain-specific self-efficacy played a mediating or moderating role between statistics anxiety and academic performance. They also further sought to understand if the effect of self-efficacy varied based on gender. The sample consisted of 115 undergraduate students. Data was collected using the Abbreviated Math

Anxiety Scale (AMAS), the Mathematics Self-Efficacy Scale (MSES), and the Emotional Self-Efficacy Scale (ESES). Finally, math ability was measured using the Wide Range Achievement Scale (WRAT) subtest. The data were analyzed using exploratory mediation analysis. The relationship between math anxiety and math performance was partially mediated by math self-efficacy; however, no mediating effect was found with emotional self-efficacy. This suggests that domain-specific self-efficacy has more influence over performance than general self-efficacy.

Cognitive Antecedents

Cui et al. (2019) described the cognitive antecedents of statistics anxiety as those functions involved in the specific computation and interpretation of statistics. This includes both the neurological resources used in reasoning and critical thinking as well as the cognitive and metacognitive strategies used in learning (Cui et al., 2019). Very little research has explored the specific biological components associated with statistics anxiety in adult online students. However, Foley et al. (2017) reported that research on math anxiety in elementary-aged children indicates an increase in activity in the amygdala. The hypothesis is that this increased activity decreases working memory and mathematical processing capacity, thus interfering with the student’s cognitive abilities. Using fMRI scans, Pizzie et al. (2016) found that various regions of the brain were active while performing mathematical equations. While testing a strategy of cognitive reappraisal for math students, Pizzie et al. (2016) found that the emotional regulation areas of the brain were more involved in reducing the anxiety and increasing the performance of patients.

In addition to biology, cognitive antecedents also include metacognition and other self-regulating behaviors. In the SCT of self-regulation, these variables may be associated with both the behavioral and cognitive dimensions (Kim et al., 2020). The specific strategies that are used for learning are known as self-regulated learning strategies. Research has demonstrated a connection between motivation, self-regulated learning strategies, and academic outcomes (Anthonysamy et al., 2020).

Self-Regulated Learning Strategies. Self-regulated learning strategies (SRLS) are the specific activities that a student uses to learn efficiently and effectively (Anthonysamy et al., 2020; Rothes et al., 2017; Zhou & Wang, 2019). The strategies used by adult students in online learning environments may differ from the strategies used by students in a traditional classroom setting (Bruso et al., 2020).

Zhou and Wang (2019) explored specific motivation orientations and their relationship with self-regulated learning strategies. They also explored how these variables predicted academic performance. To gather data, they sampled 291 students and administered several instruments, including the MSLQ. They analyzed the data using structural equation modeling. They found a valid model with the relationships between mastery-approach goal orientation, learning strategies, and academic performance. The authors determined that self-regulated learning strategies were the mediating factor between motivation and academic achievement.

Self-regulated learning strategies may include time management, simple cognitive strategies, deep or complex cognitive strategies, seeking help from others, and academic or critical thinking. Simple cognitive strategies are the techniques used to maintain information at a surface level. These strategies may include memorization, rehearsal, highlighting, etc. These are strategies that typically involve lower cognitive skills (Gutierrez de Blume, 2021). Complex cognitive skills are strategies that require higher or deeper levels of critical thinking (Gutierrez de Blume, 2021). Examples of deeper learning strategies include elaboration, summarization, connecting knowledge with prior information, metacognition, and critical thinking (Gutierrez de Blume, 2017).

Additional research around self-regulated learning has attempted to understand why students select certain self-regulatory learning strategies. Drysdale and McBeath (2018) compared motivation, self-efficacy, and learning strategies with over 1,700 university students. The correlational analysis results indicated that the extrinsically motivated students were more likely to utilize simple cognitive strategies such as the rehearsal. In contrast, intrinsically motivated students were more likely to utilize more complex cognitive strategies such as elaboration and metacognitive self-regulation. In addition to motivation, individual personality traits influence the selection of self-regulated learning strategies. Bruso et al. (2020) explored the relationship between the Big Five personality traits, including openness, conscientiousness, agreeableness, extraversion, and neuroticism, and the selection of self-regulated learning strategies. The authors identified 452 graduate students and administered the Big Five Inventory (BFI) and the Online Self-Regulated Learning Questionnaire (OSLQ). The subscales of each instrument were compared using linear regression analysis. The traits of openness, conscientiousness, agreeableness and extraversion were all significantly related to the higher adoption of self-regulated learning strategies. The traits of openness and conscientiousness explained 50% of the variance in goal setting. Conscientiousness explained 5.5% of the variance in time management.

A particular regulatory strategy that has received substantial attention in the literature is procrastination or time management. Time management has been found to be one of the most common self-regulated learning strategies deployed by institutions to support student success (Wolters & Brandy, 2021). Specifically, in online statistics courses, higher levels of anxiety have been correlated with higher levels of procrastination (Dunn, 2014; Eshet et al., 2021). Dunn (2014) found that students' academic self-regulation was the strongest predictor of procrastination in online statistics courses. A multiple linear regression explored the predictive relationship between the General Strategies for Learning (GSL) subscale of the MSLQ, the Statistics Test and Class Anxiety (STCA) subscale of the STARS, and the Intrinsic Goal Orientation subscale of the MSLQ on the results of the Procrastination Assessment Scale-Students (PASS). Analyzing the results of 101 online graduate students, the model predicted a 29.1% variance in procrastination. In other words, the students who were less active, less engaged in their learning, and more anxious were more likely to procrastinate in their statistics courses. Students who reported higher time management levels were more likely to be successful in their online courses, which indicates the importance of incorporating time management and goal-setting practices within the course curriculum (Bruso et al., 2020; Neroni, 2019; Wolters & Brandy, 2021).

There is limited research on the influence of self-regulated learning strategies and statistics anxiety. Kesici et al. (2011) were one of the first to examine self-regulated learning strategies with statistics anxiety specifically. In a survey of 320 students, Kesici et al. (2011) identified learning strategies such as rehearsal, elaboration, organization, critical thinking, metacognitive self-reflection, time and study environment management, effort regulation, peer learning, and help-seeking. These are the subscales of the MSLQ that represent self-regulated learning strategies. They explored the relationship with subscales of the Statistical Anxiety Rating Scale (STARS), including the worth of statistics, interpretation anxiety, test/class anxiety, computational self-concept, fear of asking for help, and fear of statistics instructors. A canonical correlation analysis (CCA) was used to understand how these variables may be related to each other. The authors identify several meaningful conclusions. First, they found that students who reported using more shallow learning strategies, such as the rehearsal, reported higher computational anxiety levels than students who used deeper learning strategies, such as elaboration and organization (Kesici et al., 2011). They also conclude that the students who use deeper learning strategies also report more positive attitudes towards the worth of statistics. This finding may point to the relationship between the students' motivation toward statistics and their selection of various self-regulation strategies.

González et al. (2016) explored how intrinsic motivation may influence specific engagement strategies of undergraduate students. Although they defined engagement slightly differently than Kesici et al. (2011), they do bring together the influences of motivation and self-regulated learning in regards to their reciprocal role in statistics anxiety. They also explore how these variables influence academic performance in undergraduate statistics courses. The structural equation model results suggested that the students who had higher statistical self-concept and a higher value of statistics reported lower levels of anxiety. These students were also more likely to use deeper engagement strategies and had higher performance in their courses. González et al. (2016) concluded that higher intrinsic motivation led to deeper learning strategies because the students experienced less statistical anxiety.

Summary and Conclusion

Adult students in the online learning environment face a number of hurdles in reaching their academic goals. One barrier that students may face is statistics anxiety. This domain-specific anxiety is the specific fear, apprehension, worry, or anxiety that a student experiences when faced with statistical actions, including the identification, computation, and interpretation of data (Cruise et al., 1985). The review of existing literature provided an understanding of the potential consequences of statistics anxiety including academic and non-academic. Academic consequences include disruption of academic progress, including lower course success. Non-academic consequences include aversion to statistics-heavy majors or career fields and an increase in unethical behavior.

A review of existing literature in statistics anxiety also identified several potential causal factors and has organized these factors as situational, dispositional, and cognitive antecedents (Cui et al., 2019). This organization of potential causal variables also aligns with SCT. Social cognitive theory proposes that human behavior is influenced by three domains: individual, environmental, and behavioral. These three domains influence one another, which is known as reciprocal determinism. Research in statistics anxiety has explored several of these domains but often in isolation. Very little research has been done to explore how these domains may influence one another.

A key variable that has received attention in the research on statistics anxiety is motivation. Research has demonstrated that students with higher intrinsic goal orientation and higher task value report lower levels of statistics anxiety. However, very little research has explored how this motivation may influence students' specific learning strategies in their statistics courses and how this might mediate the relationship with statistics anxiety. The purpose of this research study was to address this gap in the literature by exploring how self-regulated learning strategies, which include both cognitive, behavioral, and environmental strategies, may influence statistics anxiety in online graduate students. Given that the individual factor of motivation likely influences study strategies' behavioral and cognitive choices, it is essential that research incorporate both of the factors in the analysis. Understanding the role of a student’s self-regulated learning strategies will improve practical knowledge in the area of online graduate education by providing evidence that suggests the statistics education curriculum may need to incorporate some of these strategies. The next chapter will outline the specific research design decisions that enabled me to explore the influence of self-regulated learning strategies on motivation and statistics anxiety.

Chapter 3: Research Method

Introduction

Research suggests that many students may experience anxiety associated with statistics (Cui et al., 2019; Hoffman & Elmi, 2021; Zimmerman & Austin, 2018). Although the degree to which this anxiety impacts an individual varies, research indicates that it affects students regardless of their age (Heretick & Tanguma, 2020) and gender (MacArthur, 2020). Research has also suggested certain predictive variables that may illustrate why statistics anxiety affects some students more than others. Previous research has explored potential curriculum design elements (Rock et al., 2016), the role of the instructor (Xu et al., 2021), and various personal attributes, including self-efficacy (Palestro and Jameson, 2020), motivation (Baloglu et al., 2017), selection of various learning strategies (Schunk & DiBenedetto, 2020), and personality type (Steinberger et al., 2021). Further, it remains unknown how these variables may relate to one another and the role they play collectively in statistics anxiety.

The purpose of this quantitative correlational study was to explore the mediating role of self-regulated learning strategies on the relationship between motivation and statistics anxiety. The purpose of this chapter is to review the research design and rationale, the methodology, population and sampling procedures, recruitment procedures, participation and data collection, instrumentation and operationalization of constructs, data analysis plan, threats to validity, and ethical guidelines relevant to this study.

Research Design and Rationale

Research has demonstrated a correlation between decreased motivation and statistics anxiety (Baloglu et al., 2017; Bourne, 2018; Palestro et al., 2020; Ramos Salazar, 2018; Sandoz et al., 2017). However, it remains unclear whether there are additional variables that may have a direct or indirect effect on this relationship. This quantitative correlational study explored the influence of self-regulated learning strategies on the relationship between motivation and statistics anxiety. The independent variable was motivation, and the dependent variable was statistics anxiety. The mediating variable was self-regulated learning strategies, including management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking. A mediation model was an appropriate design for the given research study because it explored if self-regulated learning strategies may act as a potential mechanism explaining the relationship between motivation and statistics anxiety. This research design was also consistent with research designs needed to advance knowledge in this discipline because it contributed information to close the gap regarding potential influential variables contributing to statistics anxiety.

I used a survey to gather data from a convenience sample of online graduate students via social media sites including Facebook and LinkedIn. Data for each variable was collected using validated instruments. The instruments included the MSLQ (Meijs et al., 2009; Pintrich et al., 1991) and the STARS (Cruise et al., 1985). I used Hayes' (2022) PROCESS Macro in SPSS to conduct the mediation analysis, which includes ordinal linear regression to analyze the data. There were no time or resource constraints consistent with this design choice.

Methodology

This section will describe the intended population, the sample, and sampling procedures. I will also discuss the procedures used for recruitment and data collection. I will also review the operational definitions of the constructs and the instruments used to gather data.

Population

The population included adult students enrolled in online graduate higher education institutions. In fall 2020, 1,625,579 post-baccalaureate (graduate and doctoral) students were enrolled in exclusively distance education programs, which is 51% of the total enrollment in all post-baccalaureate programs (face-to-face, hybrid, and fully online) (National Center for Education Statistics, 2021). Research suggests that students who enroll in distance education programs are generally non-traditional (Ellis, 2019). Non-traditional students are generally 24 years of age or older, which is older than traditional undergraduate students. This is consistent with the National Center for Education Statistics (2019b) definition of the non-traditional or adult student. Most literature on statistics anxiety has focused on traditional students; however, several studies that have focused on non-traditional students have identified higher levels of anxiety and lower levels of self-efficacy compared to traditional students (Jameson & Fusco, 2014; Liu, 2021; Ryan & Fitzmaurice, 2017). The intended population that will benefit from this research study will be online graduate students, the majority of whom are non-traditional students.

Sampling and Sampling Procedures

The participants included in this research study were online graduate students over the age of 24. They must be currently enrolled in a fully online graduate or doctoral degree program. Additional inclusion criteria included at least one prior online statistics course within the last year. Participants were excluded if they were enrolled in a hybrid or blended learning format, were not actively enrolled, or had not completed an online statistics course. Participants were recruited using a form of convenience sampling through posted advertisements on social media sites, including Facebook and LinkedIn.

The target sample size was estimated prior to data collection based on the estimated size to achieve the desired results (Frazier et al., 2004). Sim et al. (2022) defined the minimum required sample sizes for path analysis based on their analysis. The authors include the following criteria in determining the minimum sample size: parameter bias, alpha level of .05, and 95% coverage (Sim et al., 2022). The minimum power was set at .8 or greater, and the alpha level was set at .05. According to Fritz and MacKinnon (2007), for a mediation analysis to have a small-medium effect size for path *a* and a small-medium effect size for path *b*, a sample size of 148 participants is required. According to Cohen's criteria, a medium effect size accounts for at least 13% of the variance in the dependent variable (Sim et al., 2022). These values are consistent with prior research on statistics anxiety and motivation (Baloglu et al., 2017), as well as statistics anxiety and self-regulated learning strategies (Kesici et al., 2011). In order to allow for attrition and insufficient survey completions, the target sample size was adjusted upward to 160 respondents.

Procedures for Recruitment, Participation, and Data Collection

I used a convenience sampling approach to recruit participants. The sample was gathered using social media platforms, including Facebook and LinkedIn. An online survey was built using Survey Monkey, an online survey platform that provides simple-to-deploy surveys and encrypts the data to maintain confidentiality. The ad included information about the study and a link to the Survey Monkey survey. The ad on Facebook was posted on a personal page and promoted to the target sample audience using Facebook’s Advertisement Manager tool. The ad was also posted within groups on LinkedIn, including Survey Exchange, a group that allows researchers to cross-post their research advertisements for a large collection of potential participants.

The first page of the survey included general informed consent information, including their right to exit the survey at any time. The participant indicated consent by clicking the Next button on the survey. The first section of the survey included demographic information, including age, gender identity, race/ethnicity, education level, and major. Additional background questions were used to gather contextual information about the participants. The first asked about the number of online statistics courses the student had taken and how long (in months) since the last online statistics course. These questions were be used for screening purposes to ensure that the participants met the inclusion criteria.

This research study was a cross-sectional design; therefore, there was no follow-up necessary after completion of the questionnaire. In addition to the demographic and screening questions, data was collected using questions from formal instruments and measured using Likert scales. The following section describes the instruments that were used and the variables that they measured.

Instrumentation and Operationalization of Constructs

Statistics Anxiety Rating Scale (STARS)

As stated in previous sections, statistics anxiety is defined as "the feelings of anxiety encountered when taking a statistics course or when doing statistical analyses; that is, gathering, processing and interpreting data" (Cruise et al., 1985, p. 92). There are several instruments used to assess statistics anxiety; however, the STARS is one of the original and most widely used instruments to measure statistics anxiety (Cruise et al., 1985; Hanna et al., 2008). The instrument includes 51 items and is in the public domain, which allows for its use without requiring permission or fees.

There are two sections of the measure. The first section of 23 items addresses statistics anxiety. This section includes situational statements, and the participant is asked to rate their anxiety level on a 5-point Likert scale. An example of an item is "On a scale from 1 (no anxiety) to 5 (strong anxiety), indicate how much anxiety you would experience in the following situation: doing the coursework for a statistics course."

Lower ratings indicate lower levels of anxiety. The statistics anxiety section includes three subscales: test and class anxiety, interpretation anxiety, and fear of asking for help. Test and class anxiety includes eight items, and the sum of the responses can range from 8 to 40. Interpretation anxiety includes 11 items, and the sum of the responses can range from 11 to 55. Fear of asking for help includes four items, and the sum of the responses can range from 4 to 20. The Cronbach's alpha levels for these subscales range between 0.84 and 0.90, indicating high levels of internal consistency (Chew et al., 2018; Hanna et al., 2008; Nesbit & Bourne, 2018).

The second section of the STARS includes 28 items that address attitudes towards statistics. The participant rates their agreement to statements regarding statistics on a 5-point Likert scale. An example of an item is "On a scale from 1 (strong disagreement) to 5 (strong agreement), indicate your level of agreement with the following statement: statistics takes more time than it is worth." A lower score in this section also indicates lower anxiety. This section includes three subscales: worth of statistics, computational self-concept, and fear of statistics teachers. The worth of statistics includes 16 items, and the sum of the responses can range from 16 to 80. Computational self-concept includes seven items, and the sum of the responses can range from 7 to 35. Fear of statistics teachers includes five items, and the sum of the responses can range from 5 to 25. The Cronbach's alpha levels for these subscales range between 0.79 and 0.94, indicating high levels of internal consistency (Chew et al., 2018; Hanna et al., 2008; Nesbit & Bourne, 2018).

Hanna et al. (2008) explored the structure of the STARS and suggested that the instrument represents a six-factor model with each factor represented by a single subscale standing. They suggested that each subscale measured a unique construct; however, they also pointed out that the instrument measures statistics anxiety as a broad construct, making the initial recommendation to divide the instrument into two sections: one measuring statistics anxiety and another factor measuring attitudes towards statistics. Papousek et al. (2012) supported this model after their research applied the STARS to a sample of German students. They suggested the subscales of test and class anxiety, interpretation anxiety, and fear of asking for help combine to create one composite score for statistics anxiety. Chew et al. (2018) confirmed this approach through confirmatory factor analysis, which identified the two-factor model of statistics anxiety and attitudes about statistics was a fit and was supported theoretically. In this research study, the variable of statistics anxiety was measured by the sum of the scores on all six subscales: test and class anxiety, interpretation anxiety, fear of asking for help, the worth of statistics, computational self-concept, and fear of statistics teachers.

Motivated Strategies for Learning Questionnaire (MSLQ)

The MSLQ was developed by Pintrich et al. (1991) and is a self-report measure grounded in a self-regulated learning framework. This tool is also in the public domain; therefore, prior permission or fees are not required. The instrument has been extensively applied to higher education students in a variety of learning environments where it has been found to be a valid and reliable instrument (Khampirat, 2021; Maun et al., 2020).

This instrument has also been used to explore the area of statistics anxiety, including motivation (Baloglu et al., 2017; Dunn, 2014; Valle et al., 2021), self-efficacy (Hoegler & Nelson, 2018), and self-regulated learning strategies (Dunn, 2014; Kesici et al., 2011). The MSLQ includes 81 items and is comprised of two sections: motivation (MSLQ-Part A) and learning strategies (MSLQ-Part B). The motivation section includes five scales: intrinsic goal orientation, extrinsic goal orientation, control for learning beliefs, task value, self-efficacy for learning and performance, and test anxiety. The revised learning strategies section includes five scales: management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contact with others, and academic thinking. The MSLQ is designed to be used as one single measure, a two-factor measure of motivation and self-regulated learning strategies, or individual scales, which I will describe below. (Pintrich et al., 1991; Stefano et al., 2013).

Motivation. In this research study, motivation was measured using three scales from the MSLQ: intrinsic goal orientation (four items), task value (five items), and self-efficacy for learning and performance (eight items). These scales are three key indicators for academic motivation (Khampirat, 2021). The reliability of the subscales is between moderate and high, with Cronbach’s alpha levels ranging from 0.74 to 0.93 (Pintrich et al., 1991). The self-report instrument includes statements that are rated by the participant on a 7-point Likert scale ranging from (Pintrich et al., 1991). There are no reverse-scored items in these subscales. An example of one of the questions is,

> Please rate yourself on a scale of 1 (not at all true of me) to 7 (very true of me) based on your motivation for and attitudes about your course: The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.

Acosta-Gonzaga and Ramirez-Arellano (2021) used all six of the previously mentioned subscales to measure the latent construct of motivation; however, in their study exploring self-efficacy and statistics anxiety, Hoegler and Nelson (2018) isolated the self-efficacy for learning and performance subscale as the only subscale from the MSLQ because that was most appropriate for their research design. Khampirat (2021) noted a strong association between the subscales of intrinsic goal orientation, task value, and self-efficacy for learning and performance as strong measures of the latent factor of academic motivation.

Self-regulated learning strategies. Self-regulated learning strategies were measured using a revised version of Part B, the learning strategy section of the original MSLQ. Recognizing that adult students have different needs and may utilize different strategies to be successful, Meijs et al. (2019) designed a revised survey with a focus on identifying learning strategies that adult distance education students deploy to be successful. This instrument is also in the public domain and therefore does not require permission or fees for use. This revised version, known as MSLQ-B, includes 25 items across five subscales: management of time and effort (six items), complex cognitive strategy use (five items), simple cognitive strategy use (five items), contacts with others (four items), and academic thinking (five items). The reliability of each scale is acceptable, with Cronbach's alphas between 0.74 to 0.80. Self-regulated learning strategies will be considered as the sum of all subscales and will also be analyzed individually in the mediation analysis.

The instrument uses a 7-point Likert scale, and the participant is asked to rate their agreement with a statement. An example of the question type is "On a scale ranging from 1 (totally disagree) to 7 (totally agree), rate your agreement with the following statement: I memorize keywords to remind me of important concepts in this course". Two of the items are reversed, and in these instances, the number rating that the student provides will be reversed; for example, a 1 becomes a 7, and a 7 becomes a 1. An example of a reversed question is "I rarely find time to review my notes or readings before an exam." The authors validated their survey with a sample of over a thousand adult online students who are more closely aligned with the demographics of a non-traditional student. Cronbach's alpha levels are considered good, ranging from 0.70 to 0.80 (Meijs et al., 2019).

Neroni et al. (2019) utilized the MSLQ-B with a sample of 1,195 online higher education students in the Netherlands. They evaluated the predictive validity of the instrument and found that management of time and effort was the strongest predictor of academic performance. In addition, they found that complex cognitive strategy use and contact with others were also significant predictors of performance. The variables that were not significant predictors of academic performance were simple strategy use and academic thinking. Their analysis revealed Cronbach's alpha levels that were slightly lower than Meijs et al. (2019), ranging from 0.63 to 0.79.

Data Analysis Plan

RQ1: To what extent do self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) mediate the relationship between intrinsic goal orientation and statistics anxiety in adult students in online learning environments?

$H1_0$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do not significantly mediate the relationship between intrinsic goal orientation and statistics anxiety in adult students in online learning environments.

$H1_1$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do significantly mediate the relationship between intrinsic goal orientation and statistics anxiety in adult students in online learning environments.

RQ2: To what extent do self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) mediate the relationship between self-efficacy and statistics anxiety in adult students in online learning environments?

$H2_0$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do not significantly mediate the relationship between self-efficacy and statistics anxiety in adult students in online learning environments.

$H2_1$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do significantly mediate the relationship between self-efficacy and statistics anxiety in adult students in online learning environments.

RQ3: To what extent do self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) mediate the relationship between task value and statistics anxiety in adult students in online learning environments?

$H3_0$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do not significantly mediate the relationship between task value and statistics anxiety in adult students in online learning environments.

$H3_1$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do significantly mediate the relationship between task value and statistics anxiety in adult students in online learning environments.

Descriptive Statistics

Demographic information was collected through the survey. The data was first reviewed to ensure the participant met the inclusion criteria. As previously stated, the inclusion criteria were that the participants are currently enrolled in a fully online graduate or doctoral degree program. Demographic information was also used to characterize the sample through variables including gender identity, age, education level for current enrollment, major or program of study, number of statistics courses taken, and months since the last statistics course. Race/ethnicity included six levels: (1) American Indian Alaska Native, (2) Asian, (3) Black or African American, (4) Native Hawaiian or other Pacific Islander, (5) Two or more races, and (6) White. Gender identification was a categorical variable and measured with the following levels: (1) Man, (2) Woman, and (3) Non-binary. Participants were asked to indicate the education level for the program in which they were currently enrolled: (1) High-school, (2) Undergraduate, (3) Graduate, and (4) Doctoral. Major or program of study will include the following categories: (1) Science, Technology, Engineering, or Math, (2) Business, (3) Human Services (Psychology, Counseling, and Social Work), (4) Education, (5) Other. If a participant selected other, they were given the option to specify their program of study. Participants selected their age from the following categories: (1) Under 18, (2) 18-24 years old, (3) 25-34 years old, (4) 35-44 years old, (5) 45-54 years old, (6) Over 55 years old. Participants identifed the number of statistics courses they have completed, which were presented in the following categories: (0) currently enrolled in my first statistics course, (1) 1-2 courses, (2) 3-4 courses, (3) More than 5 courses. Finally, the participants indicated how long (in months) since they completed their most recent online statistics course: (0) currently enrolled in my first statistics course, (1) 1-5 months, (2) 6-11 months, (3) More than a year. The statistical software program SPSS Version 27 was used to analyze the data.

Mediation Analysis

The nature of the research question required a mediation analysis, which may be described as a regression-based approach that explores the potential direct or indirect influence of a third variable on the relationship between an independent and dependent variable (Hayes, 2022). This research study sought to explore the mediating effect that self-regulated learning strategies may have on the relationship between motivation and statistics anxiety. In this analysis, there are five self-regulated learning strategies: management of time and effort, complex and simple cognitive strategy use, contact with others, and academic thinking. Each of the five self-regulated learning strategies was analyzed individually as potential mediators. In this model, motivation was hypothesized to have an indirect effect on statistic anxiety by way of the effect of the self-regulated learning strategies.

Baron and Kenny (1986) developed one of the original methods for measuring the effect of a third variable on the relationship between two other variables. A moderator variable affects the strength or direction of the relationship between a predictor variable and outcome variable, whereas a mediator variable attempts to identify the causal mechanisms that explain the relationship between the predictor and outcome variables (Baron & Kenny, 1986). In the Baron and Kenny (1986) model, the analysis involves a series of linear regressions. The first linear regression identifies the relationship between the independent variable and the mediator, known as path a. The second linear regression identifies the relationship between the mediator and the dependent variable, known as path b. The final linear regression identifies the direct effect between the independent and dependent variables, known as path c. In a perfect mediation scenario, the relationship between the predictor and outcome variables will be reduced to zero after controlling for paths a and b. This new relationship is referred to as path c'.

Hayes (2022) built upon the Baron and Kenny model and devised the PROCESS macro. This tool can be used in multiple statistical software packages, including SPSS. One key advantage of the Hayes approach is the utilization of percentile-based bootstrapping. The percentile bootstrap method is more powerful than other methods, such as the delta method or the Sobel method (Hayes, 2009; Sim et al., 2022). Bootstrapping is the recommended approach to establishing confidence intervals in mediation analysis (Hayes, 2022). Bootstrapping is a resampling method that generates thousands of new samples based on the original sample data. This approach is valuable because it compensates for the distribution of the original sample data that may not be normal. Bootstrapping is also valuable because it boosts the size of the analyzed data, leading to greater confidence that the sample is truly representative of the population (Hayes, 2022). Based on prior research and recommended best practices in mediation analysis, the confidence interval for this study was established at 95%.

Data Cleaning

The statistical test that was used to test the hypothesis was ordinal linear regression. In order to utilize this nonparametric statistic, the data must meet certain assumptions. First, the relationship between the variables must be linear. The scatterplot was reviewed to confirm a linear relationship. Next, there must be no multicollinearity between variables. A collinearity diagnosis was performed to assess for multicollinearity. The Durbin-Watson statistic was reviewed to confirm if the values of the residuals were independent. Homoscedasticity was reviewed to confirm if the variance of the residuals was constant. The Normal Q-Q Plot was evaluated to confirm if the residuals were normally distributed. Finally, the Cook's Distance was performed to confirm if there were no influential cases biasing the model (Laerd Statistics, 2013). The results of these tests were used to confirm that the data met the necessary assumptions to perform an ordinal linear regression.

Threats to Validity

In order for a research study to contribute to positive social change, the results of the study must be generalizable to the population. Generalizability requires certain design decisions before, during, and after the study to avoid certain threats to the validity and generalizability of the study. Threats to validity can be classified into four categories: external, internal, construct, and statistical conclusion validity (Garcia-Perez, 2012).

External Validity

External validity refers to the challenges within a research design that reduce the ability to generalize the study results to the broader population (Frey, 2018a). This is of particular concern in research designs that use convenience sampling because it is more difficult to ensure that the sample is truly representative of the population (Frey, 2018a). A majority of the recent studies on statistics anxiety sample participants from within one institution and often within one field of study. Although this approach has advantages, it is difficult to produce a truly representative sample. A convenience sampling using the internet to recruit participants may be an advantage to the prior approach and allow for recruitment from varying institutions. This approach may produce a sample that is more diverse and a better representation of the population. This mitigated the threat to external validity and increases the ability to generalize the research study results to the population.

Internal Validity

Internal validity refers to the confidence with which one can attribute the findings of the data to the study itself rather than additional confounding interactions. Internal validity essentially asks, "How well was the study conducted?" Attrition is one threat to internal validity. This threat refers to the drop-out rate or discontinuation of the participants (Creswell & Creswell, 2018). This threat was mitigated by sampling more than the minimum required sample size. Maturation may also be a threat to internal validity. This threat refers to the passage of time in which participants might change or mature (Creswell & Creswell, 2018). The design of this study was a cross-sectional design, and data was collected only one time.

However, the length of time between the participants' statistics courses and their completion of this survey may vary. In some cases, as time has passed, the participants may not feel as anxious as they might initially. In addition, memories are likely to be corrupted in anxiety-inducing situations (Garibbo et al., 2019). This puts into question the accuracy of the participants' self-reported anxiety. One strategy used to mitigate this threat was to include in the inclusion criteria for the sample that the participants have taken their online statistics course within the last year. Also, the length of time from their last course was collected in the demographic section of the survey and analyzed to evaluate potential impacts on the results. Finally, selection may also be a threat to internal validity. Individuals who participated in this study were able to self-select to participate on a voluntary basis. The individuals who volunteered to participate may be substantively different from the population in terms of attitudes, opinions, values, etc. (Frey, 2018b). One strategy recommended to mitigate this threat was to use statistical analysis that might control for such differences, including a multiple regression analysis (Frey, 2018b).

Construct Validity

Construct validity is a principle in psychological research that ensures a tool or instrument measures the construct it intends to measure. For example, a measure of intelligence ought to measure intelligence and not happiness or speed. Construct validity is a consequence of analyzing data that has been collected using flawed or insufficient measurement tools. Similar to internal validity, construct validity emphasizes the importance of using valid and reliable tools to gather data. The threat to construct validity was minimized by using tools that have been empirically validated, which was the case with the STARS, MSLQ, and MSLQ-B. These tools have been applied in several research studies across many disciplines and settings. The reported reliability of the instruments is good. Using these instruments to gather data on the variables of statistics anxiety, motivation, and learning strategies helped mitigate the risk of construct validity.

Statistical Conclusion Validity

The final threat to validity is statistical conclusion validity (SCV). This threat to validity focuses on the statistical analysis conducted within the study and helps protect from inaccurate or incorrect conclusions based on faulty methods (Garcia-Perez, 2012). SCV incorporates Type-I and Type-II errors, which are errors generated when the research incorrectly accepts or rejects the null hypothesis. This is often the case when the statistical analysis is performed incorrectly or when the sample size is inadequate. Garcia-Perez (2012) suggests that following replicable analysis methods and properly testing for data assumptions are key steps to mitigate the threat of SCV. I mitigated this threat by following the appropriate procedures to input, clean, and analyze the data as reported previously in this chapter. Bootstrapping also helped mitigate this threat through resampling, which results in an empirically created sampling distribution (Hayes, 2022). This helped mitigate the threat of an inadequate sample size.

Ethical Procedures

In addition to making research design decisions before, during, and after the study, it was also important to consider ethics throughout the entire research cycle. Ethics in research is a core principle according to the American Psychological Association. The ethical treatment of human participants requires the researcher to ensure that participants can expect their data to remain confidential, be fully informed of the benefits and risks of treatment and be given opportunities to withdraw if they desire (American Psychological Association, 2017). The Walden Institutional Review Board (IRB) was in place to add a layer of protection for participants and to ensure that researchers follow all ethical guidelines. I followed all recommendations and requirements as outlined by the Walden IRB in order to help ensure the ethical treatment of participants.

An example of a specific ethical concern results from working with a vulnerable population. Examples of vulnerable populations include minors, individuals with diminished mental capacity, and prisoners. Vulnerable populations also include individuals who lack sufficient coping skills to adequately deal with the stress associated with the research (Allen, 2017). Additional guidelines and safeguards exist for research studies that plan to work with a vulnerable population. Vulnerable groups include individuals who, on their own, are unable to understand their participation in research fully and unable to make the decisions necessary about their treatment (Allen, 2017). The target population for this research did not involve minors or otherwise vulnerable populations. However, even though no vulnerable population had been identified, the

Walden IRB approval was still an essential step in the research process to ensure that all participants are protected.

A core ethical guideline in research is to ensure that participants are free to terminate their participation at any time. In order to ensure that participants could withdraw at any time, the participants were free to discontinue the survey if they chose at any time and without penalty. In order to protect the participants' identity and confidentiality, names were not collected as part of the questionnaire, and the IP reporting mechanism in Survey Monkey was deactivated. In addition, when the descriptive summary of the sample was provided in the research report, it was not shared in such a way that an individual could be identified. The characterization of the sample was presented at the group level and not at the individual level. The data was stored on the Survey Monkey site until the survey closed and then downloaded to an Excel file. The file was saved on a password-protected computer. These steps were important to ensure that the rights of the participants are honored throughout the research process.

Summary

The goal of this chapter was to review the research design and rationale, the methodology, including population and sampling procedures, recruitment procedures, participation and data collection, instrumentation and operationalization of constructs, data analysis plan, threats to validity, and ethical guidelines relevant to this study. This quantitative correlational study built on existing research by exploring the potential mediating effect of self-regulated learning strategies on the relationship between motivation and statistics anxiety. The independent variable was motivation, and the dependent variable was statistics anxiety. The mediating variable was self-regulated learning strategies, including management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking. The participants for this study were above the age of 24 years, enrolled in an online graduate degree program, and have taken an online statistics course within the previous 12 months. The participants were recruited using a convenience sample by posting an advertisement on social media sites, including Facebook and LinkedIn. The advertisement included a link to the research survey hosted on the survey platform Survey Monkey. The survey included informed consent, demographic questions, and survey questions designed to gather data that was used to answer the research question. The survey questions included questions from validated and available instruments, including the MSLQ (Meijs et al., 2019; Pintrich et al., 1991) and the STARS (Cruise et al., 1985). In order to align with ethical standards, the survey did not gather names or other personally identifiable information. The data was confidential and stored on a password-protected computer. The data was analyzed using Hayes's (2009) PROCESS macro for mediation analysis. These research designs decisions were made to increase external and internal validity, which increased the ability to generalize the research study results to the population of online graduate students. In Chapter 4 I will provide the results of the research study.

Chapter 4: Results

Introduction

The purpose of this quantitative study was to explore the extent to which self-regulated learning strategies mediate the relationship between motivation and statistics anxiety in online higher education students. The independent variables were intrinsic goal orientation, self-efficacy, and task value; each was measured using scales from the MSLQ. The dependent variable was statistics anxiety, which was measured by combining the scores from the test and class anxiety, interpretation anxiety, fear of asking for help, interpretation anxiety, computational self-concept, and fear of statistics teachers' subscales from the STARS. The mediator variable was five specific self-regulated strategies for learning, which were represented by the scores on the subscales from the MSLQ-B, including management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking. This study fills a gap in the literature that explores the effect of self-regulated learning strategies on the established relationship between motivation and statistics anxiety in online graduate students.

The research question and related hypothesis were as follow.

RQ1: To what extent do self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) mediate the relationship between intrinsic goal orientation and statistics anxiety in adult students in online learning environments?

$H1_0$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do not significantly mediate the relationship between intrinsic goal orientation and statistics anxiety in adult students in online learning environments.

$H1_1$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do significantly mediate the relationship between intrinsic goal orientation and statistics anxiety in adult students in online learning environments.

RQ2: To what extent do self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) mediate the relationship between self-efficacy and statistics anxiety in adult students in online learning environments?

$H2_0$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do not significantly mediate the relationship between self-efficacy and statistics anxiety in adult students in online learning environments.

$H2_1$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do significantly mediate the relationship between self-efficacy and statistics anxiety in adult students in online learning environments.

RQ3: To what extent do self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) mediate the relationship between task value and statistics anxiety in adult students in online learning environments?

$H3_0$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do not significantly mediate the relationship between task value and statistics anxiety in adult students in online learning environments.

$H3_1$: Self-regulated learning strategies (management of time and effort, complex cognitive strategy use, simple cognitive strategy use, contacts with others, and academic thinking) do significantly mediate the relationship between task value and statistics anxiety in adult students in online learning environments.

The purpose of this chapter is to provide an overview of the data collection process, descriptive and demographic characteristics of the sample, and results of the mediation analysis used to address the research questions.

Data Collection

The data collection period began on June 23, 2022, when the survey was posted on Facebook and LinkedIn to my personal page and to groups on both social media sites. The groups that were selected had a large audience of online graduate students. After one week, I collected four complete responses. Given the low response rate, I opted to alter my data collection plan. After amending my IRB approval and receiving permission from

Walden University, I posted the survey to Amazon Mechanical Turk (Mturk). MTurk is a crowdsourcing tool that hires individuals and compensates them for completing tasks, including completing online surveys. MTurk offers an advantage to recruiting exclusively through social media because of its broad reach to many potential participants; additionally, data can often be collected very quickly (Sheehan, 2018). The advertisement on MTurk was posted on 7/8/22, and by 7/10/22, the threshold for survey participants (N = 160) was met.

After closing the survey, the results were downloaded from SurveyMonkey into an Excel file. A total of 194 participants began the survey. Upon review, 18 participants were initially disqualified because they were enrolled in high-school or undergraduate programs. Fourteen participants completed the demographic section but discontinued the survey. Their results were eliminated from the analysis. Four participants skipped several sections of the survey, making their results largely incomplete; they were also eliminated from the analysis. The final sample consisted of 158 participants.

Results

Descriptive Statistics

Demographic information was captured on the following items: age, gender identity, race/ethnicity, number of completed online statistics courses, and major or program of study. Table 1 contains a summary of the demographic information to characterize the sample appropriately.

Table 1

Demographic Information

	N	%
Gender		
Man	47	29.7%
Woman	110	69.6%
Non-binary	1	0.6%
Age		
24-30	97	61.4%
31-40	28	17.7%
41-50	15	9.5%
51+	18	11.4%
Race/Ethnicity		
American Indian/Alaska Native	4	2.5%
Asian	9	5.7%
Black or African American	20	12.7%
Two or more races	2	1.3%
White	123	77.8%
Number of completed online statistics courses		
Currently enrolled in first statistics course	3	1.9%
1-2	91	57.6%
3-4	58	36.7%
5+	6	3.8%
Major		
Business	16	10.1%
Criminal Justice	1	0.6%
Education	21	13.3%
Health	5	3.2%
Human Services (Psychology, Counseling, and Social Work)	43	27.2%
Science, Technology, Engineering, Math	72	45.6%

Most individuals in the sample identified as women between the ages of 24 and 40. Many respondents were white. The demographics of the sample are consistent with current literature on statistics anxiety in adult students (Edirissoriya et al., 2021). A surprise in the data was the higher proportion of STEM majors compared to non-STEM majors. Gonzalez et al. (2016) point out that students from undergraduate STEM programs may have more experience with math or statistics courses, which may increase their proficiency or comfort level with the subject matter. This varying level of proficiency with statistics may create a difference between the STEM and non-STEM majors groups, which would create a limitation within the data. A one-way ANOVA was conducted to determine if statistics anxiety differed for STEM and Non-STEM students, but the differences between statistics anxiety for the two groups were not statistically significant, $F(1,150) = .638$, $p = .426$.

Following the descriptive analysis, the data was prepared for inferential analysis. According to the instrument manual, two items were reverse coded (Pintrich et al., 1991). The items were added, and the mean score was computed as the scale score. Reliability was assessed for each scale and is presented in Table 2. The items from the MSLQ included intrinsic goal orientation (IGO, 4 items, $\alpha = .777$), self-efficacy for learning and performance (SE, 8 items, $\alpha = .78$), and task value (TV, 6 items, $\alpha = .762$). All Cronbach's alpha levels are above the minimum acceptable level of .7, which indicates these scales have acceptable reliability.

The items for the MSLQ-B included academic thinking (THNK, 5 items, $\alpha = .679$), complex cognitive strategies (CPLX, 5 items, $\alpha = .657$), simple cognitive strategies (SIMP, 5 items, $\alpha = .637$), contact with others (CONT, 4 items, $\alpha = .729$), and management of time and effort (MTE, 6 items, $\alpha = .797$). Three of the five subscales, specifically academic thinking, complex cognitive strategies, and simple cognitive strategies, have Cronbach's alpha levels lower than the minimum acceptable standard, which indicates questionable reliability. According to the manual, the items were added, and the mean score was computed as the scale score (Meijs et al., 2019).

The items from the STARS included test and class anxiety (TCA, 8 items, α = .828), interpretation anxiety (IA, 11 items, α = .799), computational self-concept (CSC, 7 items, α = .784), worth of statistics (WOS, 16 items, α = .853), fear of asking for help (FAH, 4 items, α = .84), and fear of statistics teachers (FST, 5 items, α = .812). According to the instrument manual, the sum of the items was used as the subscale score (Cruise et al., 1985). The Cronbach's alpha levels for all the subscales exceeded the minimum acceptable standard of .7, which indicates that these subscales are reliable. The subscales were added together to create the dependent variable of statistics anxiety.

Table 2

Reliability Statistics for Subscales

Variable	a	Scale Items
MSLQ		
Intrinsic goal orientation (IGO)	.777	4
Self-efficacy for learning and performance	.78	8
Task value (TV)	.762	6
MSLQ Part-B		
Academic thinking (THNK)	.679	5
Complex cognitive strategies (CPLX)	.657	5
Simple cognitive strategies (SIMP)	.637	5
Contact with others (CONT)	.729	4
Management of time and effort (MTE)	.797	6
STARS		
Test and class anxiety (TCA)	.828	8
Interpretation anxiety (IA)	.799	11
Computational self-concept (CSC)	.784	7
Worth of statistics (WOS)	.853	16
Fear of asking for help (FAH)	.84	4
Fear of statistics teachers (FST)	.812	5

Assumptions

After cleaning the data and exploring the demographic information of the sample, preliminary data analysis was performed to confirm that the sample met several important assumptions before the primary data analysis. The first assumption was that the relationship between the variables must be linear. A visual inspection of the scatterplot revealed a linear relationship between the variables; therefore, this assumption was met. The second assumption was that there would be no multicollinearity between variables. A collinearity diagnosis was performed to assess for multicollinearity. The tolerance thresholds for all the independent variables were greater than .01, which is the recommended minimum value, indicating there was no concern with multicollinearity. The variance inflation factor ranged from 1.578 to 3.976, and because all values were less than 10, this further reinforced there was no concern with multicollinearity. The next assumption was that the value of the residuals is independent. There was the independence of residuals, as assessed by a Durbin-Watson statistics of 1.51; therefore, this assumption was met. The fourth assumption was that the variance of the residuals is constant. A visual inspection of a plot of studentized residuals versus unstandardized predicted values verified homoscedasticity, which satisfied this assumption. The fifth assumption was that the residuals are normally distributed, which was confirmed by way of a visual inspection of the Normal Q-Q plot. The final assumption was that there would be no influential cases biasing the model. This was evaluated using Cook’s Distance statistics. There were no values for Cook’s Distance greater than 1, therefore, there were no cases that were influential in this data set. The results of these tests confirmed that the data met the necessary assumptions to perform an ordinal linear regression.

Mediation Analysis

A mediation analysis was performed to analyze each research question. Andrew Hayes’s PROCESS macro was installed in SPSS v 27. A mediation analysis explores the direct or indirect effect a mediating variable has on the relationship between an independent and dependent variable. In a complete mediation, the relationship between the independent and dependent variables is reduced to zero in the presence of the mediator. This implies that the relationship exists only through the influence of the mediating variable. A partial mediation exists when the relationship between the independent and dependent variables is reduced, which suggests that the mediating variable plays a role in influencing the relationship. The PROCESS macro utilizes ordinal least squares (OLS) regression to analyze the relationship between the independent variable and the mediating variable (path a), the mediating variable and the dependent variable (path b), and the relationship between the independent variable and the dependent variable (path c). The indirect effect is computed as the product of the regression coefficients of paths a and b (Hayes, 2022). The indirect effect refers to how much difference in the dependent variable is anticipated as a result of the mediating variable’s effect (Hayes, 2022). The direct effect estimates the difference in the dependent variable when the mediator is held as constant (Hayes, 2022).

Significance was evaluated using the bootstrapping method as per the original data analysis plan. Bootstrapping allowed for automated resampling of 5000 data points. The bootstrapping method is a nonparametric method that uses a 95% confidence interval and a non-zero method, meaning if the confidence interval does not contain zero, then the researcher can reject the null hypothesis at $p < .05$ (Hayes & Scharkow, 2013; Preacher & Hayes, 2004). Historically, the Sobel method was the most common method of assessing effect size. The bootstrapping method is preferred to the Sobel method because the Sobel method has limitations with power and trustworthiness, particularly with smaller samples (Hayes & Scharkow, 2013).

Intrinsic Goal Orientation and Self-regulated Learning

To investigate the first research question, a simple mediation analysis was performed using Hayes's (2022) PROCESS macro in SPSS version 27. The outcome variable for the analysis was statistics anxiety. The predictor variable for the analysis was intrinsic goal orientation. The mediator variable was self-regulated learning strategies. The analysis was performed five times, replacing the mediator variable with one of the five self-regulated learning strategies each time.

Intrinsic goal orientation and academic thinking. Intrinsic goal orientation exerts an effect on statistics anxiety indirectly through academic thinking (9.463, 95% C.I. [4.028, 15.342], $p < .05$). The results of the mediation analysis are included in Table 3.

Table 3

Intrinsic Goal Orientation and Academic Thinking

				95% CI	
	b	*SE*	*p*	Lower	Upper
IGO → THNK	.706	.071	.000***	.567	.846
THNK → STARS	13.399	3.659	.000***	6.168	20.63
IGO → STARS	8.088	3.288	.05*	1.59	14.585

Direct effect	-1.376	4.082	.7365	-9.442	6.69
Indirect effect	9.463	2.865	.05*	4.028	15.342

Note. IGO = intrinsic goal orientation. THNK = academic thinking. STARS = statistics anxiety.
*p < .05, **p < .01, ***p < .001

Intrinsic goal orientation and complex cognitive strategies. The 95% confidence interval for the indirect effect of complex cognitive strategies mediating intrinsic goal orientation and statistics anxiety contains zero. Therefore, we cannot reasonably reject the null hypothesis (.657, 95% C.I. [-2.962, 4.739], $p < .05$). The results of the mediation analysis are included in Table 4.

Table 4

Intrinsic Goal Orientation and Complex Cognitive Strategy Use

				95% CI	
	b	*SE*	*p*	Lower	Upper
IGO → CPLX	.479	.064	.000***	.353	.605
CPLX → STARS	1.373	4.239	.747	-7.003	9.748
IGO → STARS	8.808	3.288	.05*	1.590	14.585
Direct effect	7.43	3.872	.057	-.222	15.082
Indirect effect	.657	1.942	.05*	-2.962	4.739

Note. IGO = intrinsic goal orientation. CPLX = complex cognitive strategy use. STARS = statistics anxiety.
*p < .05, **p < .01, ***p < .001

The OLS regression used to identify path b, which combines the independent variable and mediator to predict the outcome variable, was significant in this model, $F(2, 148) = 3.059$, $p < .001$. Both intrinsic goal orientation and complex cognitive strategies contributed significantly to the model. Although mediation was not significant in the total model, this path was significant.

Intrinsic goal orientation and contact with others. Intrinsic goal orientation exerts an effect on statistics anxiety indirectly through contact with others (7.223, 95% C.I. [3.838, 11.255], $p < .05$). The results of the mediation analysis are included in Table 5.

Table 5

Intrinsic Goal Orientation and Contact with Others

	b	*SE*	*p*	95% CI Lower	95% CI Upper
IGO → CONT	.463	.889	.000***	.288	.639
CONT → STARS	15.593	2.76	.000***	10.14	21.047
IGO → STARS	8.808	3.288	.05*	1.590	14.585
Direct effect	.865	3.254	.791	-5.566	7.294
Indirect effect	7.223	1.191	.05*	3.838	11.255

Note. IGO = intrinsic goal orientation. CONT = contact with others. STARS = statistics anxiety.
**p* < .05, ***p* < .01, ****p* < .001

Intrinsic goal orientation and management of time and effort. The 95% confidence interval for the indirect effect of complex cognitive strategies mediating intrinsic goal orientation and statistics anxiety contains zero. Therefore, we cannot reasonably reject the null hypothesis (-2.455, 95% C.I. [-7.191, .316], $p < .05$). The results of the mediation analysis are included in Table 6.

Table 6

Intrinsic Goal Orientation and Management of Time and Effort

	b	*SE*	*p*	95% CI Lower	95% CI Upper
IGO → MTE	.147	.075	.051	-.001	.295
MTE → STARS	-16.665	3.343	.000***	-23.272	-10.059
IGO → STARS	8.808	3.288	.05*	1.590	14.585
Direct effect	10.542	3.092	.000***	4.432	16.653
Indirect effect	-2.455	1.9	.05*	-7.191	.316

(*table continues)*

Note. IGO = intrinsic goal orientation. MTE = management of time and effort. STARS = statistics anxiety.
**p* < .05, ***p* < .01, ****p* < .001

The OLS regression used to identify path b, which combines the independent variable and mediator to predict the outcome variable, was significant in this model, *F*(2,

148) = 15.934, $p < .001$. Both intrinsic goal orientation and complex cognitive strategies contributed significantly to the model. Intrinsic goal orientation had a positive effect on statistics anxiety (10.542, $p < .001$), whereas management of time and effort had a negative effect (-16.665, $p < .001$). Although mediation was not significant in the total model, this path was significant.

Intrinsic goal orientation and simple cognitive strategies. The 95% confidence interval for the indirect effect of simple cognitive strategies mediating intrinsic goal orientation and statistics anxiety contains zero. Therefore we cannot reasonably reject the null hypothesis (4.257, 95% C.I. [-.396, 9.968], $p < .05$). The results of the mediation analysis are included in Table 7.

Table 7

Intrinsic Goal Orientation and Simple Cognitive Strategy Use

				95% CI	
	b	*SE*	*p*	Lower	Upper
IGO → SIMP	.55	.068	.000***	.416	.684
SIMP → STARS	7.746	3.937	.051	-.034	15.526
IGO → STARS	8.088	3.288	.05*	1.59	14.585
Direct effect	3.83	3.91	.329	-3.896	11.557
Indirect effect	4.257	2.545	.05*	-.396	9.968

Note. IGO = intrinsic goal orientation. SIMP = simple cognitive strategy use. STARS = statistics anxiety.
*$p < .05$, **$p < .01$, ***$p < .001$

Self-efficacy and Self-regulated Learning

To answer the second research question, a simple mediation model using Hayes's (2022) PROCESS macro in SPSS v 27 was deployed. The outcome variable for the analysis was statistics anxiety. The predictor variable for the analysis was self-efficacy. The mediator variable was self-regulated learning strategies. The analysis was performed five times, replacing the mediator variable with one of the five self-regulated learning strategies each time.

Self-efficacy and academic thinking. Self-efficacy exerts an effect on statistics anxiety indirectly through academic thinking (12.034, 95% C.I. [7.584, 17.051], $p < .05$). The results of the mediation analysis are included in Table 8.

Table 8

Self-efficacy and Academic Thinking

	b	*SE*	*p*	95% CI Lower	95% CI Upper
SE → THNK	.665	.076	.000***	.515	.815
THNK → STARS	18.101	3.401	.000***	11.38	24.822
SE → STARS	1.318	3.426	.701	-5.452	8.088
Direct effect	-10.716	3.877	.01**	-18.378	-3.055
Indirect effect	12.034	2.417	.05*	7.584	17.051

Note. SE = self-efficacy for learning and performance. THNK = academic thinking. STARS = statistics anxiety.
*$p < .05$, **$p < .01$, ***$p < .001$

Self-efficacy and complex cognitive strategies. The 95% confidence interval for the indirect effect of complex cognitive strategies mediating self-efficacy and statistics anxiety contains zero. Therefore, we cannot reasonably reject the null hypothesis (3.87, 95% C.I. [-.286, 8.543], $p < .05$). The results of the mediation analysis are included in Table 9.

Table 9

Self-efficacy and Complex Cognitive Strategy Use

	b	*SE*	*p*	95% CI Lower	95% CI Upper
SE → CPLX	.479	.064	.000***	.353	.605
CPLX → STARS	1.373	4.239	.747	-7.003	9.748
SE → STARS	8.808	3.288	.015	1.590	14.585
Direct effect	7.43	3.872	.057	-.222	15.082
Indirect effect	.657	1.942	.05*	-2.962	4.739

Note. SE = self-efficacy for learning and performance. CPLX = complex cognitive strategy use. STARS = statistics anxiety.
*$p < .05$, **$p < .01$, ***$p < .001$

Self-efficacy and contact with others. Self-efficacy exerts an effect on statistics anxiety indirectly through contact with others (5.447, 95% C.I. [1.919, 9.45], $p < .05$). The results of the mediation analysis are included in Table 10.

Table 10

Self-efficacy and Contact with Others

				95% CI	
	b	*SE*	*p*	Lower	Upper
SE → CONT	.324	.095	.001***	.136	.512
CONT → STARS	16.803	2.621	.000***	11.625	21.982
SE → STARS	1.318	3.462	.701	-5.452	8.088
Direct effect	-4.129	3.158	.19	-10.369	2.11
Indirect effect	5.447	1.914	.05*	1.919	9.45

Note. SE = self-efficacy for learning and performance. CONT = contact with others. STARS = statistics anxiety.
*$p < .05$, **$p < .01$, ***$p < .001$

Self-efficacy and management of time and effort. Self-efficacy exerts an effect on statistics anxiety indirectly through management of time and effort (-4.376, 95% C.I. [7.584, 17.051], $p < .05$). The results of the mediation analysis are included in Table 11.

Table 11

Self-efficacy and Management of Time and Effort

				95% CI	
	b	*SE*	*p*	Lower	Upper
SE → MTE	.265	.074	.001***	.118	.412
MTE → STARS	-16.537	3.536	.000***	-23.525	-9.55
SE → STARS	1.318	3.426	.701	1.590	14.585
Direct effect	5.694	3.342	.091	-.911	12.3
Indirect effect	-4.376	2.129	.05*	-9.65	-.124

Note. SE = self-efficacy for learning and performance. MTE = management of time and effort. STARS = statistics anxiety.
*$p < .05$, **$p < .01$, ***$p < .001$

Self-efficacy and simple cognitive strategies. Self-efficacy exerts an effect on statistics anxiety indirectly through simple cognitive strategies (4.475, 95% C.I. [1.645, 8.172], $p < .05$). The results of the mediation analysis are included in Table 12.

Table 12

Self-efficacy and Simple Cognitive Strategy Use

				95% CI	
	b	*SE*	*p*	Lower	Upper
SE → SIMP	.403	.076	.000	.252	.553
SIMP → STARS	11.114	3.575	.002	4.05	18.781
SE → STARS	1.318	3.426	.701	-5.452	8.088
Direct effect	-3.157	3.628	.386	-10.326	4.013
Indirect effect	4.475	1.647	.05	-1.645	8.172

Note. SE = self-efficacy for learning and performance. SIMP = simple cognitive strategy use. STARS = statistics anxiety.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Task Value and Self-regulated Learning

Hayes's (2022) PROCESS macro in SPSS v 27 was used to answer the third research question. The outcome variable for the analysis was statistics anxiety. The predictor variable for the analysis was task value. The mediator variable was self-regulated learning strategies. The analysis was performed five times, replacing the mediator variable with one of the five self-regulated learning strategies each time.

Task value and academic thinking. Task value exerts an effect on statistics anxiety indirectly through academic thinking (10.831, 95% C.I. [5.814, 17.563], $p < .05$). The results of the mediation analysis are included in Table 13.

Table 13

Task Value and Academic Thinking

				95% CI	

	b	*SE*	*p*	Lower	Upper
TV → THNK	.671	.081	.000***	.511	.831
THNK → STARS	16.135	3.385	.000***	9.446	22.824
TV → STARS	3.342	3.584	.353	-3.741	10.424
Direct effect	-7.489	4.047	.066	-15.486	.508
Indirect effect	10.831	2.941	.05*	5.814	17.563

Note. TV = task value. THNK = academic thinking. STARS = statistics anxiety.
*$p < .05$, **$p < .01$, ***$p < .001$

Task value and complex cognitive strategies. The 95% confidence interval for the indirect effect of complex cognitive strategies mediating task value and statistics anxiety contains zero. Therefore we cannot reasonably reject the null hypothesis (3.56, 95% C.I. [-1.443, 9.304], $p < .05$). The results of the mediation analysis are included in Table 14.

Table 14

Task Value and Complex Cognitive Strategy Use

				95% CI	
	b	*SE*	*p*	Lower	Upper
TV → CPLX	.617	.062	.000***	.493	.74
CPLX → STARS	5.775	4.704	.222	-3.52	15.071
TV → STARS	3.342	3.584	.353	-3.741	10.424
Direct effect	0.219	4.601	.962	-9.32	8.83
Indirect effect	3.65	2.736	.05*	-1.443	9.304

Note. TV = task value. CPLX = complex cognitive strategy use. STARS = statistics anxiety.
*$p < .05$, **$p < .01$, ***$p < .001$

Task value and contact with others. Task value exerts an effect on statistics anxiety indirectly through contact with others (6.838, 95% C.I. [3.052, 11.039], $p < .05$). The results of the mediation analysis are included in Table 15.

Table 15

Task Value and Contact with Others

				95% CI	
	b	*SE*	*p*	Lower	Upper
TV → CONT	.408	.098	.000***	.214	.601
CONT → STARS	16.774	2.672	.000***	11.493	22.055
TV → STARS	3.342	3.584	.353	-3.741	10.424
Direct effect	-3.497	3.377	.302	-10.169	.318
Indirect effect	6.838	2.015	.05*	3.052	11.039

Note. TV = task value. CONT = contact with others. STARS = statistics anxiety.

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

Task value and management of time and effort. Task value exerts an effect on statistics anxiety indirectly through management of time and effort (-5.21, 95% C.I. [-10.818, -1.544], $p < .05$). The results of the mediation analysis are included in Table 16.

Table 16

Task Value and Management of Time and Effort

				95% CI	
	b	*SE*	*p*	Lower	Upper
TV → MTE	.299	.077	.001***	.146	.452
MTE → STARS	-17.449	3.524	.000***	-24.213	-10.485
TV → STARS	3.342	3.584	.353	-3.741	10.424
Direct effect	8.551	3.493	.016	1.648	15.455
Indirect effect	-5.21	2.361	.05*	-10.878	-1.544

Note. TV = task value. MTE = management of time and effort. STARS = statistics anxiety.
*$p < .05$, **$p < .01$, ***$p < .001$

Task value and simple cognitive strategies. Task value exerts an effect on statistics anxiety indirectly through simple cognitive strategies (6.429, 95% C.I. [2.118, 12.597], $p < .05$). The results of the mediation analysis are included in Table 17.

Table 17

Task Value and Simple Cognitive Strategy Use

				95% CI	
	b	*SE*	*p*	Lower	Upper
TV → SIMP	.563	.074	.000***	.417	.709
SIMP → STARS	11.415	3.87	.01**	3.768	19.062
TV → STARS	3.342	3.584	.353	-3.741	10.424
Direct effect	-3.088	4.12	.455	-11.227	5.052
Indirect effect	6.429	2.622	.05*	2.118	12.592

Note. TV = task value. SIMP = simple cognitive strategy use. STARS = statistics anxiety.
*$p < .05$, **$p < .01$, ***$p < .001$

Summary

Intrinsic goal orientation was found to indirectly affect statistics anxiety through contact with others and academic thinking. Self-efficacy was found to indirectly affect statistics anxiety through simple cognitive strategies, contact with others, management of time and effort, and academic thinking. Task value was found to indirectly affect statistics anxiety through simple cognitive strategies, academic thinking, management of time and effort, and contact with others. Complex cognitive strategy use was the only self-regulated learning strategy that did not mediate the relationship between motivation and statistics anxiety. Contact with others and academic thinking had a mediating effect on all three variables for motivation. In considering the direction of the effect (positive or negative), management of time and effort is the only self-regulated learning strategy that appears to reduce participants' reported statistics anxiety. In the following chapter, I will explore a further interpretation of these results, the practical application for educators, and how these findings have implications for positive social change.

Chapter 5: Discussion, Conclusions, and Recommendations

Introduction

Statistics anxiety has been explored in psychological and educational research for many years (Cruise et al., 1985; Cui et al., 2019). This domain-specific anxiety impacts students of all ages, genders, academic programs, and learning environments (DeVaney, 2010; MacArthur, 2020). Research suggests that statistics anxiety may have negative impacts on academic performance (Zhang et al., 2019), academic integrity (Eshet et al., 2020), and career selection (Beilock & Maloney, 2015). Social cognitive theory has been applied to this phenomenon to frame and understand the potential cognitive, behavioral, and environmental variables that influence a person's development of statistics anxiety (Cui et al., 2019). This quantitative study aimed to explore the mediating effect of self-regulated learning strategies on the relationship between motivation and statistics anxiety. The results of this study may be useful in curriculum design for online graduate programs. Further understanding of the root cause of statistics anxiety helps educators design a course curriculum that mitigates the threat of statistics anxiety.

The data suggest that self-regulated learning plays a role in influencing students' motivation and statistics anxiety. Intrinsic goal orientation was found to have an indirect effect on statistics anxiety through contact with others and academic thinking. Self-efficacy was found to have an indirect effect on statistics anxiety through simple cognitive strategies, contact with others, management of time and effort, and academic thinking. Task value was found to have an indirect effect on statistics anxiety through simple cognitive strategies, academic thinking, management of time and effort, and contact with others. In this chapter, I will discuss my research findings, provide future research recommendations, and offer practical applications for educators responsible for designing online statistics courses.

Interpretation of the Findings

This study's findings align with prior research that identified statistics anxiety as a phenomenon in online learning environments (DeVaney, 2010). Although this research does not compare statistics anxiety between students in face-to-face learning and online learning environments, this study supports findings from prior research that suggest adult students in online learning environments are not immune to struggles with statistics anxiety. The findings of this study suggest that the learning strategies students select may play a more meaningful role in mitigating statistics anxiety than their motivation to actually learn statistics. Faber and Drexler (2019) found that motivation was a stronger predictor of statistics anxiety than the student’s prior statistics experience. Baloglu et al. (2014) found that students with higher task values demonstrated lower levels of statistics anxiety. Hoegler and Nelson (2018) found that self-efficacy played a mediating role between statistics anxiety and academic performance; however, these studies did not explore the application of self-regulated learning strategies. Whereas prior literature seems to demonstrate that higher levels of self-efficacy and task value lead to lower levels of statistics anxiety, the model in this study suggests that the students’ use of self-regulated learning strategies may play a key role in that relationship.

Four of the five self-regulated learning strategies had a mediating effect on motivation and statistics anxiety. The complex cognitive strategy was the only learning strategy that did not demonstrate a mediating effect on any independent variables of intrinsic goal orientation, self-efficacy, or task value. This finding is inconsistent with prior literature, in which deep learning or complex cognitive strategies have been associated with lower levels of statistics anxiety (Gonzalez et al., 2016). Gonzalez et al. (2016) found that deep learning strategies significantly reduced statistics anxiety and increased persistence in statistics courses. There was a significant relationship between complex cognitive strategies and all three variables of motivation; however, this relationship did not translate into a mediating effect on statistics anxiety. One possible interpretation is that the students who demonstrated deeper or complex cognitive strategies may also be classified as high-achieving nontraditional students. High achieving students may also exhibit fear of failure in stressful learning environments. Pride in being a model student can easily devolve into fear of failure for high-achieving adult learners (Wong et al., 2019). This pressure and fear of failure may result in hypervigilance, which may explain how the pressure students place on themselves to succeed can manifest through complex learning strategies and statistics anxiety (Choi, 2021).

Statistics anxiety is an example of domain-specific anxiety. Students who experience statistics anxiety may not report symptoms of anxiety in other areas of their life or learning. While researching another domain-specific anxiety, reading anxiety, Elgendi et al. (2021) found that higher reading difficulty led to increased academic anxiety, but not necessarily generalized anxiety. This may also be true with statistics anxiety. It is important to recognize the difference between general and domain-specific anxiety, as students may not report or recognize the fear, apprehension, or avoidance they feel as anxiety because they don't associate those feelings with anxiety in any other areas of their life. Therefore, because they do not recognize these feelings as anxiety, they may not seek the help they need or develop skills or strategies to help them cope with this domain-specific anxiety.

Another domain-specific anxiety is test anxiety. This construct is incorporated as a facet of statistics anxiety; however, it also broadens to include tests in other academic disciplines outside of statistics courses. Zong et al. (2021) explored test anxiety and motivation with students, and their results suggested that motivation was not a predictor of test anxiety. Alternately, they discovered that resiliency was a critical trait that mitigated test anxiety. This further reinforces the findings of this study, which suggest that learning strategies play more of a role in the development and mitigation of statistics anxiety than simply motivation alone. Therefore, it is critical that academic interventions not overly emphasize student motivation but should instead focus on resiliency skills and self-regulated learning strategies that reduce domain-specific anxiety.

During the interpretation of the findings, Hayes (2022) encourages researchers to consider the signs, positive or negative, of the indirect effect. Interestingly, management of time and effort indicated a negative mediating effect on self-efficacy and task value. In this case, those with higher self-efficacy and task value will experience lower statistics anxiety through the indirect effect of management of time and effort. MacKinnon et al. (2007) also referred to this as an inconsistent effect or inconsistent mediation. Hair et al. (2021) referred to this as competitive mediation. In this case, management of time and effort plays a suppressive role and decreases the total effect of the independent variable on the dependent variable. These findings suggest that management of time and effort may be a key learning strategy for reducing statistics anxiety. This result is consistent with prior literature, which emphasized the critical role of time management in student success. Wolters and Bradley (2021) discussed time management through the lens of self-regulation. The authors summarized time management as the behavioral execution of the cognitive and metacognitive evaluation of a task. The results of this study also support the findings that time management plays a significant role in student success, as well as in reducing statistics anxiety. Dunn (2014) applied these principles to statistics anxiety and found that effective time management reduced statistics anxiety. Dunn (2014) also found that intrinsic motivation and self-regulation worked together to decrease procrastination behaviors and statistics anxiety. Dunn (2014) surmised intrinsic motivation might be the mediating variable, but this was not analyzed.

According to social cognitive theory, the self-regulated learning strategies an individual chooses is tied to the individuals' beliefs and values about a topic (Zimmerman, 1989). The results of this study suggest that the learning strategies a student selects plays a significant role in either increasing or decreasing their statistics anxiety. This is consistent with the principle of reciprocal determinism in social cognitive theory. This principle underscores the complex relationship that cognitive, environmental, and behavioral variables have in forming the human experience (Bandura, 1989). The actions that a student takes regarding managing their time, reaching out to others, or exercising critical thinking will influence their motivation. At the same time, their motivation will influence the learning strategies they choose to deploy.

As opposed to the suppressive effect of time management, the remaining self-regulated learning strategies indicated a positive indirect effect, specifically simple cognitive strategy use, contact with others, and academic thinking. Although the effect size was small, this suggests that their mediating effect raised the participants' statistics anxiety; however, these three scales had low reliability with this sample, which is a potential limitation. It is important to interpret all these results with caution. Even a mediating model cannot capture all the influential variables that are at work (Agler & De Boech, 2017). A mediation model is not a causal conclusion, and there were several limitations with the data in this study.

Limitations of the Study

The first limitation was the reliance on self-report instruments to gather data. Although the instruments in this research study have been used extensively in prior research, it does not guarantee their reliability. Confirming what has been found in prior research, the reliability of the MSLQ-Part A and the STARS questionnaire was medium to high. (Khampirat, 2021; DeVaney, 2016; Chew et al., 2018; Nesbit & Bourne, 2018, Nielsen & Kreiner, 2018; Frey-Clark et al., 2019). However, the results of Cronbach's alpha for three of the five scales of the MSLQ Part-B were lower than the minimum threshold: academic thinking, simple cognitive strategy use, and complex cognitive strategy use. This presents a limitation as it introduces a concern about reliability and, therefore, the generalizability of the findings. Interpretation of results using these three scales should include caution. This may explain the results regarding complex cognitive strategy use that are inconsistent with prior literature.

The purpose of this study was to explore mediating effect of a third variable on an established relationship between two other variables. However, the challenge of this model is the inability to isolate additional confounding or influential variables (Agler & De Boech, 2017). I gathered information about the sample that may influence these relationships, including age, major, and prior experience with statistics courses. Whereas it is not realistic to be able to isolate all potential confounding variables that may play a role in the relationship between motivation and statistics anxiety, ensuring that the sample represented the target population as closely as possible was one strategy to mitigate the threat of additional variables. The most noticeable difference between this sample and prior literature was most STEM students compared to non-STEM students. However, an ANOVA confirmed that there was no statistically significant difference between these two groups when it came to their levels of statistics anxiety.

The final potential limitation was during the data collection process. As a result of the slow return rate of the original distribution method, I turned to Amazon Mechanical

Turk (MTurk) to recruit the remaining participants. Whereas this method allowed me to reach my sampling target in a shorter time frame, it is unknown if this approach may have influenced the quality of the results. Chmielewski and Kucker (2020) advised researchers that use MTurk to exercise caution when interpreting the results as this digital crowdsourcing approach may decrease the reliability and validity of responses. I recruited a manageable sample of 140 participants from MTurk, allowing me to adequately screen and clean the data before incorporating it into SPSS for analysis. However, as with all data collected from self-reports by individuals, it is essential to exercise caution when interpreting the results.

Recommendations

Future research should continue to build on these findings by exploring potential mediating variables that play a role in statistics anxiety. Until we identify the root cause of this domain-specific anxiety, it is unlikely that we will be able to design interventions that truly mitigate its effect. The results of this study suggested that some of the learning strategies that students deploy in statistics courses may potentially aggravate statistics anxiety. In research conducted on general academic anxiety, Choi (2021) found that fear of failure strongly influenced anxiety. Future research should explore if this is also true in statistics anxiety.

In addition to the root cause of statistics anxiety, more needs to be learned about the impact of statistics anxiety. Research has been inconclusive on the negative effect of statistics anxiety related to academic performance. This begs the question, if a student reports high levels of anxiety but is successful in their statistics course, is there a negative impact of statistics anxiety? MacArthur (2020) compares students' statistics anxiety and their general attitudes about the worth of statistics and found that students' attitudes remain stable before, during, and after their course, whereas statistics anxiety peaked early in the course but went down as the course progressed. This may suggest that anxiety is not the root issue, but rather the concern is students' attitudes toward statistics. They suggest that perhaps the focus of research should not be on anxiety per se but on the negative attitudes and associations that students have with statistics.

Also, while much of the research in this area has focused on traditional college students, it is essential that further research continues to focus exclusively on online learning environments and adult students. The online learning environment is different from the traditional experience and comes with its unique set of challenges and opportunities (Nwabuoku, 2020). Additional research is necessary to fully understand how students in the online learning environment experience and mitigate statistics anxiety. The same is true for adult or non-traditional students. Their needs are different from traditional-aged college students, and it is important that research identify what support strategies are most successful for these students (Mamun et al., 2020).

Implications

Practical Recommendations

The results of this study suggest that specific self-regulated learning strategies influence online students' statistics anxiety. This is significant because it provides evidence for academic leaders who may be designing academic interventions aimed at reducing statistics anxiety and increasing students' statistics literacy. Practical online learning interventions ought to focus on cultivating positive learning strategies that promote academic success and reduce statistics anxiety (McIntee et al., 2022). The first learning strategy that may be helpful to develop in online students is time management. Students who exhibit healthy time management will accurately estimate the time needed for certain tasks, engage in time-saving behaviors, and avoid procrastination (Khiat, 2022). Khiat and Vogel (2022) discuss academic interventions that seek to train students on the use of effective time management strategies. They found that interventions that incorporate this training throughout the duration of a course are more effective than those that discuss these strategies only before the course. Their study suggests that incorporating these strategies into course design also increased students' academic motivation. Educators that develop online statistics courses may help students reduce their anxiety if they help equip their students with effective time management strategies.

In addition to training students to use effective time management strategies, technological interventions can also shape the experience for students to influence time management in a more passive way. Online courses are generally delivered through a learning management system (LMS). Khiat (2022) explored the use of certain settings or strategies within the LMS that had an impact on students' time management. One key aspect of their intervention was providing an accurate time estimate of all student learning activities. This is important because a student's perception of the workload of a course directly influences the learning strategies that they use to approach the material (Khiat, 2022). Therefore, it is recommended that educators who design statistics courses provide accurate estimates of time for all learning activities.

Another promising application of learning strategies in the online environment is through the use of gamification. This theory of course design uses highly engaging video game elements aimed to increase students' motivation. Gamified courses may include a curriculum that grants points for the completion of learning activities, awards badges for each module completed, and issues a certificate upon course completion. Xu et al. (2021) conducted a meta-analysis of the literature on the effect of gamified learning. They found that gamification leverages the power of extrinsic motivation to alter the students' intrinsic motivation.

The results of this study also suggest that contact with others is an effective strategy for influencing statistics anxiety. A wealth of research supports the positive impact of peer tutoring in higher education. Students with peer tutors embedded in their courses report feeling more engaged with their course and that they have a deeper understanding of the course material (Cacciamani et al., 2019; Mendoza & Kerl, 2021). One academic intervention that has been explored through the literature is Supplemental Instruction (SI). This program utilizes a peer student who has successfully completed the course and employs that student to host group study sessions for students in historically difficult courses (Arendale, 2014). Khan (2020) found that students in courses where SI was offered demonstrated deeper learning strategies in math compared to students in courses without SI. The potentially positive impact of peer tutoring is a promising intervention for online students in statistics courses.

Positive Social Change

In addition to practical recommendations that may be applied to statistics courses, the results of this study have implications for positive social change. As previously mentioned, statistical literacy is an important skill for adults (Engel, 2017). It is essential that adults know how to interpret and analyze statistical information when it is presented to them. This applies not only to online statistics courses but to all areas of adult life. Statistical information is presented in the form of news communication, election results, medical data, etc. It is essential for adults to be well-informed on these important issues and to be critical consumers of the data they are being presented (Engel, 2017). The results of this study suggest potential strategies that may help students reduce statistics anxiety, which in turn may increase their statistical knowledge. These findings offer practical recommendations that may improve the experience for students in online statistics courses. This is a key step in the mission to educate and equip adults with the statistical literacy skills they need to be successful.

Methodological and Theoretical Implications

The results of this study suggest that certain self-regulated learning strategies may help lower statistics anxiety for adult students. This further reinforces the principle of reciprocal determinism from the social cognitive theory that explains the reinforcing nature of cognitive, behavioral, and environmental variables in producing the human experience. In this study, the behaviors of time management had an indirect effect on the cognitive variable of motivation. However, the results also suggested that certain self-regulated learning strategies had the opposite effect on statistics anxiety. Although this supports the theoretical principle of reciprocal determinism, it also underscores the critical need for additional research in this area to understand further the role these variables play in increasing or decreasing statistics anxiety.

Further research on statistics anxiety rooted in social cognitive theory should continue to explore the reciprocal nature of cognition, behavior, and environment. Whereas the research method of mediation analysis offers insight into potential causal mechanisms, the interpretation of the results is limited. Experimental research may offer more confidence in causal interpretations. Additional research should focus on studying the effect of academic interventions. For example, a pilot study of a time management intervention in one section of a statistics course compared with the results from another section offers insight into the intervention's role in reducing statistics anxiety in those students. Deploying an experimental research design to study statistics anxiety may provide additional practical information to the field by identifying promising strategies or interventions that play a role in reducing statistics anxiety.

Conclusion

Students taking statistics courses often report anxiety in the collecting and interpreting of statistical data (Puklek & Cukon, 2020). This domain-specific anxiety involves lower levels of computational self-concept and lower perceived value or worth of statistics (Heretick & Tanguma, 2020). The negative effect of statistics anxiety includes challenges with academic performance (Zhang et al., 2019), academic integrity violations (Eshet et al., 2020), and an aversion to quantitative career fields such as STEM (Beilock & Maloney, 2015). The root cause of statistics anxiety remains unknown; however, research suggests cognitive, behavioral, and environmental factors may play a role (Cui et al., 2019). This is supported theoretically by social cognitive theory, which suggests that these three components, cognitive, behavioral, and environmental variables, influence one another in a principle known as reciprocal determinism (Bandura, 1978).

The purpose of this research study was to explore the influence of self-regulated learning strategies on the relationship between motivation and statistics anxiety. Five specific self-regulated learning strategies were examined: academic thinking, contact with others, complex cognitive strategies, management of time and effort, and simple cognitive strategies. A mediation analysis was performed to identify the potential indirect effect of intrinsic goal orientation, task value, and self-efficacy on statistics anxiety through each of these self-regulated learning strategies. Management of time and effort was found to have a mediating effect on task value, self-efficacy, and statistics anxiety. In this model, management of time and effort played an important role in lowering statistics anxiety.

The results of the study suggest that self-regulated learning strategies may help reduce statistics anxiety. This study has practical implications for educators designing online statistics courses. Online courses incorporating time management strategies and ensuring a balanced workload may help reduce statistics anxiety in students. Educators may also consider including peer tutoring to encourage contact with others, another strategy that demonstrated an effect on statistics anxiety. Future research in this area should continue to explore the reciprocal effect of various cognitive, behavioral, and environmental factors that may explain the root cause of statistics anxiety.

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Appendix A: Copy of Measures

Section 1: Demographics

1. What education level is the program in which you are currently enrolled?

   (1) High school, (2) Undergraduate, (3) Graduate

2. How long (in months) since you completed your last online statistics course?

   (0) Currently enrolled in my first statistics course, (1) 1-5 months, (2) 6-11 months, (3) More than a year.

3. How old are you? Enter age in years.

4. Gender: How do you identify?

   (1) Man, (2) Woman, (3) Non-binary.

5. What is your race/ethnicity?

   (1) American Indian Alaska Native, (2) Asian, (3) Black or African American, (4) Native Hawaiian or other Pacific Islander, (5) Two or more races, and (6) White

6. How many online statistics courses have you taken?

   (0) Currently enrolled in my first statistics course, (1) 1-2, (2) 3-4, (3) More than 5.

7. Major or program of study for current degree pursuit?

   (1) Science, Technology, Engineering, or Math, (2) Business, (3) Human Services (Psychology, Counseling, and Social Work), (4) Education, (5) Other. If other, please specify below.