May 2023

Longitudinal Relations among Expectancy-Value Beliefs, Achievement, and Intentions to Leave for Health Science Students

Kyle C. Mefferd

LONGITUDINAL RELATIONS AMONG EXPECTANCY-VALUE BELIEFS, ACHIEVEMENT, AND INTENTIONS TO LEAVE FOR HEALTH SCIENCE STUDENTS

By

Kyle C. Mefferd

Bachelor of Science – Kinesiological Sciences
University of Nevada, Las Vegas
2012

Master of Science – Kinesiological Sciences
University of Nevada, Las Vegas
2015

A dissertation submitted in partial fulfillment
of the requirements for the

Doctor of Philosophy – Educational Psychology

Department of Educational Psychology, Leadership, & Higher Education
College of Education
The Graduate College

University of Nevada, Las Vegas
May 2023

UNLV | GRADUATE COLLEGE

Dissertation Approval

The Graduate College
The University of Nevada, Las Vegas

March 20, 2023

This dissertation prepared by

Kyle C. Mefferd

entitled

Longitudinal Relations among Expectancy-Value Beliefs, Achievement, and Intentions to Leave for Health Science Students

is approved in partial fulfillment of the requirements for the degree of

Doctor of Philosophy – Educational Psychology
Department of Educational Psychology, Leadership, & Higher Education

Jonathan Hilpert, Ph.D.
Examination Committee Chair

Gwen Marchand, Ph.D.
Examination Committee Member

Lisa Bendixen, Ph.D.
Examination Committee Member

Rachael Robnett, Ph.D.
Graduate College Faculty Representative

Alyssa Crittenden, Ph.D.
Vice Provost for Graduate Education &
Dean of the Graduate College

ABSTRACT

Utilizing expectancy-value theory (EVT), the present study observed the temporal relations among health science students' expectations, subjective task values (STV), and costs with academic achievement and intentions to leave a health science program. The present study is among the first to examine this population of students and is one of the earliest to utilize a longitudinal design with a random-intercepts cross-lagged panel model (RI-CLPM) for EVT data. The study's novel contributions not only add to the EVT literature by incorporating a methodologically more advanced form of the traditional cross-lagged panel model, but also extends the reach of EVT research by investigating a student population that if supported via motivational interventions can directly combat the shortage of health care professionals such as those in nursing and occupational therapy fields. Based on the longitudinal data from almost 900 health science students – including nursing, pre-nursing, and occupational therapy students – the analysis displayed unidirectional spill-over effects between constructs such that students with higher than expected STVs at semester onset had lower than anticipated cost midsemester. Likewise, those with higher than expected STVs midsemester were predicted to have higher than anticipated end of semester expectations. Regarding student outcomes as predicted from EVT data, theoretically informative results illustrated students with higher than expected STVs at midsemester and end of semester were predicted to have a higher GPA. Similarly, at the end of the semester those with higher than anticipated expectations and lower than expected costs were predicted to have lower intentions to leave their program. The current findings contribute to understandings of the motivational processes involved in health sciences students' achievement and intentions to leave a program. Specifically, the study illustrated that interventions early in a

semester that seek to modify student motivations, in particular enhancing subjective task values, can downstream increase academic achievement and reduce students' ITL.

ACKNOWLEDGEMENTS

This dissertation would not have been possible without the support and encouragement from my dissertation committee, Dr. Jonathan Hilpert, Dr. Gwen Marchand, Dr. Lisa Bendixen, and Dr. Rachel Robnett. Thank you for sticking by me throughout these years.

I would like to thank Dr. Hilpert for accepting me as a doctoral student and seeing me through the finish line. With you as my advisor, these last few years have been extremely fruitful. This would not be possible without you.

To Dr. Marchand, thank you for introducing me to theories of motivation through your courses. Without this experience and knowledge my passion for motivational sciences would not exist.

To Dr. Bendixen, thank you for having a series of great courses! Your courses showed me the rigor and fun that comes with educational psychology.

To Dr. Robnett, thank you for your suggestions, support, and words of encouragement. throughout this process.

To Dr. Harsha Perera, thank you for showing me the beauty of advanced methodology and statistics. Without your passion, guidance, and support I would not have pushed myself to learn beyond statistics taught in the classroom.

To Dr. Matthew Bernacki, thank you for continuing to look out for me throughout all these years. I knew I would only apply for a PhD in educational psychology if a tough but excellent advisor would take me on. Our first meeting all those years ago told me this would be a great experience with your help, and it has been!

Lastly, to my family and friends. I am nothing without your love.

DEDICATION

To God, *fiat mihi secundum verbum tuum.*

To my beautiful wife, Chrisabelle Mefferd. I have loved you since we were 16 and I always will.

To my children, you are my world. I am nothing without you.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 – INTRODUCTION AND THEORETICAL FRAMEWORK

Expectancy-value theory (EVT) perspectives have been used to understand the processes underlying academic outcomes like achievement and intentions to leave (ITL) an academic program (J. Eccles et al., 1983), and is used in the present study to investigate health science students' (i.e., pre-nursing, nursing, occupational therapy [OT]) expectations of success and values. The health science student population is of interest as an estimated 30%-50% of nursing students are predicted to drop out (Brown & Marshall, 2008; Dante et al., 2011; Newton & Moore, 2009; Peter, 2005), and roughly 83% of OT programs report student attrition (Bowyer et al., 2018). While not directly assessed, it can be assumed pre-nursing students drop-out at the average STEM undergraduate rate between 48%-69% (X. Chen, 2013). Moreover, many pre-nursing students are never admitted to a nursing program due to low grade point average (GPA) or science GPA which are common predictors of success in a nursing program (Gartrell et al., 2020; Wolkowitz & Kelley, 2010).

Regardless of whether or not if a pre-nursing student is rejected, or if a student drops out of a nursing or OT program, this is an issue for the healthcare workforce given the shortage of nurses and OTs is projected to be approximately 900,000 (*Fact Sheet: Nursing Shortage*, 2020; Juraschek et al., 2019) and 60,000 (Lin et al., 2015) by 2030, respectively. Students who drop out report poor academic performance and academic difficulty as primary reasons for leaving (Boehm et al., 2017; Bressoud, 2020; Jeffreys, 2007; Ramsburg, 2007; Seymour, 1997; Seymour & Hunter, 2019). Understanding health science students' expectations and values can lead to interventions aimed at increasing motivation to increase performance and retention and enhance the rate of qualified healthcare personnel entering the workforce.

Exploring the temporal relations among EVT beliefs, achievement, and ITL may identify factors that impact academic outcomes during critical periods of a student's semester. Additionally, exploring these temporal relationships can allow future researchers to target these factors at specific points in time to allow for the most efficacious interventions. For example, a longitudinal study may reveal targeting and reducing costs mid-semester has the most potent influence on reducing nursing students' ITL and increase academic achievement.

Motivational literature rarely examines health science students. However, when it does, the focus is on cross-sectional data or the relationships between motivation and academic outcomes are explored at a single time point (Khalaila, 2015; Volkert et al., 2018). This is detrimental considering performance and ITL are based on how expectations and values influence each other over time (Musu-Gillette et al., 2015). Additionally, cross-sectional analysis do not allow for the control of prior measurements of variables and do not provide insight into the causal influence these variables have on academic performance and ITL (Hustinx et al., 2009; Pinxten et al., 2014). Understanding changes in relationships between motivation constructs and academic outcomes are critical for supporting students (Perez et al., 2014).

For this reason, the longitudinal relationships between expectations, subjective task values, and costs in health science education were observed with ITL and academic performance. Costs is largely understudied and was included due to the theorized influence on academic outcomes. The relationships were derived from three time points (semester onset, mid-semester, and end of semester) taken during a 16-week semester. Research exploring EVT constructs in domains like pre-nursing and nursing education is scarce (Khalaila, 2015; Volkert et al., 2018), and nonexistent in OT education.

In addition to contributing to the literature on health science student motivation, this work will provide an additional understanding of the longitudinal relationships between EVT constructs and how each construct uniquely predicts and explains academic performance and ITL while utilizing a random-intercepts cross-lagged panel design (RI-CLPM). This methodology allows for the distinguishing of within-person (unstable) and between-person (stable) effects and can reveal how these distinct components influence academic outcomes. This becomes important as teasing apart the unstable from stable portions of EVT constructs in a RI-CLPM can reveal which variables not only influence academic outcomes, but also expose which variables are susceptible to future interventions. For example, a RI-CLPM may illustrate early in a semester that students who exhibit higher than anticipated within-student (unstable) portions of expectations are predicted to have better academic achievement and lower ITL. We provide a review of EVT, and following this, we elaborate on the current study.

Healthcare Workforce Shortage: Solutions from Expectancy-Value Theory

One attempt to resolve the shortage of healthcare professionals is to increase the number of students admitted to health science programs (Al-Alawi et al., 2020; *The Future of Nursing*, 2011). Although this can improve the number of students matriculating into the healthcare workforce, more strategies can be applied, such as increasing the retention of health science students. Improving retention can maximize the number of graduates entering healthcare professions and counter the healthcare worker deficit.

EVT is a theory of motivation commonly used to describe why students choose to pursue or leave a college major (Wigfield & Eccles, 2020). It has been applied to understanding how motivational constructs influence academic outcomes and the ITL of science, technology, engineering, and mathematics (STEM) undergraduates (Perez, Dai, et al., 2019). Although STEM undergraduate courses are taken by pre-nursing students, and are related to nursing or OT program success (Lysaght et al., 2009; Wolkowitz & Kelley, 2010), EVT is rarely studied in pre-nursing students and professional programs like nursing or OT school. This is unfortunate given the health science student retention rate can be countered by assessing how motivational constructs influence one another over time and recognizing the influences on academic outcomes (Kim et al., 2021; Y. Lee et al., 2022). Particularly, this is important in a high intensity and high stakes environment like those pursuing nursing school, and those already in nursing or OT programs where a single low grade, or low GPA, can lead to students dropping out, switching majors, remediating courses, repeating semesters, or dismissal from their program (Abele et al., 2013; Uyehara et al., 2007).

Due to the high probability of rapidly changing motivational beliefs among health science students it is prudent to capture fluctuations with a longitudinal design (Pekrun & Marsh, 2022). Quick changes in motivation have been studied (Martin et al., 2015) but is rarely done in EVT literature (Kosovich et al., 2017). The few longitudinal EVT studies that use more than two time points to examine the change in relationships between motivational constructs are rarely intensive and often span multiple measurement occasions taken yearly (Arens et al., 2018; Guo, Marsh, et al., 2015; Pinxten et al., 2014; Simpkins et al., 2006) versus within a single semester (Grigg et al., 2018; Perez, Dai, et al., 2019). Consequently, information between time points with long intervals is loss. This may be detrimental considering identifying key moments where motivational change is greatest can allow researchers to explore why certain time points are impactful. For example, large changes in motivation may be linked to a semester with a difficult course that provides challenging exams, or a semester where students first experience a real clinical setting (Jamshidi et al., 2016).

Knowing where motivational change is greatest can lead to timely interventions aimed at increasing health science student motivations by targeting specific EVT variables. Researchers have explored how the relationships of EVT constructs over time predict academic performance (Arens et al., 2018; Dinkelmann & Buff, 2016; Guo, Marsh, et al., 2015) and some used this information to suggest interventions aimed at increasing performance and retention (Archambault et al., 2010; Robinson, Lee, et al., 2018). A similar approach can increase health science student retention. Interventions can be implemented singularly to enhance the initial values of EVT constructs, longitudinally to maintain or change the relationships of EVT constructs, or both. In the following we provide a theoretical rationale for which EVT constructs may be impactful for health science students and elaborate on the present study's contributions to the EVT literature.

Overview of Present Research

Expectancy-value theory is composed of constructs including a student's expectations for success (expectancies) and the values a student holds for a task (Wigfield & Eccles, 2000). Expectancies refer to a student's belief they will be successful on a task. Put another way, this is the belief a health science student has in the probability of being successful in a course or program. A similar construct to expectancies is self-concept. This is a student's self-measure of how skilled they are at a task. For example, a student is said to have high anatomy self-concept if they feel they are good at anatomy, or if they believe they can study anatomy and understand and apply it. While related, this is conceptually distinct from student expectancies because expectations of success hold a future perspective while self-concept is oriented in the present. Empirically, self-concepts of ability are so highly and directly linked with expectations they cannot be distinguished (Eccles, 2009). This has resulted in the use of self-concept in EVT studies to reflect expectancies (Arens et al., 2018; Nagengast et al., 2011; Simpkins et al., 2012). In line with this, the present study utilizes these terms interchangeably. The expectations health science students hold for their STEM courses or programs, within a semester, will be explored in the present study.

Subjective task values (STV) is the assigned value, importance, or interest a student places on a task (Eccles, 2009). This value of a task comprises four components: attainment value, intrinsic value, utility value, and cost (Cook & Artino, 2016; Dever, 2016; Schoor, 2016). Attainment value is the importance of doing well on a task; intrinsic value is the enjoyment one gains from doing a task; and utility value is how useful one finds a task or the degree to which the task contributes to their goals (Wigfield & Eccles, 2000). All STVs will be observed in the present study but will be formed into a composite STV variable (i.e. latent constructs) for the analysis.

Cost refers to how the decision to engage in one task limits the other task an individual can engage in (Wigfield & Eccles, 2000). It is commonly thought of as a negative motivational construct that dampens the overall value a student has for a task. Cost is commonly separated into three components: opportunity cost, effort cost, and psychological cost. Opportunity cost can be thought of as losing the option to engage in one task, that may or may not be valued, because of engaging in another; effort cost can be described as a student's perception of the effort required to successfully complete a task; and psychological cost is the anxiety stemmed from the potential of failing at completing a task (J. Eccles et al., 1983). All costs variables will be observed in the present study but will be formed into a compositive cost variable in the analysis. The following sections describe the expected relationships between each EVT construct and academic outcomes like achievement and ITL for health science students, the anticipated relationships between EVT constructs, and a supporting theoretical rationale.

Relations Among Expectations, Achievement, and ITL for Health Science Students

Students who to take pre-nursing courses, or apply to nursing or OT school, recognize admittance is difficult given the peer competition, rigor of prerequisite courses, and a necessary high entrance exam score. Accordingly, those accepted start with a history of positive academic achievements (Al-Alawi et al., 2020; Bowyer et al., 2018) which likely produces students who enter their program with high expectations of success.

How these initial expectations become stable or change over time within health science education is unclear as they are understudied in this population. However, past research demonstrates positive autoregressive paths between expectations at consecutive and lagged time intervals (Arens et al., 2018). Moreover, expectations and academic achievement are shown to be reciprocally positive. In other words, expectations are positively related to future achievement, and vice versa. This is demonstrated when viewing consecutive (Dinkelmann & Buff, 2016) and lagged time intervals (Guo, Marsh, et al., 2015). However, this has not been demonstrated in health science education. Understanding the relationship between expectancies and achievement can highlight moments in a semester where students' expectations are in decline and consequently influence achievement.

Intentions to leave an educational program, like nursing or OT school, is defined as a student's decision to discontinue pursuing that program (Cromley et al., 2016). Expectancies are posited to have a significant relationship with academic outcomes like ITL (Wigfield & Eccles, 2000). A common pattern revealed in the EVT literature is that expectations have a greater relationship to achievement versus decisions to remain in an academic program (J. Eccles et al., 1983; Marsh & Martin, 2011). However, while some research shows expectations longitudinally to have no relationship with educational choices (Perez et al., 2014), others have demonstrated expectations may predict them (Guo, Marsh, et al., 2015; Guo et al., 2017; Nagengast et al., 2011). However, this is rarely demonstrated longitudinally and has not been explored in health science education or with a RI-CLPM design. The present study seeks to explore the longitudinal relationship between expectancy and ITL to better demonstrate the influence expectations have on academic outcomes for health science students. This is an important step for addressing retention rate issues.

Relations Among Subjective Task Values, Achievement, and ITL for Health Science Students

Health science students, whether preparing to enter a program or presently in one, are likely to have high initial semester STV. This may be true considering those preparing to enter a nursing program recognize the value of prerequisite coursework. This high initial value may stem from the interest pre-nursing students have for prerequisite courses, as well as the usefulness the courses may provide for a future nursing program. Material presented in such courses may help students identify not only as future nursing students, but also as a future healthcare professional. Likewise, students already accepted have satisfied the goal of entering a health science program, are close in time to completing the terminal goal of becoming a healthcare professional (e.g., a nurse or OT), and are taking courses directly applicable to their profession. In this sense, health science students in professional programs may clearly recognize the usefulness (utility value) of their curriculum and view their courses as pivotal to their identity (attainment value) as current health science students and future healthcare professionals. The interest health science students hold likely vary course to course within a semester because while the goal is to become a healthcare professional, health science students may wish to enter a specialty that is less related to certain courses. However, given the positive longitudinal relationship among the STVs (Perez, Dai, et al., 2019), health science students will likely have high intrinsic value for their courses overall, and the variability of this interests may range from moderate to high, and rarely low.

Unlike expectancies, STVs in past literature are more predictive of choosing to stay in a college major versus academic performance (Cook & Artino, 2016; Eccles, 2009). However, some studies do illustrate STV constructs can be reciprocally related to achievement over time (Arens et al., 2018; Pinxten et al., 2014) – although this is unobserved with a RI-CLPM. The current study expects to observe similar results, or that students will have strong positive relationships between STVs and ITL, and weaker but positive relationships with achievement.

Relations Among Costs, Achievement, and ITL for Health Science Students

Despite its significance in the EVT model, cost has only recently garnered attention within EVT literature (Ball et al., 2019; Wigfield & Cambria, 2010). Due to the high stakes and high intensity environment of health science courses and programs, the present study expects the relationship of cost with achievement and ITL to be influential. Cost in past EVT research has been associated with academic performance (Perez, Wormington, et al., 2019), but is more often observed influencing academic outcomes like ITL (Perez et al., 2014). This has not been demonstrated with a RI-CLPM design.

Health science students may experience high opportunity cost for several reasons. One may be the loss of opportunity for income given these students rarely work (or find the balance unmanageable) to supplement finances while in school due to the rigor of their program or courses (Haughey et al., 2017; Lewis-Kipkulei et al., 2021; *The Future of Nursing*, 2011). Additionally, many health science students report sacrificing opportunities to spend time with friends and family (Mirzaei et al., 2012; Poleshuck et al., 2020). This is costly given time spent with social supports are indicated to be protective against mental health strains within this population (de Witt et al., 2019; Luo & Wang, 2009; L. Wolf et al., 2015). Moreover, health science students have indicated a loss of opportunity to sleep due to the rigor of their programs (Blome et al., 2021; Ohl et al., 2019; Tang et al., 2021) which yields various health related issues including mood disturbances and fatigue (Ohl et al., 2019).

Likewise, the psychological cost is expected to be high for health science students. One reason stems from financial stress. Approximately 60% of health science students entering a program do so with debt between $25,000-$50,000 (Jones-Schenk et al., 2017). This does not include the debt that most health science students take on to attend nursing or OT school. Specifically, admitted students accrue on average loans between $30,000-$45,000 for their program (Feeg & Mancino, 2014; *Loans for Undergraduate Students*, 2020; Millett, 2016). Additionally, students report seeking nursing or OT degrees for their wellbeing and for their family's wellbeing (Meyer et al., 2021; Wilkes et al., 2015). This increases the pressure of maintaining a high academic standing because regardless if a health science student graduates they are required to pay these loans. In addition to the threat of financial difficulties, it has been observed that the process of education within a health science program is itself a stressful experience (Deasy et al., 2016; Nerdrum et al., 2009; Papazisis et al., 2008; Tomkin & West, 2022). The fear of failure, difficulty, and overall intensity of health science programs have been linked to significant stress (Deasy et al., 2016; Grab et al., 2020; Jimenez et al., 2010; Reeve et al., 2013; L. Wolf et al., 2015).

Effort cost is the perceived amount of effort required to be successful. This is likely high considering the time and energy required to be successful in health science courses or programs is great (Kinsella et al., 2020). In fact, the psychological distress among health science students can be predicted by the effort required to be successful in their courses (Jacob et al., 2012; Nerdrum et al., 2009). Students in health science programs have demonstrated the academic demands such as the time it takes to study and learn material, may be the primary contributor of stress (Jacob et al., 2013). Moreover, studies consistently demonstrate health science students are stressed due to the amount of academic overload, or the amount of perceived effort required to be successful, and beliefs about academic performance (Govender et al., 2015; Kumar & Jejurkar, 2005; Mayor-Silva et al., 2021; Poleshuck et al., 2020).

Similar to STVs, in past literature costs are more predictive of outcomes such as choosing to leave a major versus academic performance (Perez et al., 2014). However, some studies do illustrate costs constructs can be significantly negatively related to achievement over time (Perez, Dai, et al., 2019). The relationship of cost with academic outcomes has not been demonstrated with a RI-CLPM design. The current study expects to observe similar results, or that students will have strong negative relationships between cost, and ITL and achievement.

Limitations of Previous Studies

Although extensive research has been carried out on EVT constructs most previous studies were cross-sectional in design (Acee et al., 2018; Crippen et al., 2022; Jiang & Zhang, 2023). This makes it difficult to determine the directions of the effects between EVT variables and on academic outcomes and may limit the generalizability of findings. Therefore, the present study chose to examine the longitudinal relations among EVT constructs and the associated influence on academic performance and ITL. In some previous EVT studies, a cross-lagged panel model (CLPM) was used to model the relations between EVT variables over time while controlling for prior levels of each construct (Perinelli et al., 2022). Unfortunately, the CLPM does distinguish between-person effects from within-person effects. A CLPM assumes that individuals vary over time around a common mean without between-person effects or trait-like individual differences that are stable and time-invariant (Hamaker et al., 2015; Zyphur, Voelkle, et al., 2020). The traditional CLPM assumes only state-like or within-person (unstable) effects are present. Within-person effects demonstrate how an individual's adjustment in one domain is related to that same individual's adjustment in another. For example, this could be how a student's reported level of cost early in a semester influences costs or other EVT variables at future events. Consequently, for EVT studies that used a CLPM design, the autoregressive or cross-lagged paths could reflect any mixture of between-person and within-person effects and render the results uninterpretable (Berry & Willoughby, 2017). The RI-CLPM was introduced to address this limitation of the CLPM (Hamaker et al., 2015).

In a RI-CLPM, the variance of the observed score is split into two components. The first component represents the variance of an individuals' trait-like stability. This is the order of the individual's rank position compared to others and is considered time-invariant (between-person effects) and is captured with random intercepts in the model. The second component represents temporal within-person effects and can be thought of as the fluctuations around an individual's expected score from each measurement occasion and is captured with a latent factor.

Consequently, an RI-CLPM can model autoregressive paths that truly indicate within-person carry-over effects. This can be thought of as the extent to which deviation from an individual's expected score at one measurement occasion influences the same construct at the next measurement wave. Similarly, the cross-lagged coefficients can accurately represent within-person spill-over effects while controlling for between-person stability (i.e., the random intercepts). In other words, cross-lagged effects in an RI-CLPM indicate whether an individual's deviation from their expected score in one construct predicts a deviation from their expected score in another construct at a future measurement occasion.

The correlation between the random intercepts denotes the extent to which between-person (stable) differences in one construct are related with between-person differences in another. The interpretation of factor correlations within each measurement wave is different for a RI-CLPM. Specifically, at the first measurement occasion, within-person correlations reflect how a student's deviation from their expected score on one construct is associated with the deviation from their own expected score on a different construct. In subsequent waves, the within time correlated residuals reflect the extent to which a within-person change in one construct is associated with a within-person change in another construct. Consequently, because an RI-CLPM can identify within-person carry-over (autoregressive) and spill-over (cross-lagged) effects, a more accurate understanding of the causal mechanisms in longitudinal associations between EVT variables and academic outcomes can be produced (Burns et al., 2020). For example, a model may show a nursing student with higher than anticipated costs at time 1 is predicted to have higher than expected costs at time 2 (e.g., a carry-over effect from costs to future costs). This same student may show that the higher than expected costs at time 1 also predicts lower than expected task values at time 2 (e.g., a spill-over effect from cost to future task values).

This is vital given the present study is attempting to understand which components of EVT are the greatest predictor of ITL and academic achievement it is prudent to examine the relationships over time between all the EVT constructs. The following sections will describe the present study's research questions, anticipated results, and a summary of contributions.

Research Questions

(1) How does a RI-CLPM that uses three EVT latent variables (i.e., expectancies, STVs, and costs) fit health science students' data taken over a semester and what are the carry-over and spill-over effects for health science students' expectancies, STVs, and costs?

(2) Over a semester, what are the spill-over effects among health science students' expectancies, STVs, and costs with end-of-semester outcomes like academic achievement and intentions to leave?

(3) What relationship do the stable between-student factors (random intercepts) have with academic achievement and intentions to leave, and how does this compare to the unstable within-student components for health science students?

Anticipated Results and Contributions

The present study will collect data in an ecologically meaningful context to tackle the retention rate issue in the health science student population. Likewise, within the context of this population the present study can address unresolved issues in the EVT literature. The following is a brief on both the anticipated results and contributions.

The present study expects to provide an understanding of the spill-over (cross-lagged) effects among health science students' expectancies, STVs, and costs. Students with higher expectations, STVs, and costs (compared to baseline) at earlier time point are predicted to have higher expectations, STVs, and costs (compared to baseline) at future time points, respectively. Similarly, students with higher than anticipated expectancies are projected to have higher than anticipated STVs at future occasions, and vice-versa. Inversely, students with higher than anticipated expectancies and STVs are projected to have lower than expected costs at future occasions, and those with higher than expected costs will have lower than anticipated future expectancies and STVs.

The present study also expects to provide an understanding of the spill-over effects (stemming from the unstable within-student components) for health science students' expectancies, STVs, and costs with academic achievement and intentions to leave. Expectancies and STVs that are higher than baseline will positively predict academic achievement and negatively predict ITL. Costs for students who are measurably higher relative to their baseline will negatively predict academic achievement and positively predict ITL.

Lastly, the present study expects to provide an understanding of the relationship between academic achievement and ITL with the stable between-student (RIs) components. Students who have higher stable expectancies and STVs are predicted to have higher academic achievement and lower ITL. Conversely, students with higher stable cost are predicted to have lower academic achievement and greater ITL.

Dissertation Outline

The present section outlines the remaining chapters of the dissertation. Each chapter is briefly summarized. In the following section, Chapter 2, the current EVT literature is reviewed and at times will be related to the population of interest, health science students. Chapter 3 discusses the methodology of the present research and highlights the use of modern data analysis via the use of random-intercepts cross-lagged panel models (RI-CLPM). Chapter 4 presents the results of the study. Chapter 5 presents an interpretation of the results, discusses implications for real-world use of the findings within a health science education context, expands on limitations, and offers suggestions for future research.

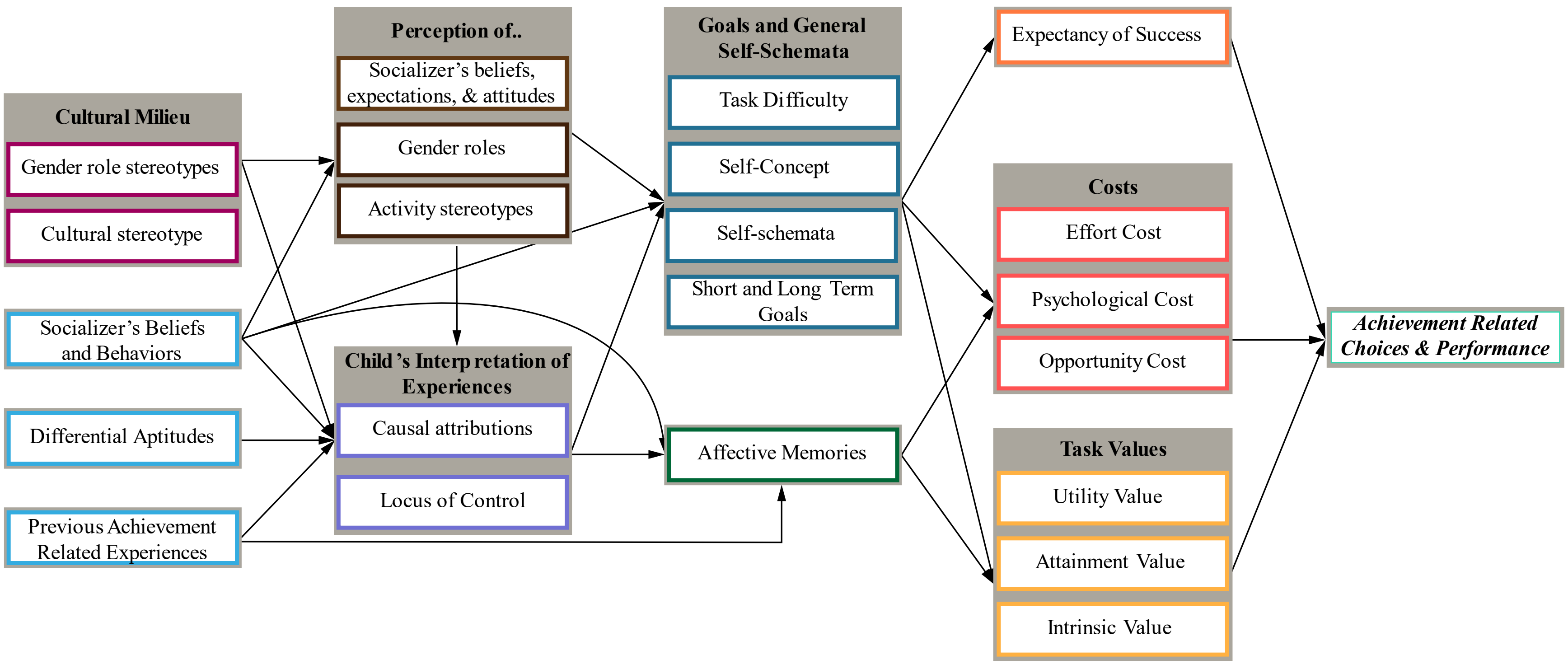
CHAPTER 2 – LITERATURE REVIEW

Expectancy-Value Theory

Expectancy-value theory (EVT) is a theoretical framework of achievement motivation typically used to understand individuals' academic achievements, achievement-related efforts, and choices in educational contexts (Guo, Parker, et al., 2015; Perez et al., 2014; Robinson, Lee, et al., 2018; Wigfield & Eccles, 2020). From this theoretical standpoint, motivation comprises an individual's expectations of success and subjective values for a task. This view holds that students' expectations and the extent to which a task is valued influence achievement as well as achievement-related choices, including remaining in educational programs (i.e., retention). EVT is multidimensional and composed of many different facets (Figure 1). However, most researchers focus on the "right hand" side of the model including expectancies, subjective task values (STV), and costs. This focus likely stems from the theorized direct relationship expectancies, STVs, and costs has on academic outcomes.

Figure 1

Expectancy-Value Theory Model



Note. Adapted from Wigfield and Eccles (2000).

Expectancies for success can be thought of as one's belief in the probability of success (J. Eccles et al., 1983). Expectancies are strongly linked with self-concept which is defined as an individual's perception of their competence at a given task (Guo et al., 2017). Empirically, self-concepts of ability are so highly and directly linked with expectations they cannot be distinguished (Eccles, 2009). This has resulted in the use of self-concept in EVT studies to reflect expectancies (Nagengast et al., 2011; Simpkins et al., 2012). In line with this, the present study has operationalized expectancies as academic self-concept.

Task value is the assigned value, importance, or interest a student places on a task (Eccles, 2009). This value of a task comprises four distinct components: attainment value, intrinsic value, utility value, and cost (Cook & Artino, 2016; Dever, 2016; Schoor, 2016). Attainment value is the importance of doing well on a task; intrinsic value is the enjoyment one gains from doing a task; and utility value is how useful one finds a task or the degree to which it contributes to their goals (J. S. Eccles & Wigfield, 2002).

Within the EVT framework, cost constructs are considered the negative consequences of engaging in a task (J. S. Eccles & Wigfield, 2002). Cost dampens the value a student has for a task and is commonly separated into three components: opportunity cost, effort cost, and psychological cost (J. S. Eccles & Wigfield, 2002). Opportunity cost refers to losing the option to engage in one task, that may or may not be valued because of engaging in another; effort cost is the perception of the effort required to successfully complete a task; and psychological cost is the negative psychological or affective consequences of engaging in a task such as the stress or anxiety that results from engaging in the task, or stemmed from the potential of failing at completing the task (J. Eccles et al., 1983; J. S. Eccles & Wigfield, 2002).

Expectancies, STV, and costs influence academic outcomes. The extent to which this occurs, and specifically in health science education, is unknown. The current study seeks to understand the longitudinal relationships among expectancies, STV, and cost in health science education, and the associated influence with intentions to leave (ITL) and academic performance. Prior to a review of the EVT literature, a review of causal inference is warranted given the present study will examine current and past EVT research through this lens, and because the current study will investigate a longitudinal EVT models for causality.

Logic of Causal Inference

Research that utilizes cross-sectional designs cannot draw causal relations between variables. Likewise, it is challenging to claim cause-and-effect between variables in social science research where controlled experimental designs are not possible (Hamaker et al., 2015). However, longitudinal designs such as those employing panel data where variables are measured at multiple occasions may be viewed through theories of causality as approaching causal inference (Zyphur, Allison, et al., 2020). This causal inference stems from an argument that longitudinal models, such as those utilizing panel data like the present study, adhere to the logic of causality if it can show the following three concepts.

(1) A cause occurs before an effect (i.e., cause → effect temporal order). In a panel model this may be demonstrated with lagged effects such as autoregressive (AR) and cross-lagged (CL) effects. Autoregressive effects show how a variable is a function of its past self while cross-lagged effects show how a variable is potentially dependent on other past variables. Put another way, these lagged effects demonstrate how a process unfolds and show how future outcomes depend on the past (Zyphur, Allison, et al., 2020).

(2) The bidirectional effects among all variables are permitted or that all variables are allowed to (potentially) predict each other over time. This is important as CL effects imply that a variable can be dependent on the past of another variable. Additionally, testing for bidirectional effects can permit researchers to assess how a past variable directly influences a different future variable (sometimes called a short-run effect), and how a past variable influences variables at even later time points (t + 2; sometime called a long-run effect) indirectly through AR terms.

(3) Potential confounding variables are controlled for. This is considered a problem for many longitudinal designs including the use of a traditional cross-lagged panel model (CLPM). Traditional CLPMs do not distinguish between-person and within-person variance which means the estimates of parameters are confounded by between-person (stable) variance and do not accurately reflect within-person (causal or unstable) changes (Hamaker et al., 2015). Recently, Hamaker et al. (2015) introduced the random-intercepts cross-lagged panel model which not only distinguishes between-person and within-person variance but may account for stable omitted unobserved variables via the between-person component.

Nonetheless, it may be researchers still cannot make strong causal statements based on correlational data, but this does not exclude the use of Granger causality (Granger, 1969) which is a method to demonstrate causality between two variables in a longitudinal study. While causality is closely related to “cause-and-effect” it is not the same and this important distinction helps define Granger causality (Hamaker et al., 2015). Specifically, when viewing data for Granger causality one is looking for temporal precedence, or that one variable occurs before another in time, and that the earlier variable is highly correlated (Granger, 1969). Therefore, the terms causal and causality in the current study are used while acknowledging that strong causal statements are based on experimental designs, and the terms causal and causality used here reflect Granger causality.

The following sections explore what past EVT research has revealed about the relationships between expectancies, STVs, and costs and the relationships between these variables and academic outcomes like achievement and intentions to leave. Where possible longitudinal designs are highlighted as well as studies that used the population of interest, health science students.

EVT Relationships with Achievement and ITL for Health Science Students

Expectancy-value theory constructs can predict academic achievement and retention in both general (Richardson et al., 2012; Robbins et al., 2004) and domain specific settings (Marsh & Craven, 2006; Perez et al., 2014; Pinxten et al., 2014), but has rarely been studied in the health science student population (Bråten & Olaussen, 2005; Khalaila, 2015). The influence of EVT constructs with achievement and ITL (e.g., retention) are reviewed below. Where possible, longitudinal studies are highlighted as this provides greater evidence for the causal ordering of the EVT constructs in relation to academic outcomes (Nagengast et al., 2011). However, most studies are cross-sectional and provide weaker evidence for causal relations. This is one limitation in the EVT research the current study aims to contribute to.

Expectancies and Achievement

EVT posits that expectancies have a direct and positive link with achievement (J. S. Eccles & Wigfield, 2002; Trautwein et al., 2012). This is seen in person-centered studies where students with motivational profiles containing high levels of expectancy outperformed those with lower levels in academic achievement (Fong et al., 2021). This is further evidenced as research shows longitudinal expectancies have a positive and stable reciprocal relationship with achievement (Abu-hilal et al., 2013; Arens et al., 2011; Denissen et al., 2007; Dinkelmann & Buff, 2016; Guo, Parker, et al., 2015). In other words, expectancies can predict academic achievement, and in turn, this achievement can predict future expectancies, and vice-versa (Arens et al., 2018; Marsh & Craven, 2006; Marsh & Martin, 2011). This is demonstrated when viewing consecutive (Dinkelmann & Buff, 2016) and lagged time intervals (Arens et al., 2018; Guo, Marsh, et al., 2015).

Students who take pre-nursing courses, or apply to nursing or OT school, recognize admittance is difficult given the peer competition, rigor of prerequisite courses, and a necessary high entrance exam score. Pre-nursing students may start with high expectations knowing success is necessary to achieve the goal of entering nursing school. Likewise, those accepted to nursing or OT school, start with a history of positive academic achievements (Al-Alawi et al., 2020; Bowyer et al., 2018) which likely produces students who enter their program with high expectations of success. How these initial expectations influence future expectancies or academic achievement within health science education is unclear as they are understudied in this population – a gap this study seeks to fill.

Expectancies may lead to positive academic outcomes for many reasons. One, is that students with better calibrated and higher expectations exhibit more elaborate prior knowledge (Muenks et al., 2018). Also, students with higher expectations are shown to utilize cognitive strategies that require deeper processing like elaboration and metacognition, and are more efficient at managing their time and study environment (Berger & Karabenick, 2011). Likewise, students with higher expectations may exert greater effort in a task (Dietrich et al., 2017).

Research supports this as students with greater expectations are shown to have increased task engagement (Guo et al., 2017; Nagengast et al., 2011; Wigfield & Eccles, 2000).

In turn, students with positive academic outcomes gain achievement-related experiences they may use when forming future expectations in the same domain. This has been demonstrated in elementary (Pinxten et al., 2014), middle school (Pinxten et al., 2014), high school (Nagengast et al., 2011; Trautwein et al., 2012), and undergraduate STEM domains (Perez, Dai, et al., 2019; Perez et al., 2014), but not within pre-nursing, nursing, or OT education. Understanding the relationship over time between expectancies and achievement can highlight moments in a semester where students' expectations are in decline and consequently influence achievement.

Subjective Task Values and Achievement

Health science students, whether preparing to enter a program or presently in one, are likely to have high initial semester STV. This may be true considering those preparing to enter a program recognize the value of prerequisite coursework (Potolsky et al., 2003). This high initial value may stem from the interest or enjoyment (intrinsic value) pre-nursing students have for prerequisite courses, as well as the usefulness (utility value) the courses will provide for a future nursing program. Material presented in such courses may help students identify (attainment value) not only as future nursing students, but as a future healthcare professional (Arreciado Marañón & Isla Pera, 2015; Gao et al., 2022).

Similarly, students already accepted have satisfied the goal of entering a health science program, are close in time to completing the terminal goal of becoming a healthcare professional (e.g., a nurse or OT), and are taking courses directly applicable to their profession. In this sense, these health science students may clearly recognize the usefulness (utility value) of their curriculum and view their courses as pivotal to their identity (attainment value) as current health science students and soon-to-be healthcare professionals. The interest health science students hold likely vary course to course within a semester because while the goal is to become a healthcare professional, health science students may wish to enter a specialty that is less related to certain courses. However, given the positive longitudinal relationship observed among the STVs (Perez, Dai, et al., 2019), health science students will likely have high intrinsic value for their courses overall, and the variability of this interests may range from moderate to high, and rarely low.

Although unobserved within health science education, STVs are purported to have a positive relationship with achievement within the EVT model (Wigfield & Eccles, 2000). A positive relationship between STVs and achievement may exists considering STVs are associated with greater cognitive engagement for a task (Johnson & Sinatra, 2013), higher levels of effort for a task (Dietrich et al., 2017), and higher levels of effort when taking a test (Cole et al., 2008). Moreover, higher STVs are related with higher levels of critical thinking, greater use of study strategies that involve deeper levels of organization and elaboration, more effective use of time management, and more efficient study environments (Berger & Karabenick, 2011; Credé & Phillips, 2011). Some direct evidence for a positive relationship does exists as past research has shown students with higher STVs outperform those with lower levels of STVs (Fong et al., 2021).

Instead of observing how each distinct value construct influences achievement, many researchers form a composite “task value” variable. This may diminish the impact any one task value construct may have on achievement and may reduce reliability. Academic achievement has been shown to predict a future “task values” composite variable – although this relationship is not always reciprocal (Perez et al., 2014). In fact, often the association between a task value composite variable and achievement has little to no relationship (Meece et al., 1990; Perez et al., 2014). Mixed results have emerged when observing studies that analyzed the relationship between distinct components of task value and achievement - this is reviewed below. The current study seeks to contribute to EVT literature by observing the longitudinal influence STVs has on achievement.

Intrinsic Value. Intrinsic value is found to have a positive relationship longitudinally and reciprocally with academic achievement (Guo, Marsh, et al., 2015; Pinxten et al., 2014). The EVT model assumes this to be true (J. Eccles et al., 1983), however, this relationship may weaken when controlling for expectations (Y. Lee et al., 2022; Pinxten et al., 2014). In fact, a number of studies show a positive but unstable relationship between intrinsic value and achievement as longitudinally the relationship diminishes (Arens et al., 2018; Guo, Parker, et al., 2015; Marsh et al., 2005). With time, the enjoyment students find in a task may be less important for success and likely ability related beliefs influence achievement more. A greater assessment of the longitudinal relationship between intrinsic value and achievement is required to clarify the association. Exploring this relationship in health science education may be important as health science students report finding specific courses taken during their program or within a semester more enjoyable than others and this interest may influence achievement (Hunt et al., 2020; Rushworth & Happell, 2000).

Attainment Value. The EVT model indicates a direct and positive influence between attainment value and achievement (J. Eccles et al., 1983). This may be true as attainment value is shown to predict test taking effort and achievement (Cole et al., 2008). However, while achievement is shown with mixed results to be related to attainment value within cross-sectional designs (Li et al., 2007), longitudinally this relationship may weaken (Arens et al., 2018) or when controlling for expectations this relationship may not hold (Trautwein et al., 2012). Considering attainment value is related to identity (Robinson, Lee, et al., 2018), its relationship with achievement may be critical for health science students as they enter and progress through school likely identifying as "good" students or as future health care professionals. This identity can be challenged by a semester with one or more difficult courses which subsequently may lead to declines in performance. A greater understanding of how attainment value longitudinally influences academic achievement is needed to better address these concerns.

Utility Value. The EVT model proposes that utility value positively influences academic achievement (J. Eccles et al., 1983). A positive relationship is further supported by research that demonstrates utility value positively influences engagement in tasks (Harackiewicz et al., 2008; Hulleman et al., 2010; Johnson & Sinatra, 2013; Priess-Groben & Hyde, 2017) and test taking effort (Cole et al., 2008). Direct evidence from many cross-sectional studies shows a positive relationship between utility value and achievement (Canning & Harackiewicz, 2015; Guo, Parker, et al., 2015; Hulleman et al., 2010; Yeager et al., 2014).

In fact, due to its theorized "superficialness" or how closely related it is to extrinsic motivation (Wentzel & Wigfield, 2009), utility value is often the STV component chosen to manipulate for many intervention studies to increase student motivation and performance. Put another way, because utility value appears most similar to extrinsic motivation (Eccles & Wigfield, 2002), relative to attainment or interest value, it may be most susceptible to interventions. Indeed a wealth of intervention studies demonstrate utility value holds a positive predictive relationship with achievement (Brisson et al., 2017; Harackiewicz, Canning, et al., 2016; Hulleman & Harackiewicz, 2009; Rosenzweig et al., 2020). However, it should be noted, some research has demonstrated little (Trautwein et al., 2012) to no relationship (Guo, Marsh, et al., 2015; Kosovich et al., 2017; Weidinger et al., 2020) with achievement.

Although scarce, some longitudinal research examining the relationship between utility value and achievement shows a positive relationship over time (Robinson, Lee, et al., 2018; Trautwein et al., 2012). This may be observed in health science students as the utility of courses taken in pre-nursing, nursing, or OT school can be readily viewed as applicable to future goals (i.e., entering nursing school or being a proficient nurse or OT). However, the relationship between utility value and achievement remains unclear in health science education. Examining this relationship in pre-nursing students, and those in health science programs like nursing and OT students, can illuminate the degree to which health science students find courses or their programs useful, and how this influences achievement.

Cost and Achievement

Despite its significance in the EVT model, cost has only recently garnered attention within EVT literature (Ball et al., 2019; Wigfield & Cambria, 2010). Due to the high stakes and high intensity environment of health science courses and programs, the present study expects the relationship of cost with achievement to be influential. Cost in past EVT research has been associated with poor academic performance (Hong et al., 2020; Perez, Wormington, et al., 2019; Rosenzweig et al., 2020). This negative relationship is supported by past studies that illustrate costs constructs can be significantly negatively related to achievement over time (Flake et al., 2015; Perez, Dai, et al., 2019).

This negative relationship may be true considering cost is demonstrated to have little to no association with cognitive strategies that involve deep processing like elaboration. Instead, a relationship has been observed for strategies, like rehearsal, that relate more to superficial learning (Berger & Karabenick, 2011). Additionally, in recent literature high cost was related to lower engagement in tasks – even when students exhibited high expectations or task values (Kim et al., 2021). The current study expects to observe similar results, or that students will have strong negative relationships between costs and achievement.

Costs is often subsumed within STVs (Eccles, 2009) despite being distinct and predicted in the EVT model to have a negative relationship with achievement (J. Eccles et al., 1983). When cost is viewed separate from STV its independence is supported by cross-sectional (Durik et al., 2006; Flake et al., 2015; Hong et al., 2020; Luttrell et al., 2010; Watt et al., 2012) and longitudinal research (Robinson, Lee, et al., 2018; Trautwein et al., 2012). The distinct constructs of cost are rarely explored as costs is often viewed as a composite variable of its sub-constructs (Gaspard et al., 2017). When observed, the three cost measures have been negatively related to achievement (Barron & Hulleman, 2015; Conley, 2012; Kosovich et al., 2017). However, the influence of cost on achievement is unexplored in health science education where levels of cost may be high considering the time and effort required to be successful in health science courses or programs (Bednarz et al., 2010; Rochford et al., 2009; Tomkin & West, 2022). Exploring the longitudinal relationships between the distinct cost constructs and academic performance within health science education will add to the EVT literature and illuminate the potentially demotivating side of health science education (Wigfield & Cambria, 2010). A review of the cost constructs is provided below.

Effort Cost. Effort cost is likely high for health science students given the difficulty of their courses (Merkley, 2015), and considering the time and energy required to be successful in health science education is great (Kinsella et al., 2020). In fact, the psychological distress among health science students can be predicted by the effort required to be successful in their courses (Jacob et al., 2012; Nerdrum et al., 2009). Students in health science programs have demonstrated the academic demands such as the time it takes to study and learn material, may be the primary contributor of stress (Jacob et al., 2013). Moreover, studies consistently demonstrate health science students like nursing students (Mayor-Silva et al., 2021), OT students (Govender et al., 2015; Kumar & Jejurkar, 2005; Poleshuck et al., 2020), and pre-nursing students are stressed due to the amount of academic overload, or the amount of perceived effort required to be successful, and beliefs about academic performance.

Effort cost is theorized to negatively influence achievement (J. Eccles et al., 1983). This theory is supported by research (Flake et al., 2015) with one study showing effort cost may be the greatest negative predictor of achievement from among the three cost constructs (Robinson, Lee, et al., 2018). However, over time the relationship between effort cost and achievement may not be stable (Perez et al., 2014). The perceived effort to be successful in a task may become less influential on achievement relative to positive factors such as expectations or STV. Exploring the impact of effort cost on achievement throughout the duration of a semester can add to the EVT literature and illustrate the relationship between the two variables within health science education.

Opportunity Cost. Health science students may experience high opportunity cost for several reasons. One may be the loss of opportunity for income given these students rarely work (or find the balance unmanageable) to supplement finances while in school due to the rigor of their program or courses (Haughey et al., 2017; Lewis-Kipkulei et al., 2021; *The Future of Nursing*, 2011). This may be detrimental since health science students, like OT (Govender et al., 2015; Grab et al., 2020) and nursing students (Aljohani et al., 2021), have reported financial issues as a large contributor of stress. Additionally, many nursing (Mirzaei et al., 2012) and OT (Poleshuck et al., 2020) students report sacrificing opportunities to spend time with friends and family. This is costly given health science students are shown to have higher mental stress compared to peers (Bartlett et al., 2016; Karaca et al., 2019; Nerdrum et al., 2009), and time spent with social supports are indicated to be protective against mental health strains among nursing (Luo & Wang, 2009; L. Wolf et al., 2015) and OT students (de Witt et al., 2019; Govender et al., 2015; Pfeifer et al., 2008). Moreover, OT (Ohl et al., 2019) and nursing students (Blome et al., 2021; Tang et al., 2021) have indicated a loss of opportunity to sleep due to the rigor of their programs. Poor sleep hygiene yields various health related issues including mood disturbances and greater fatigue (Ohl et al., 2019).

Opportunity cost is predicted in the EVT model to negatively influence achievement, and this is demonstrated in the literature (Flake et al., 2015), but has yet to be observed longitudinally. This variable requires further exploration to determine its relationship with academic achievement over time, and particularly within a health science education context where students report significant sacrifices in many aspects of life in order to engage with course content (Bednarz et al., 2010; Harris et al., 2013).

Psychological Cost. The psychological cost is expected to be high for health science students. One reason stems from financial stress. Approximately 62% of students entering a nursing program do so with debt – roughly 30% with debt between $25,000-$50,000 (Jones-Schenk et al., 2017). This does not include the debt that approximately 74% of nursing students take on to attend nursing school. Specifically, nursing students accrue on average loans between $30,000-$40,000 for their nursing program (Feeg & Mancino, 2014; Millett, 2016). The amount of debt OT students enter their program with is less known (Jacobs, 2019). Considering roughly

65% of undergraduate students take on loans, one can assume OT students enter their program close to the national average loan accrued for a bachelors with a debt ranging between $30,000-$45,000 (*The NCES Fast Facts Tool Provides Quick Answers to Many Education Questions*, n.d.). An OT student may take on additional loans to complete their program – this appears to range between approximately $15,000-$45,000 (*Best Occupational Therapy Colleges Tuition Comparison*, n.d.; *How Much Does Becoming an Occupational Therapist Cost?*, n.d.), however, these figures are understudied within OT education (Jacobs, 2019).

Another psychological cost relates to why some students seek health science degrees. Specifically, students report seeking these professional healthcare degrees for their wellbeing and for their family's wellbeing (Meyer et al., 2021; Wilkes et al., 2015). This increases the pressure of maintaining a high academic standing because these students may rely on the financial gains provided by a future healthcare career to support familial responsibilities, and regardless if a nursing or OT student graduates they are required to repay loans. In addition to the threat of financial difficulties, it has been observed that the process of education within a health science program is itself a stressful experience (Deasy et al., 2016; Nerdrum et al., 2009; Papazisis et al., 2008). In fact, the fear of failure, difficulty, and overall intensity of health science programs have been linked to significant stress (Deasy et al., 2016; Grab et al., 2020; Jimenez et al., 2010; Reeve et al., 2013; L. Wolf et al., 2015).

Many arguments can be made to support the concept of high psychological costs in the health science student population. If true, there is direct evidence to illustrate that psychological costs can be damaging to academic achievements as it is shown in cross-sectional (Flake et al., 2015) and longitudinal designs (Perez et al., 2014) to be negatively related to achievement. This has not been demonstrated in a health science student population. Consequently, the influence of psychological cost on academic achievement is unknown in this domain. The extent to which this impacts achievement needs more exploration in general, and specifically for fields like health science education.

Expectations and Intentions to Leave

Intentions to leave (ITL) an educational program like nursing school, is defined as a student's decision to continue (or discontinue) pursuing that program (Cromley et al., 2016). Expectancies are posited to have a positive relationship with academic outcomes like intentions to leave (Wigfield & Eccles, 2000), however, this is demonstrated longitudinally to have weak associations (Musu-Gillette et al., 2015), or is shown to have no relationship (Perez et al., 2014). A common pattern revealed in the EVT literature is that expectations have a greater relationship to achievement versus decisions remain in an academic program (J. Eccles et al., 1983; Marsh & Martin, 2011). However, some cross-sectional research does show that expectations may predict educational choices (Fong et al., 2021; Guo, Parker, et al., 2015; Guo et al., 2017; Y. Lee et al., 2022; Nagengast et al., 2011). Additionally, while some research shows expectations longitudinally to have no relationship with educational decisions (Perez et al., 2014), others have demonstrated expectations may predict educational choices (Guo et al., 2017; Guo, Marsh, et al., 2015; Nagengast et al., 2011). However, this is rarely demonstrated longitudinally and has not been explored in health science education. The present study seeks to explore the longitudinal relationship between expectancy and ITL to better demonstrate the causal influence expectations have on retention for health science students throughout the duration of a semester. This is an important step for addressing retention rate issues.

STVs and Intentions to Leave

Subjective task values are assumed to be an important factor for determining student retention (Cook & Artino, 2016; J. Eccles et al., 1983). This has been demonstrated within cross-sectional (Fong et al., 2021; Perez et al., 2014) and longitudinal (Musu-Gillette et al., 2015) research as the relationship between STVs and retention is positive and reciprocal. However, this relationship is commonly demonstrated by combining the task value constructs into a one or two "task value" composite variable (J. Eccles et al., 1993; Musu-Gillette et al., 2015; Nagengast et al., 2011), versus identifying the relationship between retention and the distinct STV components. What is known of the relationship between the distinct value components and retention is reviewed below.

Intrinsic Value. Intrinsic value is demonstrated in cross-sectional research as influential in predicting educational choices such as choosing to continue an educational program (Abu-hilal et al., 2013; Archer et al., 2010; Guo et al., 2017; Kjærnsli & Lie, 2011; Y. Lee et al., 2022; Maltese & Tai, 2011; Purcell et al., 2008). However, results have emerged showing longitudinally intrinsic value may not be a stable predictor of educational choices (Lauermann et al., 2017; Watt et al., 2012). The longitudinal relationship between intrinsic value and educational choices, such as intentions to leave an educational program, needs further investigation. Addressing this gap within a health science population can contribute to the EVT literature and reveal the impact interests or enjoyment for a health science education has on students' decision to leave.

Attainment Value. Attainment value is demonstrated to influence students' academic choices such as choosing to pursue or persist in an academic domain (Masson et al., 2016). Additional proof stems from studies exploring the longitudinal relationship between attainment value and retention which demonstrates a positive relationship (Perez et al., 2014; Robinson, Lee, et al., 2018; Robinson, Perez, et al., 2018). Students pursue domains that align with their identity, and once in such a domain are likely to stay (Bøe et al., 2011). However, the stability of the relationship between attainment value and retention needs additional clarity and remains undetermined for students in health science education. Understanding the longitudinal and causal relationship between attainment value and retention may be particularly important for students who enter and progress through health science programs identifying as a "nurse (or OT) in training " (ten Hoeve et al., 2017). Unfortunately, this identity may be threatened by academic difficulties. The current study seeks to contribute to the EVT literature by further revealing the longitudinal relation between attainment value and retention and seeks to understand what impact this has on health science students throughout the duration of a semester.

Utility Value. Utility value has been observed as influencing students' decisions to pursue specific domains (Bøe, 2012; Hulleman et al., 2010; Updegraff et al., 1996), and is shown to predict retention (Guo et al., 2017; Y. Lee et al., 2022). Mixed results appear as utility value has been shown to be unrelated to retention in cross-sectional (Kosovich et al., 2017) and longitudinal research (Robinson, Lee, et al., 2018). Exploring the longitudinal relationship between utility value and retention for health science students can illuminate this relationship. This not only adds to the EVT literature but will demonstrate if finding a health science program useful can influence a student's decision to remain in that program.

Cost and Intentions to Leave

Cost is shown to negatively influence educational decisions. Once in an educational program the relationship between cost and retention is demonstrated over time to continue to be negative (Perez et al., 2014; Robinson, Lee, et al., 2018). However, this relationship has only been explored in a few studies and most do not incorporate the distinct constructs of cost, but at times use a composite "cost" variable. Some cross-sectional (Flake et al., 2015) and longitudinal (Perez et al., 2014; Robinson, Lee, et al., 2018) research has demonstrated that effort cost and opportunity cost are negatively related with retention while psychological cost is not (Perez et al., 2014). One recent study demonstrated only effort cost as a significant predictor of retention (Y. Lee et al., 2022). Overall, the mixed findings and general lack of exploration show more research is required. Exploring the longitudinal relationship between the constructs of cost and retention within health science education may illustrate the largely unexplored negative consequences this part of the EVT model has on retention.

CURRENT STUDY

The reviewed evidence is suggestive of a longitudinal model in which expectancies, STVs, and costs are expected to be reciprocally related to one another over time, and predictive of achievement and ITL. Therefore, the present study investigated the longitudinal relationships between expectancies, STVs, and costs at three time points over the duration of a 16-week semester with achievement and ITL for health science students. We chose to study the entire duration of a semester as this will best illustrate the causal influences in relationships between motivation and academic outcomes. We measured academic self-competence in lieu of expectancy as is commonly done in EVT research. Task values were traditionally defined in the current study as attainment value, interest value, and utility value. Cost was separated from task values into a distinct dimension, and was observed as three components: opportunity cost, effort cost, and psychological cost. We incorporated ITL and academic achievement taken at the end of the semester and analyzed for relationships with the motivation variables. The overall semester GPA was the measure of academic achievement.

HYPOTHESIS FOR RELATIONS AMONG EXPETANCY-VALUE BELIEFS, ACHIEVEMENT, AND INTENTIONS TO LEAVE

Based on the weight of evidence and theory reviewed, the following predictions are advanced:

H1: Regarding the carry-over effects, students with expectations, STVs, and costs higher than expected are predicted to have higher expectations, STVs, and costs (compared to baseline) at future time points, respectively. Regarding the spill-over effects, students with higher than anticipated expectancies are projected to predict higher than expected STVs at future occasions, and vice-versa. Inversely, students with higher than anticipated expectancies and STVs are predicted to have lower than expected costs at future occasions while those with higher than expected costs will have lower than anticipated future expectancies and STVs.

H2: Expectancies and STVs that are higher than baseline will positively predict academic achievement and negatively predict ITL while costs, that are higher relative to baseline, will negatively predict academic achievement and positively predict ITL.

H3: Students with higher stable (i.e., random intercepts) expectancies and STVs are predicted to have higher academic achievement and lower ITL. Conversely, students with higher stable cost are predicted to have lower academic achievement and greater ITL. Compared to the unstable within-student components, the stable components will have greater influence given these are less prone to change.

CHAPTER 3 – METHODOLOGY

Participants and Procedure

Participants were 763 students enrolled at three universities located in Australia (n=447), and three universities located in the Southwestern United States (n=316). Students majored in pre-nursing, nursing, or occupational therapy and were recruited via email. Students were additionally recruited from a one-time discussion, on the first day of the semester, with faculty who briefly summarized the research and allowed the study to take place within their course. These faculty were provided prompts to discuss (for approximately 2-minutes) the benefits of the study. Only students from the United States were informed they would receive 0.1% extra credit added to their final course score per survey completed, therefore, a maximum of 0.3% was obtainable (this was also indicated in the course syllabus).

The sample was 92.5% (n=706) female and 7.5% male (n=57). This uneven distribution of sexes is common in the populations explored (*Employed Persons by Detailed Occupation, Sex, Race, and Hispanic or Latino Ethnicity*, 2021). The mean age of students in years was 28.9 ± 10.2. Of the sample taken from the United States, 7.7% (n=24) reported they were African American, 44.2% (n=140) reported they were white, 24.8% (n=78) reported they were Hispanic or Latino, 22.3% (n=70) reported they were Asian or pacific islander, and 1.1% (n=3) reported they were “other.” Of the sample taken from Australia, 71.3% (n=319) reported they were Australian, 2.9% (n=13) reported they were English, 3.4% (n=15) reported they were Indian, 4.0% (n=18) reported they were from New Zealand, 4.6% (n=21) reported they were Filipino, 1.7% (n=8) reported they were South African, 0.6% (n=3) reported they were Italian, and 11.5% (n=51) reported they were “other”.

Participants completed a series of survey instruments via computerized administration at three time points during an academic semester: Week 1 (Time 1 [T1]), Week 8 (Mid-semester; Time 2 [T2]), and Week 16 (End of semester; Time 3 [T3]). Students were given one week to complete each survey. The time points were chosen as they reflect key moments in a semester including the initial beliefs a student holds at the semester onset, and the possible changing motivational beliefs that may occur as students' academic outcomes become clear (e.g., receiving a midterm grade that a student may use to judge the likelihood of passing a course). The surveys contained items assessing students' expectations, STVs, and costs. At T1 students were asked demographic information, and at T3 students were about their intentions to leave their major or program. The Institutional Review Board at all universities approved the study procedures and protocol. Consent was given for all participating students who were also reminded at all three waves of measurement that participation is voluntary.

Planned Missing Data Design

Students who gave consent to participate in the study were emailed a link to a digital survey in weeks 1, 8, and 16 and were asked to complete it within the week sent. Frequent points of measurement capture the dynamic longitudinal relations of the motivational constructs with achievement and ITL. Although the total number of survey items is 40 (see Appendix A), the survey given to students is tailored to take approximately four minutes to complete. This was done by utilizing a three-form planned missing data design (PMDD), which allows researchers to maximize planned missingness mechanisms by providing participants with a balanced subset, typically 66% – 75%, of items from an overall survey (Jorgensen et al., 2014; Lang et al., 2020).

Commonly, this is accomplished by splitting a survey into 4-blocks: An X-, A-, B-, and C-block. The X-block, or “common block,” contains items that students will see every measurement wave. After subtracting the total item count in the X-block from the overall survey count, the remaining survey items are distributed evenly across the A-, B-, and C- blocks in a balanced design that ensures an even number of items per construct can be found across the blocks (see Appendix B). Following the block creation, the next step is to combine the blocks into three-forms: (1) XAB, (2) XAC, and (3) XBC. Each form in the present study accounts for 72.5% (29 items per form) of the overall survey items.

Students will be randomly placed into one of three groups. Each group is randomly assigned to start with one of the above-mentioned forms during the first week of the semester. During consecutive measurement points each group will receive the next form, and so on. In other words, if Group 1 were to be randomly assigned the XAB form, then in weeks 8 and 16 they would be assigned forms XAC and XBC, respectively. The PMDD allows researchers to minimize the item count in a survey, decrease the chance of participant fatigue, and utilize an anticipatory approach that increases the likelihood of reducing missing data from participants. This is a more practical option for researchers attempting to collect data on a large scale.

Measurements

Academic Achievement

Student’s semester grade point average (GPA) was obtained through school records. Student semester GPAs, on a 0-4 scale, reflected a measure of student academic success averaged across all courses taken during the semester.

Expectations

Students' expectations were measured using a subscale adapted from Eccles and Wigfield (1995). The instrument was designed to measure expectations of success utilizing an EVT framework (J. Eccles et al., 1983), and does so with five items rated on a five-point Likert scale. Items 2, 3, and 5 used Likert scales that ranged from (1) *very poor* to (5) *very good*. An example of these items included "How good are you in your nursing courses?" Item 1 ("Compared to other students, how well do you expect to do in your nursing courses this semester?") ranged from (1) *much worse than other students* to (5) *much better than other students*. Item 4 ("If you were to order all the students in your cohort from worst to best in your nursing courses, where would you put yourself?") ranged from (1) *one of the worst* to (5) *one of the best*. Past research has demonstrated good internal consistency for these items with a Cronbach's alpha of .92 (J. Eccles & Wigfield, 1995). Omega coefficients of composite reliability for expectations at each of the three time points for the current sample are shown in Table 1.

Subjective Task Values

Students' subjective task values were measured using an instrument from Gaspard et al. (2017). The instrument was designed to measure subjective task values utilizing an EVT framework (J. Eccles et al., 1983), and does so with items rated on a nine-point Likert scale, ranging from (1) *completely agree* to (9) *completely disagree*. The subjective task values instrument contained three subscales for the three task value constructs. The constructs contained a different number of items with intrinsic value comprising four items; attainment value comprising eight items; utility value comprising thirteen items. Sample items from the subscales include the following: attainment value ("Performing well in my nursing courses is important to me"), utility value ("Knowing the contents in my nursing courses will be helpful for my future career"), intrinsic value ("I like doing things related to my nursing courses"). Past research has demonstrated good scale reliability for each of the subscales: attainment value (personal importance, $\rho = .71$; importance of achievement $\rho = .90$), utility value (utility for daily life, $\rho = .82$; utility for job, $\rho = .90$; utility for school, $\rho = .78$), intrinsic value ($\rho = .93$). Scale reliability noted here were taken from the biology subject portion of Gaspard et al.'s (2017) study as this most closely resembles the subjects found in the present study. However, scale reliabilities were high even when viewing other academic subjects from Gaspard et al. (i.e., math, physics, German, English). Omega coefficients of composite reliability for subjective task values at each of the three time points for the current sample are shown in Table 1.

Costs

Students' costs were measured using an instrument from Flake et al. (2015). The instrument was designed to measure costs utilizing an EVT framework (J. Eccles et al., 1983), and does so with items rated on a nine-point Likert scale, ranging from (1) *completely agree* to (9) *completely disagree*. The cost instrument contained three subscales for the three cost constructs viewed in the present study. The constructs contained a different number of items with effort cost comprising five items; opportunity cost comprising four items; emotional cost comprising six items. Sample items from the subscales include the following: effort cost ("My nursing courses demand too much of my time"), opportunity cost ("I have to sacrifice too much for my nursing courses"), emotional cost ("My nursing courses are too exhausting"). Past research has demonstrated good internal consistency for each of the cost subscales: Effort cost with a Cronbach's alpha of .95; opportunity cost with a Cronbach's alpha of .89; emotional costs with a Cronbach's alpha of .94. Omega coefficients of composite reliability for costs at each of the three time points for the current sample are shown in Table 1.

Intentions to Leave

Students' intentions to leave were measured using an instrument from Perez et al. (2014). The instrument was designed to measure intentions to leave utilizing an EVT framework (J. Eccles et al., 1983), and was designed to measure students' intentions to leave their STEM major or program. To capture this, six items rated on a nine-point Likert scale, ranging from (1) *completely agree* to (9) *completely disagree*, were used. An example of these items included "I am likely to leave my OT program." Past research has demonstrated good internal consistency for these items with a Cronbach's alpha of .93 (Perez et al., 2014). Omega coefficients of composite reliability for ITL for the current sample are shown in Table 1.

Table 1

OMEGA Coefficient Values Per Measurement Construct and Measurement Wave

CONSTRUCT	ESTIMATE	S.E.	EST./S.E.	P-VALUE
		OMEGA TIME 1		
Expectations	0.943	0.005	190.208	0.00
Emotional Cost	0.925	0.006	165.115	0.00
Opportunity Cost	0.955	0.004	270.965	0.00
Task Effort	0.859	0.010	82.814	0.00
Utility Value	0.769	0.028	27.946	0.00
Intrinsic Value	0.887	0.013	69.595	0.00
Attainment Value	0.899	0.018	48.818	0.00
		OMEGA TIME 2		
CONSTRUCT	ESTIMATE	S.E.	EST./S.E.	P-VALUE
Expectations	0.94	0.005	186.832	0.00
Emotional Cost	0.924	0.006	167.534	0.00
Opportunity Cost	0.949	0.004	241.955	0.00
Task Effort	0.871	0.016	56.016	0.00
Utility Value	0.777	0.017	45.076	0.00
Intrinsic Value	0.9	0.01	89.494	0.00
Attainment Value	0.853	0.017	51.241	0.00
		OMEGA TIME 3		
CONSTRUCT	ESTIMATE	S.E.	EST./S.E.	P-VALUE
Expectations	0.941	0.005	203.337	0.00
Emotional Cost	0.914	0.006	145.321	0.00
Opportunity Cost	0.947	0.004	220.862	0.00
Task Effort	0.813	0.019	42.46	0.00
Utility Value	0.762	0.019	39.68	0.00
Intrinsic Value	0.914	0.008	108.584	0.00
Attainment Value	0.880	0.013	65.258	0.00
Intentions to Leave	0.927	0.071	25.267	0.00

Statistical Analyses

In sum, we examined the constructs of EVT for the following:

(1) Associated carry-over (autoregressive) effects and reciprocal spill-over (cross-lagged) effects between the within-student (unstable) EVT constructs (Figure 2).

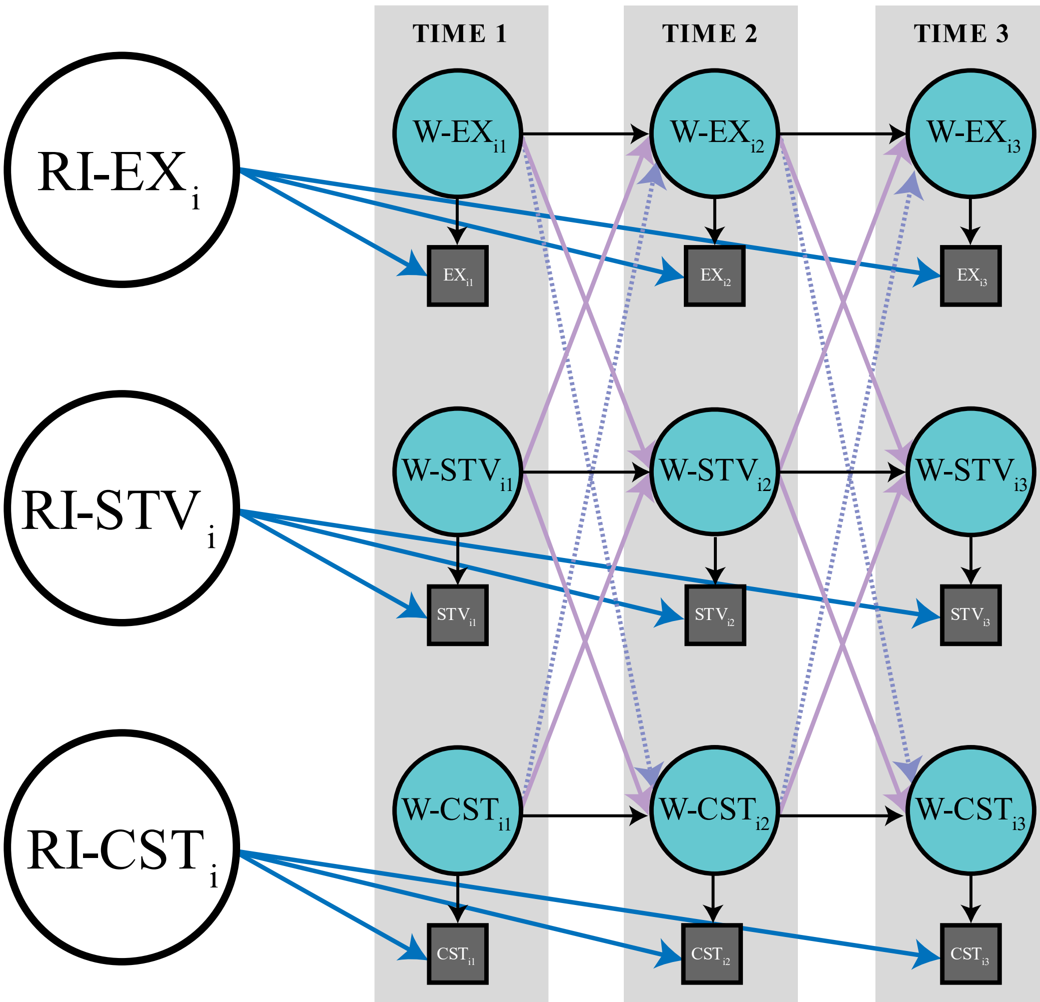
(2) Spill-over effects and causal relationships between within-student (unstable) EVT constructs with health science student ITL and academic achievement (Figures 3 & 4).

(3) Relationships among between-student (stable; random intercepts) EVT constructs with health science student ITL and academic achievement (Figures 3 & 4).

To maintain power and increase the probability of model convergence for a RI-CLPM, an exploratory factor analysis was conducted that included all seven EVT latent variables of interest: expectations, all three STVs or attainment value, interest value, and utility value, and all three costs variables or opportunity cost, psychological cost, and effort cost. This largely showed all the items loaded properly and significantly onto the constructs they were purported to load onto. This led to a confirmatory factor analysis where all items were set to only load onto one of the seven EVT factors – items were set to load onto a factor based on the results of the EFA and based on theory. Within the same CFA, all three task values variables were set to load onto a higher order STV latent variable, and similarly all three costs variables were set to load onto a higher order COST latent variable. Expectations is not multifactorial and therefore the EXPECTACTION latent variable was only derived from the items purported to load onto it. Finally, factor scores for the EXPECTACTIONS, STV, and COST latent variables were saved and used as the single indicators in the proposed RI-CLPM (Figure 2). The EFA and CFA models, as well as the RI-CLPM, are described in detail in the results section.

Figure 2

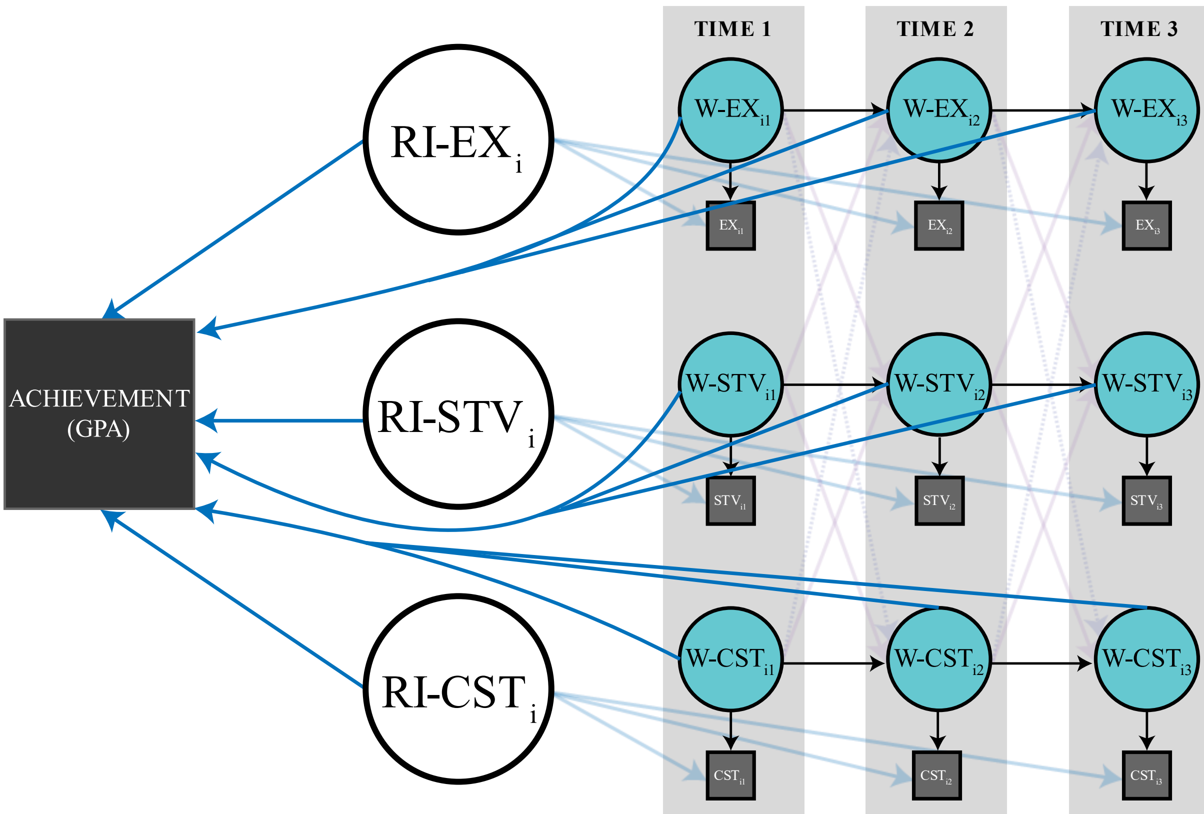
Model 1: Single Indicator RI-CLPM



Note. This figure depicts a diagram of the single indicator RI-CLPM with RI included at the latent variable level. Indicators are depicted with a single box, and covariances and residuals are removed for clarity of presentation.

Figure 3

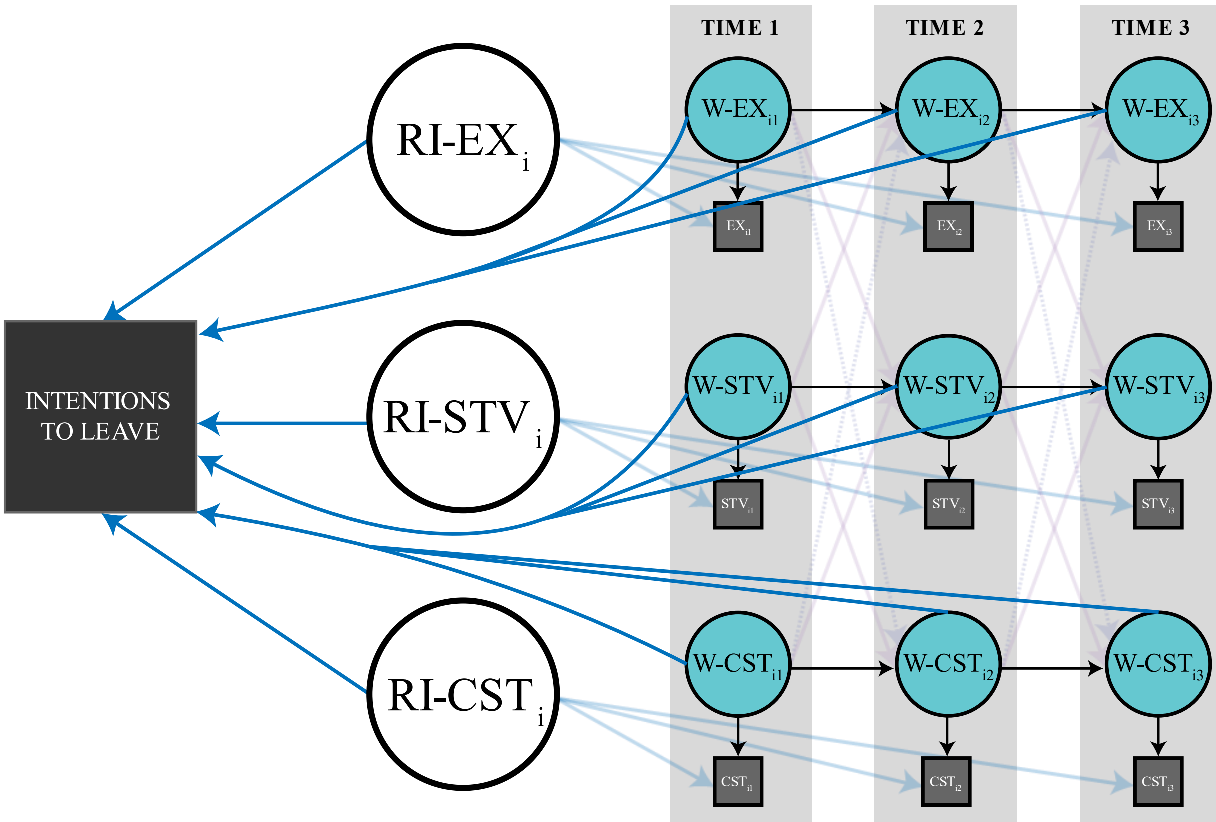
Model 2: RI-CLPM With RI and Within Components on Achievement



Note. This figure depicts a diagram of the single indicator RI-CLPM. Achievement (semester GPA) is regressed on the within (unstable) and between (RI; stable) latent variables. Indicators are depicted with a single box, and covariances and residuals are removed for clarity of presentation.

Figure 4

Model 3: RI-CLPM With RI and Within Components on Intentions to Leave



Note. This figure depicts a diagram of the multiple indicator RI-CLPM. Intentions to leave are regressed on the within (unstable) and between (RI; stable) latent variables. Indicators are depicted with a single box, and covariances and residuals are removed for clarity of presentation.

Data were analyzed using Mplus 8.7 (Muthen & Muthen, 1998-2022). All solutions were estimated using robust maximum likelihood estimation (MLR) which provides maximum likelihood parameter estimates with sandwich estimator standard errors and a chi-square test statistic that are robust to multivariate non-normality and the ordered categorical nature of the data (Asparouhov & Muthem, 2005; Beauducel & Herzberg, 2006; Rhemtulla et al., 2012; Yuan & Bentler, 2000). The chi-square test statistic produced by the MLR estimation routine in Mplus is asymptotically equivalent to the Yuan-Bentler T2* (Yuan & Bentler, 2000). For the MLR estimator in Mplus, sandwich estimator standard errors involve using the observed information in the outer block and cross-products information in the inner block.

This study will observe the relationships of EVT constructs over time using longitudinal data and is interested in the predictability of EVT constructs on one another and on academic outcomes. Using a latent variable modeling framework, the analysis was performed in four phases: (1) power analysis to determine sufficient sample size, (2) measurement and structural model exploration, (3) test of longitudinal invariance and (4) evaluation of the RI-CLPM models (Figures 2-4) using five suggested steps taken from Kline (2016).

Phase 1: Power Analysis

Power, or statistical power, is defined as the probability of rejecting a null hypothesis when it is false. This is also called a β error which represents the probability of retaining a false null hypothesis or the probability of not making a Type II error (Cohen, 1988). In this sense, power can be given by 1 – β, and is considered the probability to detect a true effect (Jobst et al., 2021). A standard acceptable level of β is 0.20 so that power is commonly set to .80 (i.e., 1 - 0.20).

Power is frequently linked to three parameters: (1) chosen alpha level (commonly .05), (2) the effect size a researcher is interested in, and (3) sample size. The first two components of power can be chosen, however, the third may be more difficult as social science researchers commonly rely on volunteers as participants and have less control over sample size. It is important for researchers to know the sample size collected (or will collect) is adequate to run analysis like structural equation models (SEM), and notably that the research questions and hypotheses can be satisfactorily addressed.

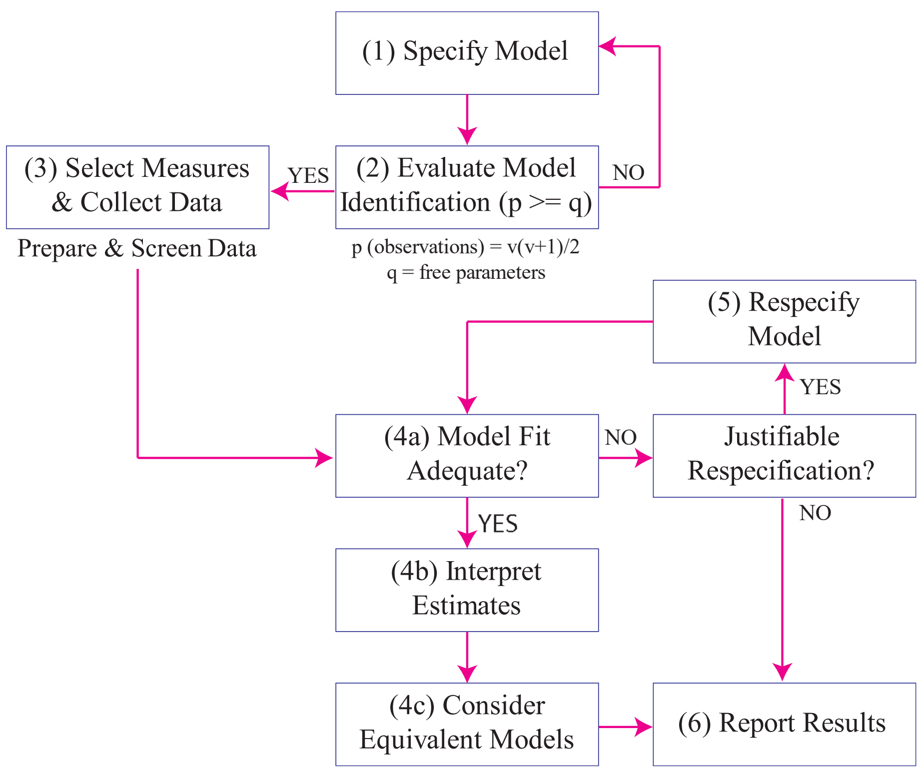
SEM is generally understood to require large samples with some researchers suggesting a minimum threshold of 200 participants (Barrett, 2007). However, increasingly complex models and certain estimation methods require large samples. Kline (2016) made a general recommendation to have a ratio of participants to free parameters at 20:1, although it may be noted that 10:1 may be a more realistic. Unfortunately, relying on rules-of-thumb is outdated and not ideal for power assessments as this may lead to under or overestimation of sample size requirements (E. J. Wolf et al., 2013). Therefore, the present study utilized four *a priori* methods for determining power and sample size adequacy. The four *a priori* methods for determining power come from Moshagen (2021) and Jobst et al. (2021), Westland (2010) and Sopper (2022), Mulder (2022), and Wolf et al. (2013). These power analyses are described in the *Results* section below.

Model Evaluations

Before moving into the second phase where the measurement and structural models are explored, an initial review of a structural equation model (SEM) is warranted. First, an SEM is composed of a measurement and structural model. The measurement model measures the defined latent variables using chosen indicators that represent the latent variables (e.g., survey instruments), and is confirmed via a factor analysis. The structural model stems from a variance-covariance matrix that is produced from observed data and can be determined with a path analysis which produces estimates that will most closely reproduce the observed variance-covariance matrix (Kline, 2016). The hypothesized model fit can be evaluated by analyzing the measurement and structural models with programs like Mplus that finds estimates for all parameters that are most likely to reproduce the observed path beta coefficients while considering the highest probability of reproducing all the correlations in the input matrix. Kline (2016) outlined five logical steps for completing an SEM analysis that guide both measurement and structural model analyses, and include suggestions for data preparation and screening. The five steps include: (1) model specification, (2) identification, (3) parameter estimation, (4) model evaluation, and (5) model modification (Figure 5).

Figure 5

Depiction of Kline's Five Steps for Completing an SEM



Model specification defines the hypothesized relationships among the variables based on theory. An initial structural model that does not fit the data well may be re-specified and re-evaluated before interpretating the estimates. Mplus SEM output includes various fit indices that allow for the assessment of a single path coefficient and the overall model fit (Klem, 2000). The application of model fit indices within SEM literature is generally flexible, and typically a combination of fit indices is used to describe a good or poor model (Hu & Bentler, 1999). Therefore, multiple fit indices were considered along with the χ^2 which is known to be oversensitive to minor model misspecifications given even moderate-sized samples and contains a restrictive hypothesis test that expects an exact fit. For the current study, fit indices selected can be found in Table 2 along with guidelines for interpreting the indices and cutoff scores.

For comparing nested models when using the MLR estimator it is common to use the Satorra-Bentler (Satorra & Bentler, 2001) scaled chi-square difference test. However, this also tends to be sensitive to trivial differences. Therefore, changes in the CFI (ΔCFI) and RMSEA (ΔRMSEA) were primarily used. A decrease in the CFI and increase in the RMSEA of less than 0.010 and 0.015, respectively, are indicative of support for a more restrictive model (F. Chen, 2007; Cheung & Rensvold, 2002). Benchmarks derived from Keith (2014; pages 62-63) were used to evaluate the magnitude of the structural path coefficients in the RI-CLPM based on the standardized beta coefficient (β) for direct effects: $\beta < .05$: too small to be meaningful; $.05 < \beta \leq .10$: small but meaningful; $.10 < \beta \leq .25$: moderate; $\beta > .25$: large.

Model identification is to check if the model is over-identified, just-identified, or under-identified. Model coefficients can only be estimated if the model is just-identified or over-identified. Model evaluation assesses model performance or fit using the fit indices described above. If necessary, a model can be modified to improve model fit, the post hoc model modification, and the fit can be reevaluated.

Table 2

Model Fit Indices and Cutoffs

Index (Range)	Description	Interpretation	Cutoff
Chi-square (χ^2)	χ^2 tests the hypothesis there is a discrepancy between the model-implied covariance matrix and the original covariance matrix (Hu & Bentler, 1999).	Nonsignificant χ^2 suggests the model fits the data	>0.05
RMSEA (0-∞)	Root mean square error of approximation (RMSEA) is a "badness of fit" index where higher values indicate a lack of fit (Browne & Cudek, 1993; Hu & Bentler, 1999). It is useful for detecting model misspecification and less sensitive to sample size compared to the χ^2 test.	0 = perfect fit	≤ 0.05 and 0.08 for close and reasonable fit
SRMR (0-∞)	Standardized root mean square residual (SRMR) is a "badness of fit" index where higher values indicate a lack of fit (Browne & Cudek, 1993; Hu & Bentler, 1999). It is useful for detecting model misspecification and less sensitive to sample size than the χ^2 test.	0 = perfect fit	<0.06
CFI (0-1)	Comparative fit index (CFI) represents the amount of variance that has been accounted for in a covariance matrix. A higher CFI value indicates a better model fit (Hu & Bentler, 1999). CFI is less affected by sample size compared to the χ^2 test (Fan et al., 1999; Tabachnick & Fidell, 2007).	Values closer to 1 indicate better fitting model	≥ 0.90 and 0.95 for acceptable and excellent fit, respectively
TLI (0-1)	Tucker-Lewis index (TLI) is a non-normed fit index that proposes a fit index independent of sample size (Bentler, 1990).	Values closer to 1 indicate better fitting model	≥ 0.90 and 0.95 for acceptable and excellent fit, respectively
AIC and BIC	Akaike information criterion (AIC) provides an estimate of the information lost when the given model is used to generate data (Kline, 2016). Bayesian information criterion (BIC) is an estimation of how parsimonious a model is among various alternate models (Kline, 2016). AIC and BIC are useful for selecting the model with the least overfitting.	Lower AIC and BIC values indicate a better-fit model	Lower AIC and BIC values indicate a better-fit model

Phase 2: Measurement and Structural Model Exploration

In the second phase, the measurement model was assessed via an exploratory factor analysis (EFA) to ensure all items loaded onto the factors they were purported to. For the EFA, all items for all EVT constructs were allowed to load onto all seven latent variables (expectations, utility value, intrinsic value, attainment value, effort cost, opportunity cost, and psychological cost). Following the EFA, a confirmatory factor analysis (CFA) was run using the loadings accepted from the EFA and was run for each of the three time points. Assuming the CFA model for each time point has an acceptable model fit then a test of longitudinal measurement invariance will be conducted.

One additional CFA was run with all six ITL items loading onto a single (ITL) factor. The CFA for the ITL latent variable was assessed independently of the longitudinal EVT CFA just discussed because the ITL variable was only measured once at the end of the semester. This resulted in ITL to be treated as a time invariant outcome variable.

Phase 3: Longitudinal Invariance

In the third phase, longitudinal measurement invariance models were tested across the three time points to assess the equivalence of the scale item scores. Measurement invariance assesses the psychological equivalence of a construct, and when met, implies that a construct has the same meaning across measurement occasions or groups (Putnick & Bornstein, 2016). Therefore, examining the longitudinal relationships among the constructs over time for invariance is critical for interpreting the carry-over (autoregressive) and spill-over (cross-lagged) effects (coefficients) without confounds (Widaman et al., 2010).

Invariance was tested in line with the taxonomy of longitudinal invariance tests proposed by Kline (2016). This involves four steps, or the sequential and additive testing of (1) configural invariance (which assesses overall model fit), (2) invariance of factor loadings (metric or weak factorial invariance), (3) invariance of item intercepts (scalar or strong factorial invariance), and (4) invariance of unique factor variances (strict factorial or residual invariance). It should be noted that only the first three steps of invariance testing must be met (i.e., scalar invariance must be met) to conduct a RI-CLPM since the fourth step, strict factorial invariance, is required for assessing differences in residuals which are not part of the latent factors used in a RI-CLPM (Putnick & Bornstein, 2016). In the configural invariance model, for each of the EVT constructs at each of the three time points, the items were specified to have a target loading on the EVT construct it was purported to index based on the CFA conducted in phase 2.

Factor Scores

Once measurement invariance across time was established, factor scores were created from the longitudinal CFA model using the "SAVEDATA" function in Mplus to consolidate the items for the three factors of interests at each time point: expectations (T1-T3), STV (T1-T3), and costs (T1-T3). Moreover, a factor score was used to consolidate the items for ITL – this factor scored was used as an outcome variable reflecting ITL.

Factor scores were used in the RI-CLPM models (Figures 2-4) to improve the likelihood of model convergence, improve model fit, and maintain power. This contrasts with an approach that includes each factors measurement model (e.g., items for costs at each time point included in the RI-CLPM). However, not only will Mplus need to calculate the measurement model for each factor at each time point, but it will then need to calculate higher order factors that represent the within-person (unstable) and between-person (stable) components of that factor.

Missing Data

The planned missing data design utilized in this study helps maintain that the data are likely missing at random (MAR) and utilize an anticipatory approach that increases the likelihood of reducing missing data from participants. However, to handle the missing data, full information maximum likelihood (FIML) via the implemented MLR estimator in Mplus was used. FIML provides unbiased parameter estimates providing that the data are MAR. Importantly, the possibility of the MAR assumption is greatly increased in the hypothesized models given the availability of repeated measurements to the extent that, if missingness for any variable at wave$_i$ is a function of a variable at wave$_i$ then this is likely to be accounted for through the availability of the same variable at wave$_j$ – given that $j \neq i$ (Marsh et al., 2016). However, even with missing data, longitudinal panel models utilize all available data from each participant.

There was missing data across the observed variables which is common even in cross-sectional designs. The first measurement occasion comprised 646 students (Table 3). At each of the subsequent measurement occasions, the study followed the students who participated at the prior wave and included those students who had not yet participated but opted into the study at later measurement waves. This sampling routine resulted in the following sample sizes for the subsequent measurement waves: T2 (n = 673) and T3 (n = 628). Across the measurement waves, a total of 763 students participated in the study. 9.0% (n = 69) of participants completed only one wave; 32.5% (n = 248) of participants completed two waves; and 58.5% (n = 446) of participants completed all three waves.

Table 3

Missing Data Count

		GPA	ITL	EX1	STV1	CST1	EX2	STV2	CST2	EX3	STV3	CST3
N	Valid	737	699	646	646	646	673	673	673	628	628	628
	Missing	26	64	117	117	117	90	90	90	135	135	135

Note. GPA = grade point average, ITL = intentions to leave, EX = expectations, STV = subjective task value, and CST = cost.

Phase 4: Random-Intercept Cross Lagged Panel Model

In the fourth phase, a random-intercepts cross-lagged panel model (RI-CLPM), a structural equation modeling technique, was conducted (with the factor scores derived from phase 3) to test the directional and reciprocal effects among all EVT constructs, and the effects of the EVT constructs on outcomes like academic achievement and intentions to leave. As an example to understand RI-CLPM one can view the multiple hypothetical relationships between two variables, X and Y, including: (1) X does not cause Y, and Y does not cause X; (2) X causes Y but Y does not cause X; (3) Y causes X but X does not cause Y; (4) both X causes Y and Y causes X. Measuring variables at multiple occasions allows for the evaluation of each of these relationships and test for causal relations.

Moreover, the addition of random intercepts (RI) to the traditional CLPM allows for the capture of trait-like (time-invariant or stable) between-person differences for each time point. This can be thought of as students' average levels for each EVT construct across all time points. This affords the opportunity to differentiate stable between-person versus unstable within-person variability for constructs and is better suited for assessing motivational developmental processes like those found within EVT (Hamaker et al., 2015). Consequently, the interpretation of autoregressive (often referred to as carry-over effects in RI-CLPM literature) and cross-lagged paths (often referred to as spill-over effects in RI-CLPM literature) in the RI-CLPM is different compared to the CLPM. For example, the RI-CLMP test whether students who report higher expectancies than usual (i.e., a within-person deviation from their expectancy baseline) may experience a subsequent increase in STVs, relative to their usual levels of STVs (i.e., a within-person deviation from their STV baseline).

Following guidelines from Hamaker et al. (2015), three overarching random intercept (RI) factors for the stable between-person portion of the model were created. The factor scores saved in phase 3 for each construct were used at all three waves as indicators of each RI construct, with all factor loadings set to 1 (Figure 2). For the unstable within-person part of the model, factor scores saved in phase 3 for each construct and at all three waves were regressing on nine within-person latent factors (i.e., one for expectations, one for STV, and one for costs at each of the three waves), with all loadings constrained to 1 (Figure 2). The latent factors in the within-person part were used to examine carry-over (autoregressive) paths, spill-over (cross-lagged) paths, and within-time correlations among the three variables. The residual variances of the factors in the measurement models were set to zero, ensuring that all variation in the observed scores was entirely captured by the within-person and between-person latent factors. The correlations between the factors in the within-person part at each wave were estimated. The correlations between the random intercept factors were also estimated to examine between-person level associations. The default correlations between the random intercept factors and within-person latent factors at the initial wave were constrained to zero. Longitudinal associations among expectations, STV, and cost were examined. To evaluate the absolute model fit, the fit indices used in phase 1 were applied (Table 2).

It may be noted the RI-CLPM is not the only alternative model to the traditional CLPM. For example, the autoregressive latent trajectory (ALT) model and the general cross-lagged panel model (GCLM) are available (Usami, 2021; Zyphur, Allison, et al., 2020; Zyphur, Voelkle, et al., 2020). The ALT model is a hybrid mixing the traditional latent growth model with the traditional CLPM. However, the ALT models requires a minimum of four (potentially five) measurement occasions, versus the RI-CLPM which requires only three. Moreover, the ALT model has common factors that are less interpretable compared to the RI-CLPM because its common factors are derived from the lagged effects versus the observed variables.

The GLCM is a progression of the traditional CLPM and resembles the RI-CLPM by incorporating stable trait factors. However, a main difference of the GLCM is that it includes moving average and cross-lagged moving averages in addition to auto-regressive and cross-lagged effects when predicting future. Unfortunately, the GLCM like the ALT model derives its common factor from the lagged effects versus the observed variables as done in the RI-CLPM. This again renders the interpretation of the stable factors less interpretable compared to the RI-CLPM (Usami, 2021).

CHAPTER 4 – RESULTS

Descriptive Statistics of EVT Variables

Descriptive statistics for outcome and predictor variables are displayed in Table 4. Many of the EVT variables appear to revolve around a similar mean and standard deviation at each time point. Expectations were 3.00 ± 1.14, 2.81 ± 1.29, and 2.93 ± 1.25 for each of the three time points, respectively. Subjective task values were 4.06 ± 1.09, 4.82 ± 1.08, and 4.73 ± 1.05 for each of the three time points, respectively. Finally, cost was 7.83 ± 0.85, 7.81 ± 0.83, and 7.76 ± 0.91 for each of the three time points, respectively. GPA was 3.45 ± 0.53, and ITL were 3.45 ± 0.53.

Table 4

Descriptive Statistics of EVT Variables

	GPA	ITL	EX1	STV1	CST1	EX2	STV2	CST2	EX3	STV3	CST3
Mean	3.45	3.45	3.00	4.06	7.83	2.81	4.82	7.81	2.93	4.73	7.76
SD	0.53	0.53	1.41	1.09	0.85	1.29	1.08	0.83	1.25	1.05	0.91
Variance	0.28	1.98	1.2	0.73	1.66	1.17	0.69	1.57	1.11	0.82	1.57
Skewness	-1.19	0.01	0.06	-2.03	-0.21	0.09	-1.25	-0.31	0.17	-1.28	-0.23
Kurtosis	0.46	-1.3	-0.82	8.14	-0.19	-0.77	1.84	-0.08	-0.73	1.83	-0.12
Minimum	2	2	1	1	2	1	4	2	1	4	2
Maximum	4	6	5	9	9	5	9	9	5	9	9

Note. GPA = grade point average, ITL = intentions to leave, EX = expectations, STV = subjective task value, CST = cost, and the numerical value next to each variables represents the measurement wave (i.e., 1 = wave 1).

Phase 1: Power Analysis

Power Analysis 1

Mashagen (2021) developed an R package called semPower that incorporates findings and formula from Jobst et al. (2021) that can help researchers determine *a priori* and *post hoc* power analyses. semPower utilizes as inputs chosen alpha value (typically a = .05), power value (typically β = .80), model degrees of freedom (df), and chosen effect measure with desired effect size. For power analyses, the choice of effect size measure is arbitrary if the measure allows for a computation of the noncentrality parameter. The root mean square error of approximation (RMSEA) is a measure of effect often used in power analysis. Specifically, the RMSEA is a measure of model misfit per model degree of freedom with larger values indicated greater misfit (Steiger, 1998). A common acceptable level of RMSEA is .08 or less. For the present study, semPower was used to conduct a power analysis for a global hypothesis test between a saturated model (df = 0) and the basic RI-CLPM depicted in Figure 2. Results of the power analyses are presented in Table 5.

Power Analysis 2

The second power analyses from Westland (2010) was developed based on (1) a function of the ratio between indicator variables to latent variables and (2) as a function of minimum effect size, power, and significance. Like other studies examining sample size and power for SEM, Westland (2010) noted there is little to no support for positing a minimum sample size as a linear function of indicators or variables. Instead, as the study supported, a better method for calculating sample size should rely on a ratio of indicators to latent variables. Inputs required for the formula proposed to determine minimum sample size includes chosen alpha value (typically a = .05), power value (typically β = .80), number of latent variables, number of observed variables, and anticipated effect size based on Cohen (1988)'s formula and guidelines where small effect sizes range from .1-.23, medium from .24-.36, and large >.37. Sopper (2022) created an online calculator following the formula developed by Westland (2010) – this calculator was used for the present study. For the analyses, the effect size was varied between .1-.3 (to detect small to medium effects), alpha = .05, power = .80, and the number of latent variables and indicators were calculated for the base RI-CLPM model (Figure 2). Results of the power analyses are presented in Table 5.

Power Analysis 3

It should be noted the first two power analysis used were not specific to the RI-CLPM analysis used in the present study and the results should be interpreted cautiously. However, the third power analysis was derived from an R package (also available for Mplus) developed by Mulder (2022) called powRICLPM. This package runs a Monte Carlo simulation and functions to obtain the power to reject the null hypothesis of no effect for all parameters in a bivariate RI-CLPM given a sample size, number of repeated measures (which for the present study is three), and proportion of between-unit variance. The users must input expected (or found) standardized autoregressive and cross-lagged effects for the within-unit components of the model, hypothesized correlation between within-unit components, the hypothesized proportion of variance at the between-unit level, and hypothesized correlation between the random intercepts. The user can also vary the sample size lower and upper bounds. One major limitation of Mulder's (2022) powRICLPM is that only a bivariate model can be assessed whereas the present study is observing three variables longitudinally (i.e., expectations, STVs, and costs).

Nevertheless, powRICLPM can still provide some information about the sample size required to observe significant small to medium effect sizes in a RI-CLPM. Output from the package describes the required sample size necessary to obtain the specified model parameters. Results of the power analyses are presented in Table 5.

Power Analysis 4

To obtain sample size estimates necessary for adequate power, a "from scratch" Monte Carlo simulation was the fourth method used. This is widely adopted when trying to detect power – especially when novel and complex models are used like the one in the present study. The Monte Carlo simulation was conducted in Mplus, and adapted from Wolf et al. (2013) and from guidelines taken from Chapter 12 of the Mplus user manual (Muthen & Muthen, n.d.). In a Monte Carlo simulation, the researcher determines the to-be-tested model and inputs hypothesized levels for each freely estimated parameter – likely using results from past research utilizing similar models. Each study is unique and requires unique inputs based on the hypothesized model(s). The number of iterations and seed (random starting point) is set by the researcher. Varying the sample size up or down in the simulation and analyzing the output can tell the researcher the degree of bias in the parameter estimates, standard errors, 95% confidence intervals for parameter estimates, and power for all parameter estimates. It should be noted sample size is dependent on the loadings as factors with moderate to high average loadings (standardized loadings > .50) illustrate a significantly lower sample size could be used to obtain similar results. When running the Monte Carlo simulation, one is looking for a minimum sample size required to produce a model where all parameter estimates of interests are greater than .80

(power), no model iteration has an error or no convergence, and no bias in a parameter estimate or standard error that exceeds 5%.

For the analyses, the main RI-CLPM hypothesized model (Figure 2) was run through Mplus with set estimated parameters. Benchmarks derived from Keith (2014; pages 62-63) were used to determine the magnitude of the structural path coefficients in the RI-CLPM based on the standardized beta coefficient (β) for direct effects: $\beta < .05$: too small to be meaningful; $.05 < \beta \leq .10$: small but meaningful; $.10 < \beta \leq .25$: moderate; $\beta > .25$: large. Specifically, all Monte Carlo simulations were run with small, medium, and large effect sizes. In the model with expected large, standardized effect sizes the autoregressive paths were set to $\beta = .30$ and the cross-lagged paths were set to $\beta = .25$. In the model with expected medium, standardized effect sizes the autoregressive paths were set to $\beta = .20$ and the cross-lagged paths were set to $\beta = .15$. In the models with expected small, standardized effect sizes the autoregressive paths were set to $\beta = .10$ and the cross-lagged paths were set to $\beta = .05$. Across simulations, the variances of all observed variables were set to 1, and correlations between variables at Wave 1 and error correlations among variables at Waves 2 and 3 were set to 0.25. All simulations were run with samples sizes at 600, 800, 1000, or were run until desired power ($\beta = .80$) was achieved. All simulations were run with 10,000 replications. For each model, a random seed was generated using a random number generator in Microsoft Excel and were used across parameter and sample size combinations. Results of the Monte Carlo power analyses are presented in Table 5.

Interpretation of Power Analysis

As revealed in Table 5, various sample sizes could support the model being presented by the current study. However, a conservative interpretation of these analyses may include adopting a sample size that supports a model yielding small to medium effect sizes. Based on the powRICLPM Monte Carlo simulation, and the “from scratch” Monte Carlo simulation, which were more targeted to the present study, a sample size of 600-1000 would be acceptable.

Table 5

Power Analyses and Results

Power Analyses Method	Parameters									Estimated Minimum Sample Size To Achieve Effect Size
	a	B	Effect Size	Model df	# LV	# Indicators	ICC	RI Corr	Within Corr	Effect size guidelines (Cohen, 1998): Small=.1-.23; medium=.24-.36
semPower	0.05	0.8	RMSEA = 0.05	45	n/a	n/a	n/a	n/a	n/a	259
Westland (2010)	0.05	0.8	Cohen D = 0.1-0.3	n/a	21	63	n/a	n/a	n/a	2129 (small) - 230 (medium)
powRICLPM	0.05	0.8	Cohen D = 0.1-0.3	n/a	n/a	n/a	0.3	0.35	0.25	800 (small) - 400 (medium)
powRICLPM	0.05	0.8	Cohen D = 0.1-0.3	n/a	n/a	n/a	0.5	0.35	0.25	1200 (small) - 500 (medium)
powRICLPM	0.05	0.8	Cohen D = 0.1-0.3	n/a	n/a	n/a	0.7	0.35	0.25	1600 (small) - 600 (medium)

Monte Carlo Simulation

Effect Size	Sample Size	RMSEA	SRMR	TLI	CFI	Parameter Bias[b]	Power Achieved[c]	Note
Small	7500[a]	0.002	0.009	1.00	1.00	None	Yes	All estimates achieved .80 or greater
Medium	600	0.009	0.031	0.999	0.999	None	No	2 out of 18 estimates of interest did not achieve .80
Medium	800	0.002	0.009	1.00	1.00	None	No	2 out of 18 estimates of interest did not achieve .80
Medium	1000	0.007	0.024	0.999	1.00	None	Yes	All estimates achieved .80 or greater
Large	600	0.009	0.029	0.999	0.999	None	Yes	All estimates achieved .80 or greater
Mixed	2000	0.005	0.017	1.00	1.00	None	Yes	All estimates achieved .80 or greater

[a]A model where all autoregressive and cross-lagged paths had small but significant values required a sample size of 7500 to achieve power.
[b]Parameter bias was determined if any estimated parameter exceed 5% difference from the given population parameter.
[c]Power was achieved if all estimates from the Monte Carlo simulation met the .80 power coefficient.

Phase 2: Measurement and Structural Model Exploration

Results from the EFA for all EVT constructs showed that most items loaded appropriately (Table 6), however, item 1 for expectations loaded onto task effort. This item reads, “Compared to other students, how well do you expect to do in your nursing courses this semester?” It is possible students are considering the effort required to do well relative to their peers when answering this item and wording of this item fits with the definition of task effort. Therefore, item 1 for expectations was allowed to load onto task effort. Similarly, item 1 for task effort loaded onto opportunity cost. This item reads, “My nursing courses demand too much of my time.” It is logical that this could load on opportunity cost over task effort, therefore, it was allowed to load onto opportunity costs. Interestingly, item 2 for task effort and item 6 for utility value did not load highly or significantly onto any construct. These items were dropped from the analysis.

Table 6

Exploratory Factor Analysis

Items	EC	OC	EX	TE	AV	IV	UV
EC1	0.562*						
EC2	0.617*						
EC3	0.786*						
EC4	0.758*						
EC5	0.854*						
EC6	0.885*						
OC1		0.841*					
OC2		0.865*					
OC3		0.880*					
OC4		0.883*					
TE1		0.894*					
TE2							
TE3				0.665*			
TE4				0.830*			
TE5				0.798*			
EX1				0.754*			
EX2			0.879*				
EX3			0.786*				
EX4			0.912*				
EX5			0.909*				
AV1					0.873*		
AV2					0.926*		
AV3					0.895*		
AV4					0.567*		
AV5					0.364*		
IV1						0.766*	
IV2						0.740*	
IV3						0.905*	
IV4						0.653*	
UV1							0.834*
UV2							0.804*
UV3					0.497*		0.306*
UV4					0.495*		0.278*
UV5					0.422*		0.307*
UV6							0.288*

Note. * = p < .05; EC = Effort Cost, OC = Opportunity Cost, TE = Task Effort, EX = Expectations, AV = Attainment Value, IV = Intrinsic Value, UV = Utility Value

Following the EFA, a confirmatory factor analysis was run using the loadings accepted from the EFA and was run for each of the three time points. Each CFA at the three time points had excellent to satisfactory fit for all fit statistics (Table 7). Therefore, a test of longitudinal measurement invariance was conducted.

For the CFA conducted for the ITL construct only three items loaded significantly. Item 2, item 4, and item 6 did not load significantly. Item 2 read, "I am likely to remain in my STEM major through the completion of my degree"; Item 4 read, "It is UNLIKELY that I will leave my STEM major before I complete it"; and Item 6 read, "At the present time, I am likely to remain in my STEM major." It should be noted that all three items, while not loading highly or significantly onto the ITL factor, were highly correlated with one another while showing small correlations to items 1, 3, and 5. Taken together, items 2, 4, and 6 may reflect a different latent variable but ultimately were dropped from the analysis. A second CFA utilizing only items 1, 3, and 5 showed perfect fit (as expected for a factor derived from 3 items). Omega coefficients of composite reliability for the three ITL items for the current sample are shown in Table 1.

Table 7

Results of CFA for T1-T3

Construct and Model	χ^2	df	RMSEA	CFI	TLI	SRMR
CFA T1	1471.25	484	0.056	0.921	0.914	0.068
CFA T2	1903.53	483	0.065	0.921	0.915	0.045
CFA T3	1913.49	482	0.07	0.973	0.96	0.087

Note. No chi-square test statistic was significant at $p < .05$.

Phase 3: Longitudinal Invariance

Fit of measurement invariance models is important when determining not only if the baseline configural model is adequate but also if the next step or model in invariance testing is equivalent such as when comparing the configural model conducted in step 1 to the metric model conducted in step 2. Although measurement invariance is often evaluated with the significance of the change in χ^2 for two nested models, many researchers no longer focus on absolute fit but additionally focus on alternative fit indices such as CFI/TLI, SRMR, and RMSEA (F. Chen, 2007; Cheung & Rensvold, 2002; Meade et al., 2008). Specifically, a researcher would view the change or difference in these fit indices when addressing if one model is equivalent, better, or worse when conducting invariance testing. Assuming adequate sample size and power are met, the suggestions for acceptable change found in Table 8 were adopted for the current study.

Table 8

Invariance Testing Acceptable Criterion for Alternative Fit Indices

Index (Range)	Criterion for Acceptable Change
RMSEA	.015 (F. Chen, 2007); .01 for scalar (Rutkowski & Svetina, 2014)
SRMR	.030 for metric invariance or .015 for scalar or residual invariance (F. Chen, 2007)
CFI	-.01 (F. Chen, 2007; Cheung & Rensvold, 2002); -.02 for metric, but -.01 for scalar (Rutkowski & Svetina, 2014); -.002 (Meade et al., 2008)

Overall, there is no consensus about the best fit indices or cutoff values for alternative fit indices which forces researchers to choose fit criteria. However, based on the criteria in Table 8, the invariance models met all three suggested alternative fit indices criterion as seen in Table 9. Only the chi-square shows potential non-invariance but this may be an artifact of a large sample.

Table 9

Invariance Testing

MODEL	χ2	df	CFI	TLI	SRMR	RMSEA (95% CI)	Δ χ2 (p)	Δ CFI	Δ TLI	Δ SRMR	Δ RMSEA
Configural	7717.128	4514	0.927	0.922	0.045	.031 (.029,.032)	-	-	-	-	-
Metric	8069.436	4573	0.921	0.916	0.049	.032 (.031,.033)	271.149 (.001)	-0.006	-0.006	0.004	0.01
Scalar	8181.737	4622	0.919	0.915	0.049	.032 (.031,.033)	116.172 (.001)	-0.002	-0.001	0.00	0.00
Strict	8454.93	4685	0.914	0.911	0.063	.033 (.031,.034)	168.845 (.001)	-0.005	-0.004	0.014	0.01

Note. df, degrees of freedom; CFI, comparative fit index; TLI, Tucker–Lewis index; SRMR, standardized root mean square residual; RMSEA, root mean square error of approximation; 95% CI, 95% confidence interval around RMSEA; Δχ2, change in χ2 relative to the preceding model; (p), p value of Δχ2; ΔCFI, change in comparative fit index relative to the preceding model; ΔTLI, change in Tucker-Lewis index relative to the preceding model; ΔRMSEA, change in root mean square error of approximation relative to the preceding model.

Phase 4: Random-Intercept Cross Lagged Panel Model

In the following sections, the results of the RI-CLPM models are explained. While discussing the within-person components (unstable) it may be stated that a variable was higher or lower relative to an expected or anticipated value. Note, this is always in relation to the grand mean and while controlling for stable portions of that variable. For example, if a result indicates students with higher than anticipated expectations led to lower than expected costs, both of these statements refer to the grand means of expectations and cost while controlling for stable portions of expectations and costs, respectively.

Model 1: RI-CLPM With RI and Within Components

Bivariate correlations between variables are displayed in Table 10. As seen in Table 11 and Figure 6, the random intercepts or stable component of student expectations and costs were significantly and negatively correlated: $r = -.322$, $p < .01$. At each measurement wave, each of the within component variables (unstable component) were significantly correlated such that at Time 1: EX1 ←→ STV1, $r = .287$, $p < .01$; EX1 ←→ CST1, $r = -1.06$, $p < .01$; STV1 ←→ CST1, $r = -.231$, $p < .01$. The results imply students with higher than anticipated expectations had significantly higher than expected STVs (and vice-versa), and significantly lower than expected costs within wave 1. Students with higher than expected STVs also had significantly lower than expected costs within wave 1.

At Time 2: EX2 ←→ STV2, $r = .339$, $p < .01$; EX2 ←→ CST2, $r = -1.21$, $p < .01$; STV2 ←→ CST2, $r = -.165$, $p < .01$. The results imply students with higher than anticipated expectations had significantly higher than baseline STVs (and vice-versa), and significantly lower than baseline costs within wave 2. Students with higher than baseline STVs also had significantly lower than baseline costs within wave 2.

At Time 3: EX3 ←→ STV3, $r = .314$, $p < .01$; EX3 ←→ CST3, $r = -.873$, $p < .01$; STV3 ←→ CST3, $r = -.114$, $p < .01$. The results imply students with higher than anticipated expectations had significantly higher than expected STVs (and vice-versa), and significantly lower than expected costs within wave 3. Students with higher than expected STVs also had significantly lower than expected costs within wave 3.

Only two spill-over (cross-lagged) effects were significant. Students with STVs at T1 higher than expected were predicted to report lower than expected cost at T2 [$B = -.504$, $\beta = -.227$, $p = .016$] and students with higher than expected STVs at T2 were predicted to have greater than anticipated expectations at T3 [$B = .218$, $\beta = .10$, $p = .022$]. Only one significant carry-over (auto-regressive) effect was observed where students with greater than expected STVs at T2 were predicted to have greater than expected STVs at T3 [$B = .382$, $\beta = .398$, $p < .01$].

Table 10

Correlations

	EX1	EX2	EX3	CST1	CST2	CST3	STV1	STV2	STV3	ITL	GPA
EX1	-										
EX2	0.195*	-									
EX3	0.172*	0.151*	-								
CST1	-0.705*	-0.229*	-0.218*	-							
CST2	-0.223*	-0.827*	-0.239*	0.336*	-						
CST3	-0.167*	-0.215*	-0.776*	0.296*	0.345*	-					
STV1	0.335*	0.037	-0.016	-0.462*	-0.082*	0.079*	-				
STV2	-0.020	0.224*	0.063	0.018	-0.188*	-0.025	0.104*	-			
STV3	0.049	0.039	0.289*	-0.125*	-0.051	-0.205*	0.201*	0.438*	-		
ITL	0.004	-0.030	0.007	-0.01	0.033	0.047	-0.018	-0.021	-0.036	-	
GPA	-0.007	0.007	-0.01	-0.003	0.031	0.013	0.004	-0.063	0.056	0.006	-

Note. * is $p<.05$; GPA = grade point average, ITL = intentions to leave, EX = expectations, STV = subjective task value, and CST = cost.

Table 11

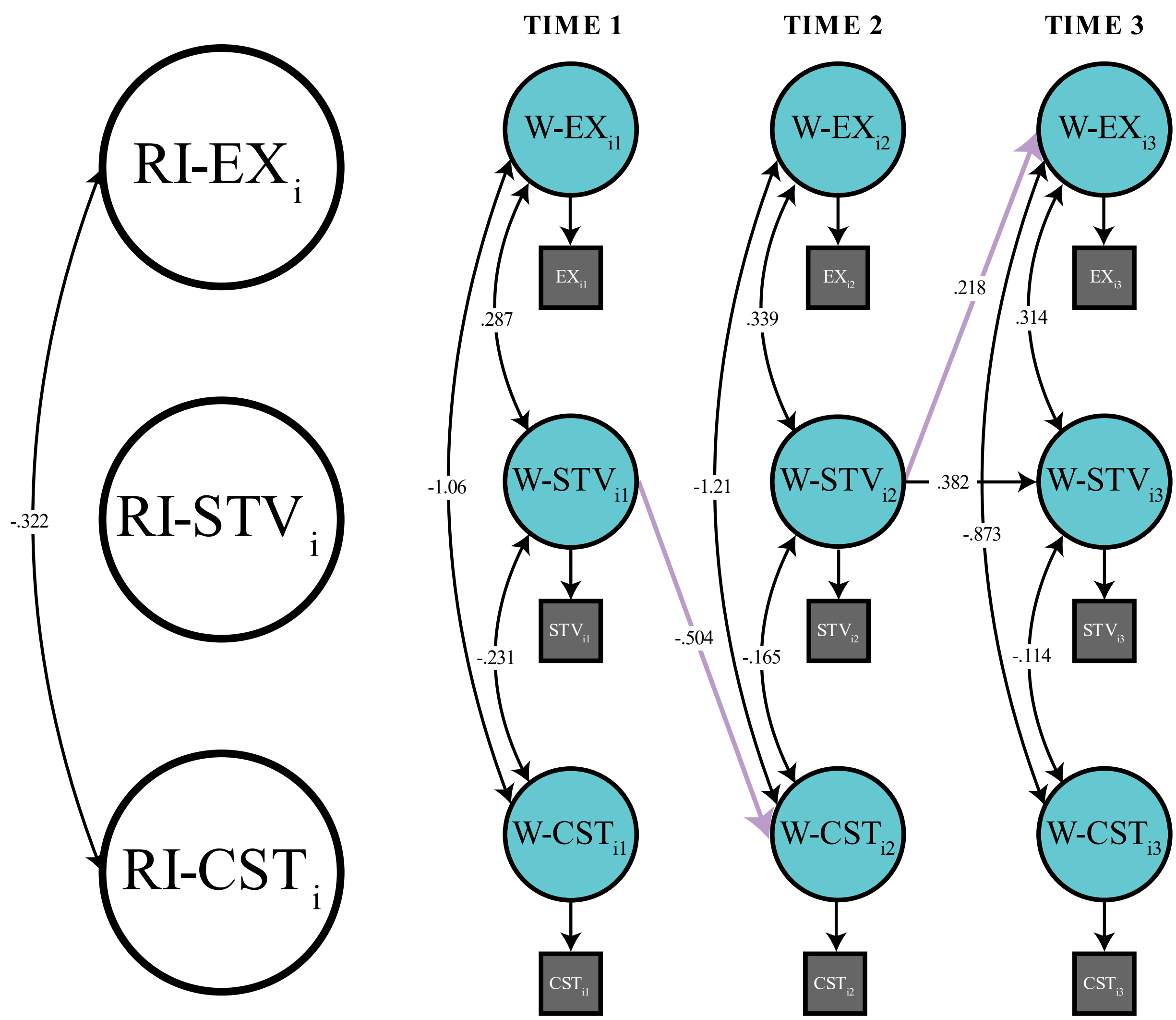
Model Result for RI-CLPM (No Outcome Variables)

	Estimate	S.E.	Est./S.E.	P-Value
WEX2 ON WEX1	-0.003	0.073	-0.036	0.972
WEX2 ON WSTV1	0.203	0.424	0.479	0.632
WEX2 ON WCST1	-0.119	0.194	-0.610	0.542
WSTV2 ON WEX1	-0.007	0.026	-0.261	0.794
WSTV2 ON WSTV1	-0.251	0.329	-0.763	0.445
WSTV2 ON WCST1	-0.070	0.102	-0.691	0.489
WCST2 ON WEX1	-0.010	0.035	-0.280	0.780
WCST2 ON WSTV1	-0.504	0.209	-2.405	0.016
WCST2 ON WCST1	-0.062	0.108	-0.572	0.567
WEX3 ON WEX2	-0.189	0.098	-1.920	0.055
WEX3 ON WSTV2	0.218	0.095	2.289	0.022
WEX3 ON WCST2	-0.371	0.206	-1.798	0.072
WSTV3 ON WEX2	-0.023	0.036	-0.650	0.516
WSTV3 ON WSTV2	0.382	0.044	8.723	0.000
WSTV3 ON WCST2	0.011	0.082	0.129	0.898
WCST3 ON WEX2	-0.019	0.052	-0.356	0.722
WCST3 ON WSTV2	-0.069	0.051	-1.356	0.175
WCST3 ON WCST2	-0.027	0.122	-0.221	0.825
RIEX WITH RISTV	-0.018	0.032	-0.557	0.577
RIEX WITH RICST	-0.322	0.070	-4.592	0.000
RISTV WITH RICST	0.016	0.018	0.875	0.382
WEX1 WITH WSTV1	0.287	0.046	6.239	0.000
WEX1 WITH WCST1	-1.057	0.102	-10.385	0.000
WSTV1 WITH WCST1	-0.231	0.031	-7.480	0.000
WEX2 WITH WSTV2	0.339	0.062	5.454	0.000
WEX2 WITH WCST2	-1.210	0.095	-12.693	0.000
WSTV2 WITH WCST2	-0.165	0.031	-5.377	0.000
WEX3 WITH WSTV3	0.314	0.050	6.321	0.000
WEX3 WITH WCST3	-0.873	0.081	-10.734	0.000
WSTV3 WITH WCST3	-0.114	0.029	-3.970	0.000

Note. W = within component, RI = random intercept, EX = expectations, STV = subjective task value, and CST = cost.

Figure 6

Model 1: RI-CLPM With RI and Within Components



Note. This figure depicts a diagram of the single indicator RI-CLPM with RI included at the latent variable level. Indicators are depicted with a single box, and covariances and residuals are removed for clarity of presentation. All non-significant paths removed for clarity.

Model 2.1 and 2.2: RI-CLPM With GPA on RI and Within Components

Model 2.1. As seen in Table 12 and Figure 7, the random intercepts or stable component of student expectations and costs were significantly and negatively correlated: $r = -.322$, $p < .01$. None of the random intercept components significantly predicated student achievement.

At each measurement wave, each of the within component variables (unstable component) were significantly correlated such that at Time 1: EX1 ←→ STV1, $r = .287$, $p < .01$; EX1 ←→ CST1, $r = -1.06$, $p < .01$; STV1 ←→ CST1, $r = -.231$, $p < .01$. The results imply students with higher than anticipated expectations had significantly higher than expected STVs (and vice-versa), and significantly lower than expected costs within wave 1. Students with higher than expected STVs also had significantly lower than baseline costs within wave 1.

At Time 2: EX2 ←→ STV2, $r = .339$, $p < .01$; EX2 ←→ CST2, $r = -1.21$, $p < .01$; STV2 ←→ CST2, $r = -.165$, $p < .01$. The results imply students with higher than anticipated expectations had significantly higher than expected STVs (and vice-versa), and significantly lower than expected costs within wave 2. Students with higher than expected STVs also had significantly lower than expected costs within wave 2.

At Time 3: EX3 ←→ STV3, $r = .314$, $p < .01$; EX3 ←→ CST3, $r = -.873$, $p < .01$; STV3 ←→ CST3, $r = -.114$, $p < .01$. The results imply students with higher than anticipated expectations had significantly higher than expected STVs (and vice-versa), and significantly lower than expected costs within wave 3. Students with higher than expected STVs also had significantly lower than expected costs within wave 3.

Only two spill-over (cross-lagged) effects were significant. Students with STVs at T1 higher than expected were predicted to report lower than expected cost at T2 [$B = -.504$, $\beta = -.226$, $p = .016$] and students with higher than base expected line STVs at T2 were predicted to have greater than anticipated expectations at T3 [B = .218, β = .10, p = .022]. Only one significant carry-over (auto-regressive) effect was observed where students with greater than expected STVs at T2 were predicted to have greater than **baseline** STVs at T3 [B = .382, β = .398, p < .01].

Model 2.2. As seen in Table 13 and Figure 8, all the significant relationships observed in Model 2.1 were observed exactly in model 2.2. However, two within component variables significantly predicted student achievement. Specifically, students with higher than expected STVs at both T1 [B = .079, β = .106, p = .018] and T2 [B = .087, β = .112, p < .013] were predicted to have higher GPA.

Table 12

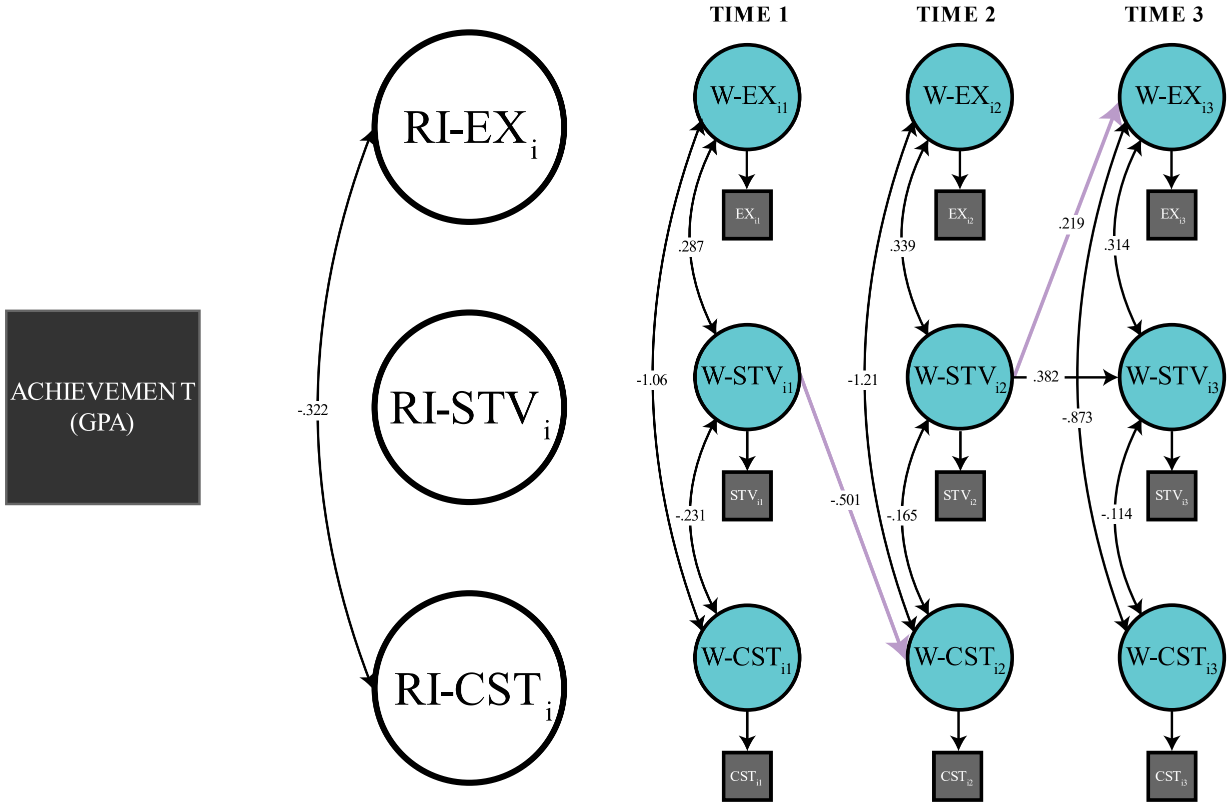
Model Result for RI-CLPM – Achievement (GPA) on RI

	Estimate	S.E.	Est./S.E.	P-Value
WEX2 ON WEX1	-0.003	0.073	-0.041	0.967
WEX2 ON WSTV1	0.203	0.423	0.479	0.632
WEX2 ON WCST1	-0.120	0.194	-0.618	0.536
WSTV2 ON WEX1	-0.006	0.026	-0.232	0.816
WSTV2 ON WSTV1	-0.246	0.327	-0.751	0.453
WSTV2 ON WCST1	-0.067	0.102	-0.659	0.510
WCST2 ON WEX1	-0.010	0.035	-0.279	0.781
WCST2 ON WSTV1	-0.501	0.208	-2.406	0.016
WCST2 ON WCST1	-0.061	0.108	-0.565	0.572
WEX3 ON WEX2	-0.189	0.099	-1.922	0.055
WEX3 ON WSTV2	0.219	0.096	2.282	0.022
WEX3 ON WCST2	-0.373	0.207	-1.803	0.071
WSTV3 ON WEX2	-0.024	0.036	-0.679	0.497
WSTV3 ON WSTV2	0.382	0.044	8.735	0.000
WSTV3 ON WCST2	0.007	0.083	0.090	0.928
WCST3 ON WEX2	-0.020	0.052	-0.382	0.703
WCST3 ON WSTV2	-0.067	0.051	-1.311	0.190
WCST3 ON WCST2	-0.030	0.124	-0.242	0.809
GPA ON RIEX	0.050	0.088	0.572	0.567
GPA ON RISTV	-0.039	0.132	-0.295	0.768
GPA ON RICST	0.093	0.099	0.940	0.347
RIEX WITH RISTV	-0.018	0.032	-0.559	0.576
RIEX WITH RICST	-0.322	0.070	-4.588	0.000
RISTV WITH RICST	0.016	0.018	0.867	0.386
WEX1 WITH WSTV1	0.287	0.046	6.246	0.000
WEX1 WITH WCST1	-1.058	0.102	-10.392	0.000
WSTV1 WITH WCST1	-0.231	0.031	-7.481	0.000
WEX2 WITH WSTV2	0.339	0.062	5.464	0.000
WEX2 WITH WCST2	-1.210	0.095	-12.710	0.000
WSTV2 WITH WCST2	-0.164	0.031	-5.352	0.000
WEX3 WITH WSTV3	0.314	0.050	6.301	0.000
WEX3 WITH WCST3	-0.873	0.081	-10.724	0.000
WSTV3 WITH WCST3	-0.114	0.029	-3.981	0.000

Note. W = within component, RI = random intercept, EX = expectations, STV = subjective task value, CST = cost, GPA = grade point average.

Figure 7

Model 2.1: RI-CLPM With Achievement (GPA) on RI



Note. This figure depicts a diagram of Achievement (semester GPA) regressed on the within RI (stable) EVT latent variables. Indicators are depicted with a single box, and covariances and residuals are removed for clarity of presentation. All non-significant paths removed for clarity.

Table 13

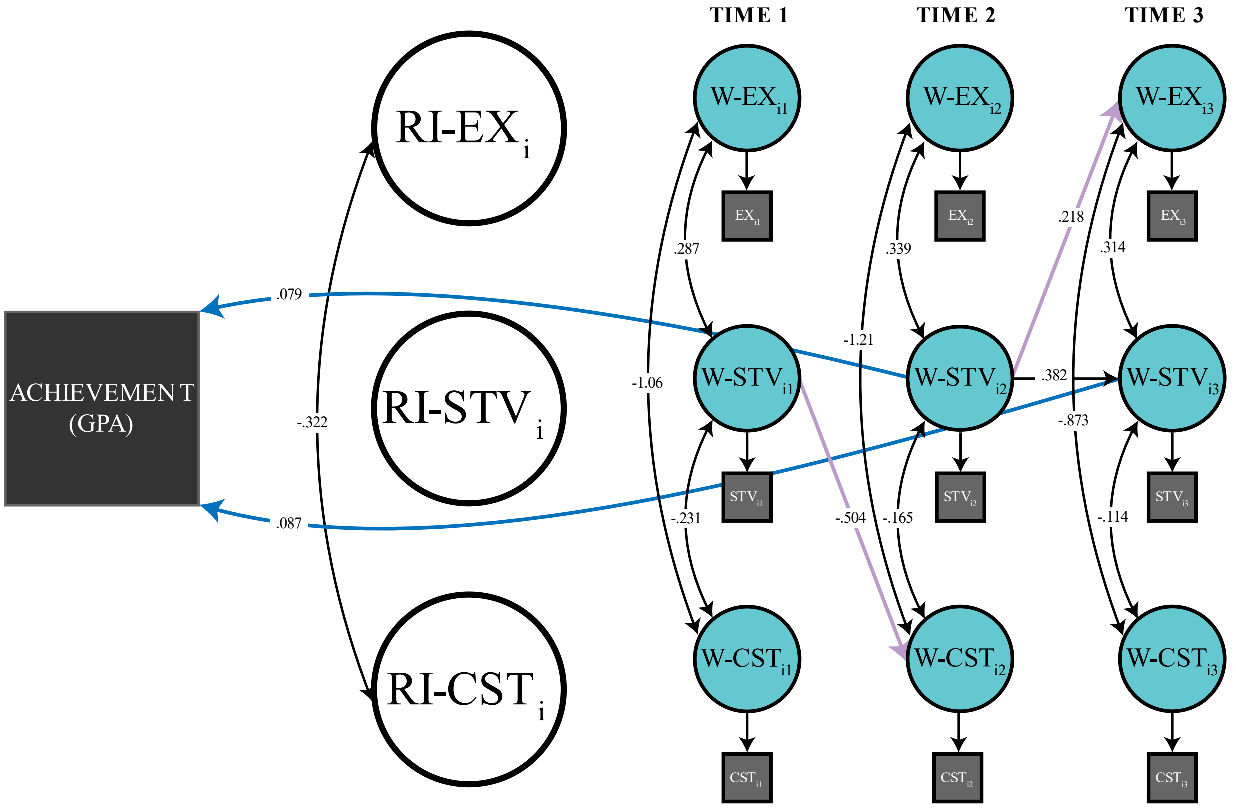
Model Result for RI-CLPM – Achievement (GPA) on Within Components

	Estimate	S.E.	Est./S.E.	P-Value
WEX2 ON WEX1	-0.003	0.073	-0.036	0.972
WEX2 ON WSTV1	0.203	0.424	0.479	0.632
WEX2 ON WCST1	-0.119	0.194	-0.610	0.542
WSTV2 ON WEX1	-0.007	0.026	-0.261	0.794
WSTV2 ON WSTV1	-0.251	0.329	-0.763	0.445
WSTV2 ON WCST1	-0.070	0.102	-0.691	0.489
WCST2 ON WEX1	-0.010	0.035	-0.280	0.780
WCST2 ON WSTV1	-0.504	0.209	-2.405	0.016
WCST2 ON WCST1	-0.062	0.108	-0.572	0.567
WEX3 ON WEX2	-0.189	0.098	-1.920	0.055
WEX3 ON WSTV2	0.218	0.095	2.289	0.022
WEX3 ON WCST2	-0.371	0.206	-1.798	0.072
WSTV3 ON WEX2	-0.023	0.036	-0.650	0.516
WSTV3 ON WSTV2	0.382	0.044	8.723	0.000
WSTV3 ON WCST2	0.011	0.082	0.128	0.898
WCST3 ON WEX2	-0.018	0.052	-0.356	0.722
WCST3 ON WSTV2	-0.069	0.051	-1.356	0.175
WCST3 ON WCST2	-0.027	0.122	-0.221	0.825
GPA ON WEX1	-0.003	0.016	-0.189	0.850
GPA ON WEX2	0.053	0.030	1.790	0.073
GPA ON WEX3	0.004	0.025	0.164	0.870
GPA ON WSTV1	0.047	0.125	0.375	0.708
GPA ON WSTV2	0.079	0.034	2.358	0.018
GPA ON WSTV3	0.087	0.035	2.473	0.013
GPA ON WCST1	0.017	0.055	0.314	0.754
GPA ON WCST2	0.108	0.075	1.445	0.148
GPA ON WCST3	0.039	0.056	0.696	0.486
RIEX WITH RISTV	-0.018	0.032	-0.557	0.577
RIEX WITH RICST	-0.322	0.070	-4.592	0.000
RISTV WITH RICST	0.016	0.018	0.875	0.382
WEX1 WITH WSTV1	0.287	0.046	6.239	0.000
WEX1 WITH WCST1	-1.057	0.102	-10.385	0.000
WSTV1 WITH WCST1	-0.231	0.031	-7.479	0.000
WEX2 WITH WSTV2	0.339	0.062	5.454	0.000
WEX2 WITH WCST2	-1.210	0.095	-12.693	0.000
WSTV2 WITH WCST2	-0.165	0.031	-5.377	0.000
WEX3 WITH WSTV3	0.314	0.050	6.321	0.000
WEX3 WITH WCST3	-0.873	0.081	-10.734	0.000
WSTV3 WITH WCST3	-0.114	0.029	-3.970	0.000

Note. W = within component, RI = random intercept, EX = expectations, STV = subjective task value, CST = cost, and GPA = grade point average.

Figure 8

Model 2.2: RI-CLPM With Achievement (GPA) on Within Components



Note. This figure depicts a diagram of Achievement (semester GPA) regressed on the within component (unstable) EVT latent variables. Indicators are depicted with a single box, and covariances and residuals are removed for clarity of presentation. All non-significant paths removed for clarity.

Model 3.1 and 3.2: RI-CLPM With ITL on RI and Within Components

Model 3.1. As seen in Table 14 and Figure 9, the random intercepts or stable component of student expectations and costs were significantly and negatively correlated: $r = -.323$, $p < .01$. None of the random intercept components significantly predicated student achievement.

At each measurement wave, each of the within component variables (unstable component) were significantly correlated such that at Time 1: EX1 ←→ STV1, $r = .287$, $p < .01$; EX1 ←→ CST1, $r = -1.06$, $p < .01$; STV1 ←→ CST1, $r = -.231$, $p < .01$. The results imply students with higher than anticipated expectations had significantly higher than expected STVs (and vice-versa), and significantly lower than baseline costs within wave 1. Students with higher than expected STVs also had significantly lower than expected costs within wave 1.

At Time 2: EX2 ←→ STV2, $r = .338$, $p < .01$; EX2 ←→ CST2, $r = -1.21$, $p < .01$; STV2 ←→ CST2, $r = -.165$, $p < .01$. The results imply students with higher than anticipated expectations had significantly higher than expected STVs (and vice-versa), and significantly lower than expected costs within wave 2. Students with higher than expected STVs also had significantly lower than expected costs within wave 2.

At Time 3: EX3 ←→ STV3, $r = .314$, $p < .01$; EX3 ←→ CST3, $r = -.873$, $p < .01$; STV3 ←→ CST3, $r = -.113$, $p < .01$. The results imply students with higher than anticipated expectations had significantly higher than expected STVs (and vice-versa), and significantly lower than expected costs within wave 3. Students with higher than expected STVs also had significantly lower than expected costs within wave 3.

Only two spill-over (cross-lagged) effects were significant. Students with STVs at T1 higher than expected were predicted to report lower than expected cost at T2 [$B = -.504$, $\beta = -.227$, $p = .016$] and students with higher than **baseline** STVs at T2 were predicted to have greater than expected expectations at T3 [B = .219, β = .10, p = .022]. Only one significant carry-over (auto-regressive) effect was observed where students with greater than expected STVs at T2 were predicted to have greater than expected STVs at T3 [B = .382, β = .398, p < .01].

Model 3.2. As seen in Table 15 and Figure 10, all the significant relationships observed in Model 2.1 were observed exactly in model 2.2. However, two within component variables significantly predicted student achievement. Specifically, students with higher than anticipated expectations at T3 [B = -.140, β = -.154, p = .031] were predicted to have lower ITL. Inversely, student with higher than expected cost relative at T3 were predicted to have significantly higher ITL [B = .313, β = .164, p = .037].

Table 14

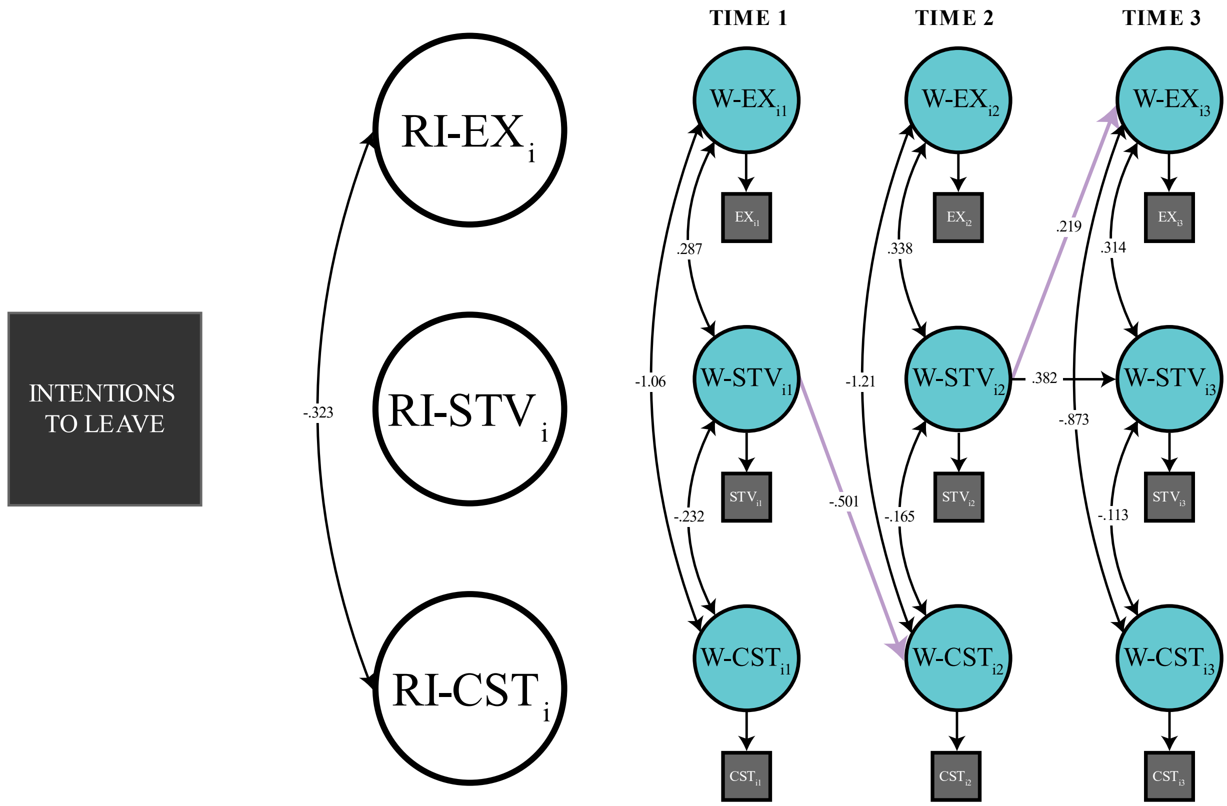
Model Result for RI-CLPM - ITL on RI

	Estimate	S.E.	Est./S.E.	P-Value
WEX2 ON WEX1	-0.002	0.073	-0.025	0.980
WEX2 ON WSTV1	0.194	0.425	0.456	0.648
WEX2 ON WCST1	-0.118	0.194	-0.609	0.542
WSTV2 ON WEX1	-0.007	0.026	-0.285	0.776
WSTV2 ON WSTV1	-0.247	0.327	-0.754	0.451
WSTV2 ON WCST1	-0.071	0.102	-0.700	0.484
WCST2 ON WEX1	-0.010	0.035	-0.284	0.776
WCST2 ON WSTV1	-0.503	0.209	-2.410	0.016
WCST2 ON WCST1	-0.062	0.108	-0.577	0.564
WEX3 ON WEX2	-0.189	0.098	-1.928	0.054
WEX3 ON WSTV2	0.219	0.095	2.294	0.022
WEX3 ON WCST2	-0.372	0.206	-1.806	0.071
WSTV3 ON WEX2	-0.023	0.036	-0.658	0.511
WSTV3 ON WSTV2	0.382	0.044	8.720	0.000
WSTV3 ON WCST2	0.011	0.082	0.130	0.896
WCST3 ON WEX2	-0.019	0.052	-0.370	0.712
WCST3 ON WSTV2	-0.069	0.051	-1.358	0.174
WCST3 ON WCST2	-0.030	0.122	-0.247	0.805
ITL ON RIEX	0.158	0.243	0.650	0.516
ITL ON RISTV	-0.578	0.402	-1.437	0.151
ITL ON RICST	0.337	0.264	1.274	0.203
RIEX WITH RISTV	-0.018	0.032	-0.552	0.581
RIEX WITH RICST	-0.323	0.070	-4.604	0.000
RISTV WITH RICST	0.016	0.018	0.873	0.383
WEX1 WITH WSTV1	0.287	0.046	6.246	0.000
WEX1 WITH WCST1	-1.058	0.102	-10.394	0.000
WSTV1 WITH WCST1	-0.232	0.031	-7.502	0.000
WEX2 WITH WSTV2	0.338	0.062	5.433	0.000
WEX2 WITH WCST2	-1.209	0.095	-12.696	0.000
WSTV2 WITH WCST2	-0.165	0.031	-5.391	0.000
WEX3 WITH WSTV3	0.314	0.050	6.323	0.000
WEX3 WITH WCST3	-0.873	0.081	-10.726	0.000
WSTV3 WITH WCST3	-0.113	0.029	-3.952	0.000

Note. W = within component, RI = random intercept, EX = expectations, STV = subjective task value, CST = cost, ITL = intentions to leave.

Figure 9

Model 3.1: RI-CLPM With RI on Intentions to Leave



Note. This figure depicts a diagram of Intentions to Leave (ITL) regressed on the RI (stable) EVT latent variables. Indicators are depicted with a single box, and covariances and residuals are removed for clarity of presentation. All non-significant paths removed for clarity.

Table 15

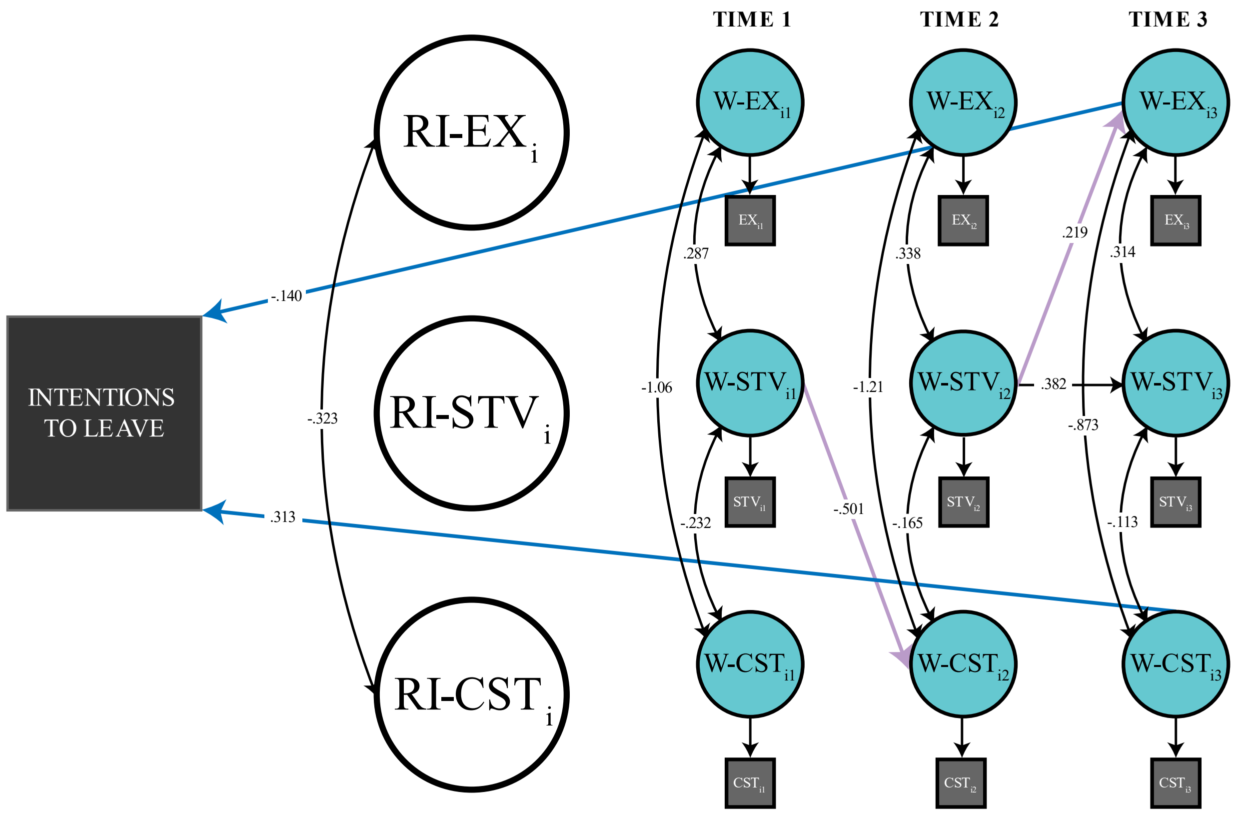
Model Result for RI-CLPM - ITL on Within Components

	Estimate	S.E.	Est./S.E.	P-Value
WEX2 ON WEX1	-0.003	0.073	-0.036	0.972
WEX2 ON WSTV1	0.203	0.424	0.479	0.632
WEX2 ON WCST1	-0.119	0.194	-0.610	0.542
WSTV2 ON WEX1	-0.007	0.026	-0.261	0.794
WSTV2 ON WSTV1	-0.251	0.329	-0.763	0.445
WSTV2 ON WCST1	-0.070	0.102	-0.691	0.489
WCST2 ON WEX1	-0.010	0.035	-0.280	0.780
WCST2 ON WSTV1	-0.504	0.209	-2.405	0.016
WCST2 ON WCST1	-0.062	0.108	-0.572	0.567
WEX3 ON WEX2	-0.189	0.098	-1.920	0.055
WEX3 ON WSTV2	0.218	0.095	2.289	0.022
WEX3 ON WCST2	-0.371	0.206	-1.798	0.072
WSTV3 ON WEX2	-0.023	0.036	-0.650	0.516
WSTV3 ON WSTV2	0.382	0.044	8.723	0.000
WSTV3 ON WCST2	0.011	0.082	0.129	0.898
WCST3 ON WEX2	-0.018	0.052	-0.355	0.722
WCST3 ON WSTV2	-0.070	0.051	-1.356	0.175
WCST3 ON WCST2	-0.027	0.123	-0.220	0.826
ITL ON WEX1	-0.010	0.043	-0.228	0.820
ITL ON WEX2	0.019	0.076	0.254	0.800
ITL ON WEX3	-0.140	0.065	-2.154	0.031
ITL ON WSTV1	-0.223	0.310	-0.720	0.472
ITL ON WSTV2	-0.008	0.088	-0.095	0.924
ITL ON WSTV3	-0.104	0.090	-1.164	0.244
ITL ON WCST1	-0.098	0.137	-0.717	0.474
ITL ON WCST2	0.089	0.184	0.484	0.629
ITL ON WCST3	0.313	0.150	2.089	0.037
RIEX WITH RISTV	-0.018	0.032	-0.557	0.577
RIEX WITH RICST	-0.322	0.070	-4.592	0.000
RISTV WITH RICST	0.016	0.018	0.875	0.382
WEX1 WITH WSTV1	0.287	0.046	6.239	0.000
WEX1 WITH WCST1	-1.057	0.102	-10.384	0.000
WSTV1 WITH WCST1	-0.231	0.031	-7.479	0.000
WEX2 WITH WSTV2	0.339	0.062	5.454	0.000
WEX2 WITH WCST2	-1.210	0.095	-12.693	0.000
WSTV2 WITH WCST2	-0.165	0.031	-5.377	0.000
WEX3 WITH WSTV3	0.314	0.050	6.321	0.000
WEX3 WITH WCST3	-0.873	0.081	-10.734	0.000
WSTV3 WITH WCST3	-0.114	0.029	-3.970	0.000

Note. W = within component, RI = random intercept, EX = expectations, STV = subjective task value, CST = cost, ITL = intentions to leave.

Figure 10

Model 3.2: RI-CLPM With Within Components on Intentions to Leave



Note. This figure depicts a diagram of Intentions to Leave (ITL) regressed on the within components (unstable) EVT latent variables. Indicators are depicted with a single box, and covariances and residuals are removed for clarity of presentation. All non-significant paths removed for clarity.

CHAPTER 5 – DISCUSSION

The present study investigated the longitudinal relationships between expectations, subjective task values, and costs with student academic achievement and intentions to leave. A primary focus of this study was to determine how EVT variables predict academic outcomes as a means for future intervention when addressing issues such as achievement and retention. This study is the first to examine all three major EVT variables (i.e., expectations, STVs, and costs) simultaneously using a random-intercept cross-lagged panel model approach, which has a greater methodological advantage over the traditional CLPM by controlling for between-person (RI; stable) and within-person (unstable) effects. In the following sections, the results of the RI-CLPM models are explained. While discussing the within-person components (unstable) it may be stated that a variable was higher or lower relative to an expected or anticipated value. Note, this is always in relation to the grand mean and while controlling for stable portions of that variable. For example, if a result indicates students with higher than anticipated expectations led to lower than expected costs, this implies that students' with expectations higher than the expectations grand mean are anticipated to have costs lower than the cost grand mean. In the following sections, the main findings of the study are discussed within the context of (1) each research question and (2) how an intervention may be applied to specific variables and time point(s).

Research Question 1: How does a RI-CLPM that uses three EVT latent variables fit health science students' data taken over a semester and what are the carry-over and spill-over effects for health science students' expectancies, STVs, and costs?

Random Intercepts (Stable Components) of the Model

Results showed an RI-CLPM utilizing EVT variables (i.e., expectancies, STVS, and costs) can produce a model that satisfactorily fits data derived from health science students taken over a 16-week semester. This baseline model, or a model without the GPA and ITL outcome variables, showed many results. At the stable between-person level (random intercepts) students with higher stable expectancies had significantly lower stable costs. This implies students with greater average expectancies may experience the costs of a health science program such as nursing school, an occupational therapy program, or being a pre-nursing student in a less impactful way relative to peers who on average have lower average expectations. It may be that students with higher expectations recognize the efforts required to be successful in a program come with sacrifice, but these efforts yield a higher probability of success.

The stable between-person (random intercepts) components for expectancies and costs did not show a significant relationship to the stable STVs component. This implies that a student's stable, or average, STVs are not related to the stable portions of expectations and costs. Some past research has demonstrated similar findings although not while utilizing a RI-CLPM (Chung & Kim, 2022). However, past research commonly shows expectations to have a significant and positive relationship with STVs (Chung & Kim, 2022; Perez, Dai, et al., 2019) while costs exhibits a significant negative relationship (Flake et al., 2015; Perez, Dai, et al., 2019). Importantly, it should be noted none of the cited references utilized an RI-CLPM where the EVT constructs were split into stable trait-like portion and unstable state-like portions. Said another way, it may be when parsing out stable from unstable portions of EVT variables that the stable parts of costs and expectations hold a stronger relationship compared to STVs. These results imply change may be warranted to the traditional EVT model. It may be the model needs to reflect stable and unstable portions of traditionally adopted EVT variables like expectations, STVs, and costs. For example, an updated EVT model may note variables that are most susceptible to change versus the current model which may inherently assume all variables are malleable.

Carry-Over Effects of Students' Within Components

The same baseline RI-CLPM demonstrated that within each measurement wave all EVT within-person (unstable) components were significantly correlated. When viewing the model in a cross-sectional sense, or within each measurement occasion, a pattern was revealed. Specifically, within each time point, students with higher than anticipated expectations exhibited higher than expected STVs, and lower than expected costs. Similarly, those with higher than expected STVs also had lower than expected costs. Taken together, this means within each measurement wave, students with higher than expected "positive" motivations (i.e., expectations and STVs) experienced less of the negative motivational or "costly" side of health science education. This is important as it suggests enhancing a student's positive motivations can combat costs and critically it has the potential to contest the unhealthy stresses associated with elevated cost perceptions such as lower effort and persistence towards a domain (Kim et al., 2021), negative emotions towards a domain (St Omer et al., 2022), test anxiety (Jiang et al., 2020), procrastination and disorganization (Jiang et al., 2018; Jiang & Rosenzweig, 2021), and difficulty with focusing and sadness and worry (Dever, 2016).

While viewing the results from within each time point is important, the main objective of this study was to view how EVT constructs predict students' future motivations. In terms of carry-over effects (autoregressive), only one significant path was found where students with higher than expected STVs at T2 were predicted to have higher than expected STVs at T3. This appears intuitive that students who value their health science education at one point in time will likely value it at another. At T2 students were at the midpoint of the semester and experienced 8-weeks of health science content. At this point, students may clearly recognize the value of health science material and logically may continue to value it for the remainder of the semester (8-weeks more) leading to an elevated valuing of health science education at T3. Additionally, this single carry-over effect from STV at T2 to STV at T3 shows STVs may hold greater stability compared to the other within-person variables (cost and expectations), but only after experiencing the content within health science education. Put another way, the lack of content or course experiences may lead students to have less understanding of how certain courses in a semester may be personally relevant, useful, or interesting until they experience them. This may explain why STVs at T1 were unrelated to STVs at T2 which falls in line with past research that demonstrated students have inaccurate motivational beliefs, and only with experiences throughout a semester may a student become more realistic in their motivational judgments (He et al., 2023; Muenks et al., 2018; Rach & Heinze, 2017).

As revealed by the model, higher than anticipated expectations at T1 did not predict higher than anticipated expectations at T2 which did not predict greater than anticipated expectations at T3. Costs followed a similar pattern where elevated costs at earlier time points did not predict elevated costs at future occasions. This implies that over time the movement of expectations from one time point to another were unrelated and that the trend of cost from one time point to another were unrelated. These findings are contrary to past research utilizing a CLPM which often exhibits positive and significant autoregressive effects between EVT variables (Arens et al., 2018; Chung & Kim, 2022; Y. Lee & Seo, 2021; Perez, Dai, et al., 2019; St Omer et al., 2022; Weidinger et al., 2020). It should be noted that no EVT study utilizing a panel model design utilized a RI-CLPM design. Therefore, these past studies did not control for between-person (stable) and within-person (unstable) effects which may explain the differences in results. However, it may be that in health science education the carry-over effects of expectations and costs, which are derived from the unstable portion of the RI-CLPM model, do not hold motivational inertia but change randomly and are generally less stable relative to STVs.

It should be noted that while nearly all the within-person components did not have significant carry-over (autoregressive) effects, the observed (measured) variables did show significant correlations between EVT variables measured at consecutive time points (Table 10). Specifically, all correlations between expectations from T1-T3 were significant and positive, all correlations between costs from T1-T3 were significant and positive, and all correlations between STVs from T1-T3 were significant and positive. However, these raw measured motivational variables do not account for error or parse stable from unstable portions of motivation as done in a RI-CLPM and should be interpreted cautiously. Nonetheless, it may be when accounting for the dynamic changes in motivation (e.g., as STVs go above or below an expected baseline) most of the relationships between EVT variables at consecutive time points does not hold, such as from expectations from T1 to T2.

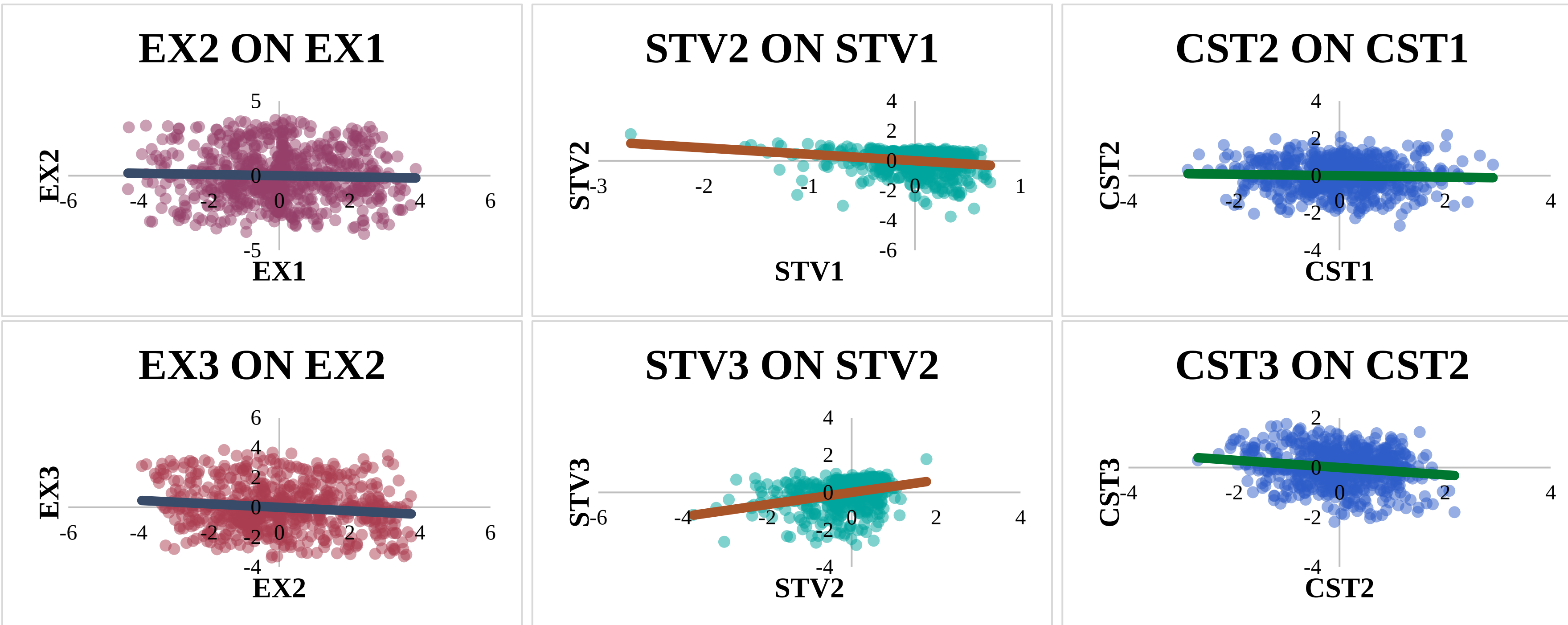
This study presents novel findings by illustrating a lack of relationship between the repeated measures of expectations and costs. However, the lack of significant carry-over effects may be explained in at least two ways. One is that the data points of the variables at different measurement occasions do not align. In other words, expectations or costs at early time points increase or decrease in a seemingly random or unstable way which results in no measurable correlation. This may be logical considering these components are the portion of the model determined unstable or susceptible to change. Another explanation may stem from a limitation of the RI-CLPM where the model inherently assumes the relationship between variables at different measurement occasions is linear. For example, if the relationship between expectations at consecutive measurement occasions took on a non-linear form (quadratic or exponential) then a correlation coefficient will likely be skewed with this nonlinear relationship.

Assuming the first explanation is true where students' expectations or costs increase or decrease in a seemingly random way may indicate that students throughout a semester may not know how to judge their expectations of success or costs. In week 1, students may have high or low levels of expectations and costs but by week 8, by which time several weeks of academic experiences (quizzes, exams, study sessions, etc.) have occurred, some students may make more accurate expectation and costs judgements while others may rate over-optimistically (while performing poorly) and others under-optimistically (while performing satisfactorily), all while considering the semester has 8-weeks remaining which may leave some students to believe there is time to change course. However, by week 16 when the final survey is administered the semester is essentially over and students have little to no room for guessing about their academic outcomes considering nearly all, if not all, grades are finalized, and a student will have most of the information necessary to make an accurate judgement of expectations and costs.

Assuming the second explanation is true, or that a RI-CLPM may not show a significant correlation between variables over time due to nonlinear relationships, an option may be to transform any data that is nonlinear to linear and rerunning the model. For example, if the relationship between expectations at T1 and T2 appeared nonlinear then a transformation could be applied. However, as shown in Figure 11, visual inspection of the relationships shows nearly no trend, linear or otherwise between expectations from T1→T2 and T2→T3. Visual inspection also reveals that cost from T1→T2 and from T2→T3 has nearly no trend. Only STVs appears to illustrate a trend from T1→T2 and from T2→T3, although only the relationship from T2→T3 was significant as revealed in the model results. This lends some evidence for the concept that students' expectations and costs are shifting randomly and in an unstable manner during a semester of health science education.

Figure 11

Plots for Within-Person Components Showing Potential Non-linear Trends



Spill-Over Effects of Students' Within Components

Only two spill-over (cross-lagged) effects were significant. One relationship was observed such that students with higher than baseline STVs at T1 were predicted to report lower than baseline cost at T2. This implies students who value their health science program or courses more at the beginning of a semester experience less than expected costs at the midpoint of a semester. Students who value their health science education will continue to experience stress over missing opportunities with family and friends, continue to fear failure or dismissal, and have anxiety over the time required to study and learn material in their health science program. However, those who perceive the value of their health science education greater than expected appear to experience the psychological and possibly even the physiological effects of costs to a lesser degree.

A second relationship observed was that students with higher than baseline STVs at T2 were predicted to have greater than baseline expectations at T3. This suggests students who value their health science program or courses at the semester midpoint show higher than anticipated expectations at the end of the semester. Students who find greater utility, hold greater interest, and find health science content personally meaningful are likely to engage with the content more while seeking mastery experiences of the information via better study strategies, greater focus and engagement with material (Dever, 2016), and greater persistence and effort (Kim et al., 2021). As a result, these students with higher than expected STVs show higher than anticipated future expectations as they may consider their course grades to be a function of their efforts.

The remaining spill-over effects in the model were non-significant. This finding is in line with past research that showed a lack of cross-lagged effects between EVT variables, but not while utilizing a more advanced methodology like a RI-CLPM (Chung & Kim, 2022; Y. Lee & Seo, 2021). In fact, most CLPM studies involving EVT tend to find weak cross-lagged effects between expectations and STVs (Marsh et al., 2005; Nuutila et al., 2018), and when found are often a unidirectional effect between expectations to STVs have been noted (Arens et al., 2018; Lauermann et al., 2017; Perez, Dai, et al., 2019; Viljaranta et al., 2014). Similar to the findings of this study, some past research have shown unidirectional effects from STVs to expectations (Ganley & Lubienski, 2016; Y. Lee & Seo, 2021; Pinxten et al., 2014).

Research Question 2: Over a semester, what are the spill-over effects among health science students' expectancies, STVs, and costs with end-of-semester outcomes like academic achievement and intentions to leave?

Spill-Over Effects of Students' Within Components on GPA

Students with higher than expected STVs at T2 and T3 were predicted to have a higher GPA at the end of the semester. While some past research has demonstrated STVs can predict academic achievement (Guo, Parker, et al., 2015; Rosenzweig et al., 2020; Trautwein et al., 2012; Weidinger et al., 2020), and sometimes even when compared to expectations (Cromley et al., 2020), often it is reported to have stronger effects on outcomes like retention (Chung & Kim, 2022; Wigfield & Eccles, 2020). The inverse was true for the present study.

Interestingly, when viewing the bivariate correlations between the EVT variables (Table 10) with GPA no significant correlations were present. It may be when controlling for (stable) between-person and (unstable) within-person effects a relationship is revealed. In other words, only in the portion of the RI-CLPM model that exposes dynamic or "changing" motivations is the relationship between EVT variables and achievement revealed.

The courses within health science education may hold very salient STVs for students given nearly all subjects taken in a health science program like a nursing or OT program are directly applicable to students' future goals such as passing a board or licensing exam and being a proficient nurse of occupational therapist. This contrasts with a general STEM course, such as an introductory chemistry course, where the relevance or value may be less readily applicable to students' seeking careers as a nurse or occupational therapist. Put another way, the value pre-nursing, nursing, or OT students hold may be significantly more motivating given the relevant nature of the material and drive students to engage with content more. In fact, past research has demonstrated students with higher STVs adopt higher utility learning strategies, have greater engagement and attention towards a domain (Harackiewicz, Smith, et al., 2016), exert more effort towards an academic task (Rieger et al., 2022), and show increased commitment and efforts towards content (Patall et al., 2016).

A benefit to utilizing a RI-CLPM or longitudinal design is revealed in the present study's results. Specifically, while direct results show higher than expected STVs over time (at T2 and T3) influence achievement, many indirect effects on achievement can be derived from additional EVT variables over the course of a semester as illustrated via the model (Figure 8). The following interpretation of the results is analogous to an endocrine circuit found throughout the human body or even the basal nuclei circuit found within the brain.

For example, an indirect effect of expectations on achievement can be found at any measurement occasion due to the positive and significant correlation between expectations and STVs. For instance, when tracing the model starting at expectations at T1 it is revealed that students with higher than anticipated levels of expectations at T1 leads to higher than anticipated STVs at T1 which in turn leads to a direct reduction of cost at T2 below baseline. This reduction leads to an increase in STVs at T2 above expected results which directly predicts higher end of semester achievement, and even does so indirectly by increasing STVs at T3 above baseline which also directly influences achievement.

Many pathways such as the one just described can be found in the model predicting achievement. Taken together, the results imply an intervention targeting STVs in the middle and end of a semester can directly and positively influence achievement. However, interventions aimed at increasing student expectations and STVs and decreasing costs at the semester onset can indirectly influence academic achievement. More on where interventions can be implemented is discussed in the *Implications for Practice* section below.

Spill-Over Effects of Students' Within Components on ITL

Students with higher than anticipated expectations at T3 were predicted to have lower ITLs while students with higher than expected costs at T3 were predicted to have higher ITL – both at the end of the semester. Cost in past literature is demonstrated to significantly predict outcomes like a student's decision to leave a program (Benden & Lauermann, 2023; Perez et al., 2014), however expectations is commonly found predicting academic achievement over outcomes like ITL (Chung & Kim, 2022; Perez, Dai, et al., 2019; Wigfield & Eccles, 2020). Nevertheless, some research does support expectations as a predictor of outcomes like ITL (Benden & Lauermann, 2023).

Interestingly, when viewing the bivariate correlations between the EVT variables (Table 10) with ITL no significant correlations were present. It may be when controlling for (stable) between-person and (unstable) within-person effects a relationship is revealed. Put another way, a relationship between EVT variables and ITL is revealed only in the portion of the model considered dynamic or "changing."

Reasonably, it can be assumed expectations and costs measured most proximal (at T3) to an outcome like ITL would be most related versus expectations and costs measured at earlier time points (T1 or T2). This is explained by the fact students who reported on expectations and costs at T3 had nearly a semester's worth of information, such as experiences studying content and outcomes like grades, to determine expected success and costs and the associated desire to leave a major or program.

The results of the ITL model can be interpreted in a similar way to the section above on how GPA can be predicted by EVT within-person (unstable) components over time, or that multiple paths can be traced over time to illustrate how outcomes like ITL can be potentially adjusted with interventions. Specifically, it is interesting to note that although greater than expected STVs did not directly influence students' ITL, which is a common finding in EVT literature (Hulleman et al., 2016; Wigfield & Eccles, 2020), it can be observed that greater than anticipated STVs indirectly influenced ITL.

For example, an intervention targeting STV at T1 and elevating it above baseline can directly reduce anticipated costs at T2 and with this reduction produce an increase in STV above at T2 above baseline. In turn, this can directly increase expectations at T3 and STVs at T3 to be greater than anticipated. The increase to expectations at T3 leads to a direct reduction in students' ITLs and an indirect reduction via expectations' significant and negative relationship with cost at T3. In other words, increasing expectations above baseline at T3 reduces cost below baseline at T3 which can directly lead to a decrease in ITLs.

Many pathways such as the one just described can be found in the model predicting ITL. The results imply an intervention targeting expectations and cost at the end of a semester can directly influence ITL. However, given this is late in a semester, it may be prudent to intervene earlier. The example provided above targeting STVs at T1 appears practical and the model demonstrates downstream this can reduce ITLs. More on where interventions can be implemented is discussed in the *Implications for Practice* section below.

Research Question 3: What relationship do the stable between-student factors (random intercepts) have with academic achievement and intentions to leave, and how does this compare to the unstable within-student components for health science students?

The stable between-person (RI) components of all three EVT variables did not significantly predict achievement or ITL. It may be a student's average stable motivations is not as influential on academic outcomes relative to the unstable within-person components. Possibly, how a student changes from an expected level of motivation determines the drive to engage with content in health science education. Put another way, it may not be enough to have a higher average of sustained motivation over time. Instead, students may need to rise above expected motivational levels to increase achievement and reduce intentions to leave a program.

The lack of significant relationships between the stable between-student (RI) components and outcomes like ITL and achievement may be beneficial considering the stable between-student (RI) components are less susceptible to change. In theory, these RI components would not respond to an intervention or may not respond easily. It may be fortuitous that the model showed factors that are susceptible to change, the within-person EVT components, directly influence academic outcomes considering these can be targeted by an intervention. More on where interventions can be implemented is discussed in the *Implications for Practice* section below.

Implications for Practice

Taken together, the results illustrate how a longitudinal design that utilizes an RI-CLPM design and implements EVT can pinpoint not only which variables to modify, but importantly when to modify them. For example, the results suggest academic outcomes such as semester GPA and intentions to leave can be predicted from the within-person (unstable) or dynamic components of the model. Specifically, achievement was greater for students who exhibited higher than expected subjective task values at mid-semester and at the end of the semester. Subjective task values also appeared to be the most stable within-person component from the EVT variables considering students who showed higher than anticipated levels of STV in the middle of the semester continued to do so even at the end. This warrants an intervention that is focused on STVs. A pragmatic intervention that can directly influence achievement may target STVs mid-semester considering an intervention applied at the end of the semester (i.e., STVs at T3) may be too late. Fortunately, as observed in the model, targeting motivational variables early in the semester may elicit motivational change over the course of the semester and in turn lead to direct positive influence on achievement.

Additional evidence taken from the model illustrated students with higher than anticipated expectations at T3, and those with lower than expected costs at T3, exhibit lower intentions to leave a health science program or major. While these results may suggest interventions targeting expectations and costs at T3, this may not be practical considering this would come late in the semester. Instead, additional results from this dynamic model may be used to reduce ITL by intervening early in the semester since the effects of an early intervention may be revealed downstream or at later points in time.

When viewing Figures 8 and 10 it appears the greatest intervention may be applied through STVs at T1. Considering much of motivational intervention research targets STVs, often specifically utility value (Brisson et al., 2017; Cromley et al., 2020; Rosenzweig et al., 2020; Shin et al., 2019; Wang & Lewis, 2022; Weidinger et al., 2020), this is beneficial. However, and in line with past research, it is clear a multifaceted approach that includes interventions on raising expectations (above baseline) and reducing costs (below baseline) at T1, and throughout the semester, can increase academic achievement and reduce ITL (Cromley et al., 2020; Harackiewicz & Priniski, 2018; Rosenzweig et al., 2022; St Omer et al., 2022).

One additional implication taken from the study's results includes highlighting the distinct roles of STVs and cost in the models presented. Within EVT literature is an ongoing debate about how distinct cost may be from task values with some researchers proposing an expectancy-value-cost model (Barron & Hulleman, 2015). Many recent studies depict how cost may operate differently in a model relative to task values (S. Y. Lee et al., 2022; Muenks et al., 2018). The current study continues to depict that cost may need to be recognized as a separate variable relative to STVs.

Limitations and Future Directions

Several limitations, as well as suggestions for future research, need to be addressed. First, this study used many groups from not only different colleges and universities, different health science programs (nursing and OT), but also two different countries. While measurement invariance was established over time it was not established between each group. This poses an issue to generalizability as students from underrepresented populations within both samples' countries may interpret or answer the survey instrument differently. We chose not to conduct several analyses of invariance that would need to be conducted increasing the chance of committing a Type I error or rejecting measurement invariance when it may possibly hold. The author felt the most important measurement invariance to establish was temporal given the longitudinal nature of the study.

Second, and in relation to the first limitation, the sample collected contained only individuals identifying as male or female – an "other" option was available but no participant selected this. Also, the sample was 93% female making the student population sampled from largely homogenous. This poses an issue to generalizability as men and even individuals from underrepresented populations may interpret or answer the survey instrument differently.

Second, the present study maintained a healthy sample size (n = 763), however, as revealed by the multiple power analyses conducted *a priori*, it is possible additional carry-over or spill-over effects could be established in the model with more participants. It may be that a sample size closer to 2000, as shown in Table 5, may be required to reveal a range of significant effects from small to large. Consequently, future studies may wish to collect a sample size larger than in the present study.

Third, the present study utilized three time points or collected data at the start of a semester, midsemester, and at the end of a semester. Additional time points can reveal more information about the movement of students' motivations at different parts of the semester and can depict a more dynamic model as a result. Also, added measurement waves in a RI-CLPM may reduce the sample size required to meet adequate power (Mulder, 2022).

Fourth, the literature shows many recent and past studies utilizing a CLPM design made a similar decision to utilize a composite STV or cost variable. In other words, the current study did not model the distinct STVs or costs constructs. While the models derived in this study showed that STVs would be a good target for interventions it does not illustrate with granularity which STV component(s) to target. The same can be said for costs. Therefore, future studies should produce a model that incorporates expectations, all three STVs, and all three costs. Naturally, this would require a large sample size and likely with many time points. It may be practical for future research to produce a series of models that compare expectations with one STV and one cost component at a time although this may still be less practical since this would produce at least 9 models for comparison.

Fifth, missing data is part of nearly any study but is likely more prevalent with a longitudinal design. This may effect results as missing data can reduce statistical power by decreasing the sample at various time points and can lead to bias in the model parameter estimates. To minimize or control for missingness, a planned missing data design was used along with full information maximum likelihood. However, missing data was still part of the present study and is therefore a limitation given specific motivational or academic outcome information was not collected.

Sixth, the data collected on EVT variables lacked a level of specificity. The items in the EVT survey instrument required health science students to consider their motivations on a more global scale considering students were asked to consider their pre-nursing, nursing, or OT program or major. The survey did not target a specific course such as pediatrics. This lack of fine granularity may also explain the lack of spill-over effects (autoregressive) observed, and it may be that at the class specific level versus program level these effects may be revealed.

APPENDIX A

Example Master Survey Instrument

Identifying Information	Item	Scale
-	What is your first and last name?	*Subject write-in*
Future Research Consent	**Item**	**Scale**
-	Do you consent to allowing your data to be used in future research? All results will be based on average results and will not identify individual students.	Yes/No
Demographic **Given in initial survey only**	**Item**	**Scale**
-	What is your age?	*Subject write-in*
-	What is your gender?	Male/Female/Other
-	What is your ethnicity?	White/Hispanic or Latino/Black or African American/ Native American or American Indian/Asian or Pacific Islander/Other
-	What is your marital status?	Single (never married)/ Married/In a domestic partnership/Divorced/Widowed
Instructions: Please reflect on your OT courses for this semester as you answer the following questions.		
Motivational Construct	**Item**	**Scale**
Expectancy (J. Eccles & Wigfield, 1995)		
1	Compared to other students, how well do you expect to do in your OT courses this semester?	1 = Much worse than other students, 2= Worse than other students, 3 = About the same as other students, 4 = Better than other students, 5 = Much better than other students
2	How well do you think you will do in your OT courses this semester?	1 = Very poor, 2=Poor, 3=Fair, 4=Good, 5 = Very good

3	How good are you in your OT courses?	1 = Very poor, 2=Poor, 3=Fair, 4=Good, 5 = Very good
4	If you were to order all the students in your cohort from worst to best in your OT courses, where would you put yourself?	1 = One of the worst, 2=Below average, 3=Average, 4= Above average, 5 = One of the best
5	How have you been doing in your OT courses this semester?	1 = Very poor, 2=Poor, 3=Fair, 4=Good, 5 = Very good
Cost (Flake et al., 2015)		
Task Effort Cost		
6	My OT courses demand too much of my time.	1=Completely Agree, 2= Mostly Agree, 3 = Somewhat Agree, 4 = Slightly Agree, 5=Neither Agree nor Disagree, 6 = Slightly Disagree, 7 = Somewhat Disagree, 8 = Mostly Disagree, 9=Completely Disagree
7	I have to put too much energy into my OT courses.	
8	My OT courses take up too much time.	
9	My OT courses are too much work.	
10	My OT courses require too much effort.	
Loss of Valued Alternatives		
11	I have to sacrifice too much to be in my OT courses.	1=Completely Agree, 2= Mostly Agree, 3 = Somewhat Agree, 4 = Slightly Agree, 5=Neither Agree nor Disagree, 6 = Slightly Disagree, 7 = Somewhat Disagree, 8 = Mostly Disagree, 9=Completely Disagree
12	My OT courses require me to give up too many other activities.	
13	Taking OT courses causes me to miss out on too many other things I care about.	
14	I can't spend as much time doing the other things that I would like because I am taking OT courses.	
Emotional Cost		
15	I worry too much about my OT courses.	1=Completely Agree, 2= Mostly Agree, 3 = Somewhat Agree, 4 = Slightly Agree, 5=Neither Agree nor Disagree,
16	My OT courses are too exhausting.	

17	My OT courses are emotionally draining.	6 = Slightly Disagree, 7 = Somewhat Disagree, 8 = Mostly Disagree, 9=Completely Disagree
18	My OT courses are too frustrating.	
19	My OT courses are too stressful.	
20	My OT courses make me feel too anxious.	
Task Values (Gaspard et al., 2017)		
Intrinsic Value		
21	My OT courses are fun to me.	1=Completely Agree, 2= Mostly Agree, 3 = Somewhat Agree, 4 = Slightly Agree, 5=Neither Agree nor Disagree, 6 = Slightly Disagree, 7 = Somewhat Disagree, 8 = Mostly Disagree, 9=Completely Disagree
22	I like doing things related to my OT courses.	
23	I simply like my OT courses.	
24	I enjoy the topics in my OT courses.	
Attainment Value		
25	It is important to me to be good at my OT courses.	1=Completely Agree, 2= Mostly Agree, 3 = Somewhat Agree, 4 = Slightly Agree, 5=Neither Agree nor Disagree, 6 = Slightly Disagree, 7 = Somewhat Disagree, 8 = Mostly Disagree, 9=Completely Disagree
26	Being good at my OT courses means a lot to me.	
27	Performing well in my OT courses is important to me.	
28	I care a lot about remembering the things we learn in my OT courses.	
29	My OT courses are very important to me personally.	
30	My OT courses are very important to me personally.	
Utility Value		
31	Knowing the contents in my OT courses has many benefits in my daily life.	1=Completely Agree, 2= Mostly Agree, 3 = Somewhat Agree, 4 = Slightly Agree, 5=Neither Agree nor Disagree, 6 = Slightly Disagree, 7 = Somewhat Disagree, 8 =
32	What we learn in my OT courses is directly applicable in everyday life.	

33	Good knowledge gained from my OT courses will help me in my future job.	Mostly Disagree, 9=Completely Disagree
34	For my future working life it will pay off to be good in my OT courses.	
35	To do well in my OT courses will help me in the remaining time in my program.	
36	If I know a lot in my OT courses, I will leave a good impression on my classmates.	
Intention to Leave (Perez et al., 2014) ****TO BE GIVEN AT END OF SEMESTER ONLY****		
1	At the present time, I am likely to switch to another major that is not related to OT.	1=Completely Agree, 2= Mostly Agree, 3 = Somewhat Agree, 4 = Slightly Agree, 5=Neither Agree nor Disagree, 6 = Slightly Disagree, 7 = Somewhat Disagree, 8 = Mostly Disagree, 9=Completely Disagree
2	I am likely to remain in my OT major through to completion of my degree.	
3	I am likely to leave my OT major.	
4	It is UNLIKELY that I will leave my OT major before I complete it.	
5	I intend to switch to another non-OT major.	
6	At the present time, I am likely to remain in my OT major.	

APPENDIX B

Planned Missing Data Design Survey Instrument (X-, A-, B-, and C-Blocks)

<table>
<tr><th colspan="3">X-Block</th></tr>
<tr><th>Identifying Information</th><th>Item</th><th>Scale</th></tr>
<tr><td>-</td><td>What is your first and last name?</td><td>*Subject write-in*</td></tr>
<tr><th>Future Research Consent</th><th>Item</th><th>Scale</th></tr>
<tr><td>-</td><td>Do you consent to allowing your data to be used in future research? All results will be based on average results and will not identify individual students.</td><td>Yes/No</td></tr>
<tr><th>Demographic **Given in initial survey only**</th><th>Item</th><th>Scale</th></tr>
<tr><td>-</td><td>What is your age?</td><td>*Subject write-in*</td></tr>
<tr><td>-</td><td>What is your gender?</td><td>Male/Female/Other</td></tr>
<tr><td>-</td><td>What is your ethnicity?</td><td>White/Hispanic or Latino/Black or African American/ Native American or American Indian/Asian or Pacific Islander/Other</td></tr>
<tr><td>-</td><td>What is your marital status?</td><td>Single (never married)/ Married/In a domestic partnership/Divorced/Widowed</td></tr>
<tr><th>Motivational Construct</th><th>Item</th><th>Scale</th></tr>
<tr><td colspan="3">Intention to Leave (Perez, Cromley, & Kaplan, 2014) **TO BE GIVEN AT END OF SEMESTER ONLY**</td></tr>
<tr><td>-</td><td>At the present time, I am likely to switch to another major that is not related to a OT major.</td><td rowspan="4">1=Completely Agree, 2= Mostly Agree, 3 = Somewhat Agree, 4 = Slightly Agree, 5=Neither Agree nor Disagree, 6 = Slightly Disagree, 7 = Somewhat Disagree, 8 = Mostly Disagree, 9=Completely Disagree</td></tr>
<tr><td>-</td><td>I am likely to remain in my OT major through to completion of my major.</td></tr>
<tr><td>-</td><td>I am likely to leave my STEM major.</td></tr>
<tr><td>-</td><td>It is UNLIKELY that I will leave my STEM</td></tr>
</table>

	major before I complete the major.	
-	I intend to switch to another non-OT major.	
-	At the present time, I am likely to remain in my OT major.	
Expectancy (Eccles & Wigfield, 1995)		
1	If you were to order all the students in your cohort from worst to best in your OT courses, where would you put yourself?	1 = One of the worst, 2=Below average, 3=Average, 4= Above average, 5 = One of the best
2	How have you been doing in your OT courses this semester?	1 = Very poor, 2=Poor, 3=Fair, 4=Good, 5 = Very good
Cost (Flake, Barron, Hulleman, McCoach, & Welsh, 2015)		
Task Effort		
3	My OT courses are too much work.	1=Completely Agree, 2= Mostly Agree, 3 = Somewhat Agree, 4 = Slightly Agree, 5=Neither Agree nor Disagree, 6 = Slightly Disagree, 7 = Somewhat Disagree, 8 = Mostly Disagree, 9=Completely Disagree
4	My OT courses require too much effort.	
Loss of Valued Alternatives		
5	I have to sacrifice too much to be in my OT courses.	1=Completely Agree, 2= Mostly Agree, 3 = Somewhat Agree, 4 = Slightly Agree, 5=Neither Agree nor Disagree, 6 = Slightly Disagree, 7 = Somewhat Disagree, 8 = Mostly Disagree, 9=Completely Disagree
Task Values (Gaspard, Häfner, Parrisius, Trautwein, & Nagengast, 2017)		
Intrinsic Value		
6	I enjoy the topics in my OT courses.	1=Completely Agree, 2= Mostly Agree, 3 = Somewhat Agree, 4 = Slightly Agree, 5=Neither Agree nor Disagree, 6 = Slightly Disagree, 7 = Somewhat Disagree, 8 = Mostly Disagree, 9=Completely Disagree
Task Difficulty (Eccles & Wigfield, 1995)		
7	How hard do you have to study for a OT course exam to get a good grade?	1 = Not at all, 2=A little, 3= Somewhat, 4=Quite a bit, 5 = A lot

REFERENCES

Abele, C., Penprase, B., & Ternes, R. (2013). A closer look at academic probation and attrition: What courses are predictive of nursing student success? *Nurse Education Today*, *33*(3), 258–261. https://doi.org/10.1016/j.nedt.2011.11.017

Abu-hilal, M. M., Abdelfattah, F. A., Alshumrani, S. A., Abduljabbar, A. S., & Marsh, H. W. (2013). Construct validity of self-concept in TIMSS's student background questionnaire: A test of separation and conflation of cognitive and affective dimensions of self-concept among Saudi eighth graders. *European Journal of Psychology of Education; Dordrecht*, *28*(4), 1201–1220. http://dx.doi.org/10.1007/s10212-012-0162-1

Acee, T. W., Weinstein, C. E., Hoang, T. V., & Flaggs, D. A. (2018). Value Reappraisal as a Conceptual Model for Task-Value Interventions. *The Journal of Experimental Education*, *86*(1), 69–85. https://doi.org/10.1080/00220973.2017.1381830

Al-Alawi, R., Oliver, G., & Donaldson, J. F. (2020). Systematic review: Predictors of students' success in baccalaureate nursing programs. *Nurse Education in Practice*, *48*, 102865. https://doi.org/10.1016/j.nepr.2020.102865

Aljohani, W., Banakhar, M., Sharif, L., Alsaggaf, F., Felemban, O., & Wright, R. (2021). Sources of Stress among Saudi Arabian Nursing Students: A Cross-Sectional Study. *International Journal of Environmental Research and Public Health*, *18*(22), Article 22. https://doi.org/10.3390/ijerph182211958

Archambault, I., Eccles, J. S., & Vida, M. N. (2010). Ability self-concepts and subjective value in literacy: Joint trajectories from grades 1 through 12. *Journal of Educational Psychology*, *102*(4), 804–816. https://doi.org/10.1037/a0021075

Archer, L., DeWitt, J., Osborne, J., Dillon, J., Willis, B., & Wong, B. (2010). “Doing” science versus “being” a scientist: Examining 10/11-year-old schoolchildren’s constructions of science through the lens of identity. *Science Education*, *94*(4), 617–639. https://doi.org/10.1002/sce.20399

Arens, A. K., Schmidt, I., & Preckel, F. (2018). Longitudinal relations among self-concept, intrinsic value, and attainment value across secondary school years in three academic domains. *Journal of Educational Psychology*. https://doi.org/10.1037/edu0000313

Arens, A. K., Yeung, A. S., Craven, R. G., & Hasselhorn, M. (2011). The twofold multidimensionality of academic self-concept: Domain specificity and separation between competence and affect components. *Journal of Educational Psychology, 103*(4), 970–981. https://doi.org/10.1037/a0025047

Arreciado Marañón, A., & Isla Pera, Ma. P. (2015). Theory and practice in the construction of professional identity in nursing students: A qualitative study. *Nurse Education Today*, *35*(7), 859–863. https://doi.org/10.1016/j.nedt.2015.03.014

Asparouhov, T., & Muthem, B. (2005). *Multivariate Statistical Modeling with Survey Data*.

Ball, C., Huang, K.-T., Rikard, R. V., & Cotten, S. R. (2019). The emotional costs of computers: An expectancy-value theory analysis of predominantly low-socioeconomic status minority students’ STEM attitudes. *Information, Communication & Society*, *22*(1), 105–128. https://doi.org/10.1080/1369118X.2017.1355403

Barrett, P. (2007). Structural equation modelling: Adjudging model fit. *Personality and Individual Differences*, *42*(5), 815–824. https://doi.org/10.1016/j.paid.2006.09.018

Barron, K. E., & Hulleman, C. S. (2015). Expectancy-value-cost model of motivation. *Psychology, 84*, 261–271.

Bartlett, M. L., Taylor, H., & Nelson, J. D. (2016). Comparison of Mental Health Characteristics and Stress Between Baccalaureate Nursing Students and Non-Nursing Students. *Journal of Nursing Education*, *55*(2), 87–90. https://doi.org/10.3928/01484834-20160114-05

Beauducel, A., & Herzberg, P. Y. (2006). On the Performance of Maximum Likelihood Versus Means and Variance Adjusted Weighted Least Squares Estimation in CFA. *Structural Equation Modeling: A Multidisciplinary Journal*, *13*(2), 186–203. https://doi.org/10.1207/s15328007sem1302_2

Bednarz, H., Schim, S., & Doorenbos, A. (2010). Cultural Diversity in Nursing Education: Perils, Pitfalls, and Pearls. *Journal of Nursing Education*, *49*(5), 253–260. https://doi.org/10.3928/01484834-20100115-02

Benden, D. K., & Lauermann, F. (2023). Relative importance of students' expectancy–value beliefs as predictors of academic success in gateway math courses. *Annals of the New York Academy of Sciences*, *n/a*(n/a). https://doi.org/10.1111/nyas.14961

Bentler, P. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*(2), 238–246. https://doi.org/10.1037/0033-2909.107.2.238

Berger, J.-L., & Karabenick, S. A. (2011). Motivation and students' use of learning strategies: Evidence of unidirectional effects in mathematics classrooms. *Learning and Instruction*, *21*(3), 416–428. https://doi.org/10.1016/j.learninstruc.2010.06.002

Berry, D., & Willoughby, M. T. (2017). On the Practical Interpretability of Cross-Lagged Panel Models: Rethinking a Developmental Workhorse. *Child Development*, *88*(4), 1186–1206.

Best Occupational Therapy Colleges Tuition Comparison. (n.d.). College Tuition Compare. Retrieved February 14, 2022, from https://www.collegetuitioncompare.com/best-schools/occupational-therapy/

Blome, M. J., Johnson, M. L., Jones, M. A., Moore, M. S., & Beck, M. F. (2021). Sleep Quality and Daytime Sleepiness in Prelicensure Baccalaureate Nursing Students. *Journal of Nursing Education*, *60*(4), 196–203. https://doi.org/10.3928/01484834-20210322-03

Bøe, M. V. (2012). Science choices in Norwegian upper secondary school: What matters? *Science Education*, *96*(1), 1–20. https://doi.org/10.1002/sce.20461

Bøe, M. V., Henriksen, E. K., Lyons, T., & Schreiner, C. (2011). Participation in science and technology: Young people's achievement-related choices in late-modern societies. *Studies in Science Education*, *47*(1), 37–72. https://doi.org/10.1080/03057267.2011.549621

Boehm, J., Cordier, R., Thomas, Y., Tanner, B., & Salata, K. (2017). The first year experience of occupational therapy students at an Australian regional university: Promoting student retention and developing a regional and remote workforce. *Australian Journal of Rural Health*, *25*(1), 22–27. https://doi.org/10.1111/ajr.12252

Bowyer, P., Tiongco, C., Rubio, L. K., Liu, J., & Whisner, S. M. (2018). Admission Requirements and Practices in Entry-Level Occupational Therapy Programs. *Journal of Occupational Therapy Education*, *2*(3). https://doi.org/10.26681/jote.2018.020301

Bråten, I., & Olaussen, B. S. (2005). Profiling individual differences in student motivation: A longitudinal cluster-analytic study in different academic contexts. *Contemporary Educational Psychology*, *30*(3), 359–396. https://doi.org/10.1016/j.cedpsych.2005.01.003

Bressoud, D. (2020). Talking about Leaving Revisited: Persistence, Relocation, and Loss in Undergraduate STEM Education. *Notices of the American Mathematical Society*, *67*(09), 1. https://doi.org/10.1090/noti2145

Brisson, B. M., Dicke, A.-L., Gaspard, H., Häfner, I., Flunger, B., Nagengast, B., & Trautwein, U. (2017). Short Intervention, Sustained Effects: Promoting Students' Math Competence Beliefs, Effort, and Achievement. *American Educational Research Journal*, *54*(6), 1048–1078. https://doi.org/10.3102/0002831217716084

Brown, J., & Marshall, B. L. (2008). A Historically Black University's Baccalaureate Enrollment and Success Tactics for Registered Nurses. *Journal of Professional Nursing*, *24*(1), 21–29. https://doi.org/10.1016/j.profnurs.2007.06.006

Browne, M. W., & Cudek, R. (1993). Alternative ways of assessing model fit. In *Testing structural equation models* (pp. 136–162). Sage.

Burns, R. A., Crisp, D. A., & Burns, R. B. (2020). Re-examining the reciprocal effects model of self-concept, self-efficacy, and academic achievement in a comparison of the Cross-Lagged Panel and Random-Intercept Cross-Lagged Panel frameworks. *British Journal of Educational Psychology*, *90*(1), 77–91. https://doi.org/10.1111/bjep.12265

Canning, E. A., & Harackiewicz, J. M. (2015). Teach it, don't preach it: The differential effects of directly-communicated and self-generated utility–value information. *Motivation Science*, *1*(1), 47–71. https://doi.org/10.1037/mot0000015

Chen, F. (2007). Sensitivity of Goodness of Fit Indexes to Lack of Measurement Invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Chen, X. (2013). *STEM Attrition: College Students' Paths Into and Out of STEM Fields* (p. 104) [Statistical Analysis Report]. U.S. Department of Education.

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating Goodness-of-Fit Indexes for Testing Measurement Invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, *9*(2), 233–255. https://doi.org/10.1207/S15328007SEM0902_5

Chung, Y., & Kim, S. (2022). Expectancies, task values, and perceived costs: Reciprocal effects on math-related career intention and achievement among middle school girls. *Learning and Individual Differences*, *96*, 102145. https://doi.org/10.1016/j.lindif.2022.102145

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Lawrence Erlbaum Associates.

Cole, J. S., Bergin, D. A., & Whittaker, T. A. (2008). Predicting student achievement for low stakes tests with effort and task value. *Contemporary Educational Psychology*, *33*(4), 609–624. https://doi.org/10.1016/j.cedpsych.2007.10.002

Conley, A. M. (2012). Patterns of motivation beliefs: Combining achievement goal and expectancy-value perspectives. *Journal of Educational Psychology*, *104*(1), 32–47. https://doi.org/10.1037/a0026042

Cook, D. A., & Artino, A. R. (2016). Motivation to learn: An overview of contemporary theories. *Medical Education*, *50*(10), 997–1014. https://doi.org/10.1111/medu.13074

Credé, M., & Phillips, L. A. (2011). A meta-analytic review of the Motivated Strategies for Learning Questionnaire. *Learning and Individual Differences*, *21*(4), 337–346. https://doi.org/10.1016/j.lindif.2011.03.002

Crippen, K. J., Imperial, L., Bolch, C. A., & Payne, C. A. (2022). Undergraduate Engineering Students' Subjective Task Value Beliefs for Modeling Problems in Chemistry. *International Journal of Science and Mathematics Education*. https://doi.org/10.1007/s10763-022-10305-2

Cromley, J. G., Perez, T., & Kaplan, A. (2016). Undergraduate STEM Achievement and Retention: Cognitive, Motivational, and Institutional Factors and Solutions. *Policy Insights from the Behavioral and Brain Sciences*, *3*(1), 4–11. https://doi.org/10.1177/2372732215622648

Cromley, J. G., Perez, T., Kaplan, A., Dai, T., Mara, K., & Balsai, M. J. (2020). Combined cognitive–motivational modules delivered via an LMS increase undergraduate biology grades. *Technology, Mind, and Behavior*, *1*(2). https://doi.org/10.1037/tmb0000020

Dante, A., Valoppi, G., Saiani, L., & Palese, A. (2011). Factors associated with nursing students' academic success or failure: A retrospective Italian multicenter study. *Nurse Education Today*, *31*(1), 59–64. https://doi.org/10.1016/j.nedt.2010.03.016

de Witt, P. A., Monareng, L., Abraham, A. A., Koor, S., & Saber, R. (2019). Resilience in occupational therapy students. *South African Journal of Occupational Therapy*, *49*(2), 33–41. https://doi.org/10.17159/23103833/2019/vol49n2a6

Deasy, C., Coughlan, B., Pironom, J., Jourdan, D., & Mannix-McNamara, P. (2016). Psychological distress and help seeking amongst higher education students: Findings from a mixed method study of undergraduate nursing/midwifery and teacher education students in Ireland. *Irish Educational Studies*, *35*(2), 175–194. https://doi.org/10.1080/03323315.2016.1146157

Denissen, J. J. A., Zarrett, N. R., & Eccles, J. S. (2007). I like to Do It, I'm Able, and I Know I Am: Longitudinal Couplings between Domain-Specific Achievement, Self-Concept, and Interest. *Child Development*, *78*(2), 430–447. JSTOR.

Dever, B. V. (2016). Using the Expectancy-Value Theory of Motivation to Predict Behavioral and Emotional Risk Among High School Students. *School Psychology Review*, *45*(4), 417–433. https://doi.org/10.17105/SPR45-4.417-433

Dietrich, J., Viljaranta, J., Moeller, J., & Kracke, B. (2017). Situational expectancies and task values: Associations with students' effort. *Learning and Instruction*, *47*, 53–64. https://doi.org/10.1016/j.learninstruc.2016.10.009

Dinkelmann, I., & Buff, A. (2016). Children's and parents' perceptions of parental support and their effects on children's achievement motivation and achievement in mathematics. A longitudinal predictive mediation model. *Learning and Individual Differences*, *50*, 122–132. https://doi.org/10.1016/j.lindif.2016.06.029

Durik, A. M., Vida, M., & Eccles, J. S. (2006). Task values and ability beliefs as predictors of high school literacy choices: A developmental analysis. *Journal of Educational Psychology*, *98*(2), 382–393. https://doi.org/10.1037/0022-0663.98.2.382

Eccles. (2009). Who Am I and What Am I Going to Do With My Life? Personal and Collective Identities as Motivators of Action. *Educational Psychologist*, *44*(2), 78–89. https://doi.org/10.1080/00461520902832368

Eccles, J., Adler, T., Futterman, R., Goff, S., Kaczala, C., Meece, J., & Midgley, J. (1983). Expectancies, values and academic behaviors. *Achievement and Achievement Motives*, 75–146.

Eccles, J. S., & Wigfield, A. (2002). Motivational Beliefs, Values, and Goals. *Annual Review of Psychology*, *53*(1), 109–132. https://doi.org/10.1146/annurev.psych.53.100901.135153

Eccles, J., & Wigfield, A. (1995). In the Mind of the Actor: The Structure of Adolescents' Achievement Task Values and Expectancy-Related Beliefs. *Personality and Social Psychology Bulletin*, *21*(3), 215–225.

Eccles, J., Wigfield, A., Harold, R. D., & Blumenfeld, P. (1993). Age and Gender Differences in Children's Self- and Task Perceptions during Elementary School. *Child Development*, *64*(3), 830–847. JSTOR. https://doi.org/10.2307/1131221

Employed persons by detailed occupation, sex, race, and Hispanic or Latino ethnicity. (2021). U.S. Bureau of Labor Statistics.

Fact Sheet: Nursing Shortage. (2020). American Association of Colleges of Nursing. https://www.aacnnursing.org/Portals/42/News/Factsheets/Nursing-Shortage-Factsheet.pdf

Fan, X., Thompson, B., & Wang, L. (1999). Effects of sample size, estimation methods, and model specification on structural equation modeling fit indexes. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 56–83. https://doi.org/10.1080/10705519909540119

Feeg, V. D., & Mancino, D. J. (2014). Nursing Student Loan Debt: A Secondary Analysis of the National Student Nurses' Association Annual Survey of New Graduates. *Nursing Economics*, *32*(5), 231–240.

Flake, J. K., Barron, K. E., Hulleman, C., McCoach, B. D., & Welsh, M. E. (2015). Measuring cost: The forgotten component of expectancy-value theory. *Contemporary Educational Psychology*, *41*, 232–244. https://doi.org/10.1016/j.cedpsych.2015.03.002

Fong, C. J., Kremer, K. P., Hill-Troglin Cox, C., & Lawson, C. A. (2021). Expectancy-value profiles in math and science: A person-centered approach to cross-domain motivation with academic and STEM-related outcomes. *Contemporary Educational Psychology*, *65*, 101962. https://doi.org/10.1016/j.cedpsych.2021.101962

Ganley, C. M., & Lubienski, S. T. (2016). Mathematics confidence, interest, and performance: Examining gender patterns and reciprocal relations. *Learning and Individual Differences*, *47*, 182–193. https://doi.org/10.1016/j.lindif.2016.01.002

Gao, Z., Wei, X., Yang, L., Cui, D., Kong, L., Qi, L., & Zhang, P. (2022). Mediating role of career self-efficacy between clinical learning environment and professional identity in nursing students. *Journal of Advanced Nursing*, *78*(4), 1012–1019. https://doi.org/10.1111/jan.15027

Gartrell, K., Kent, V., Rock, M., Williams-Cooper, K., Curran, M. S., Durry, A., Necker, B., Armstrong, L., & Mark, H. (2020). Preadmission predictors for first semester course success in a baccalaureate nursing program. *Journal of Professional Nursing*, *36*(5), 322–329. https://doi.org/10.1016/j.profnurs.2020.01.007

Gaspard, H., Häfner, I., Parrisius, C., Trautwein, U., & Nagengast, B. (2017). Assessing task values in five subjects during secondary school: Measurement structure and mean level differences across grade level, gender, and academic subject. *Contemporary Educational Psychology*, *48*, 67–84. https://doi.org/10.1016/j.cedpsych.2016.09.003

Govender, P., Mkhabela, S., Hlongwane, M., Jali, K., & Jetha, C. (2015). OT student's experiences of stress and coping. *South African Journal of Occupational Therapy*, *45*(3), 34–39. https://doi.org/10.17159/2310-3833/2015/v45n3/a7

Grab, J., Long, M., Norris, J., Pilchik, K., & Fisher, G. (2020). Exploring the Impact of OT Student Stress: Professor and Student Perspectives. *The American Journal of*

Occupational Therapy, *74*(4_Supplement_1), 7411510318p1-7411510318p1. https://doi.org/10.5014/ajot.2020.74S1-PO8021

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, *37*(3), 424–438. https://doi.org/10.2307/1912791

Grigg, S., Perera, H. N., McIlveen, P., & Svetleff, Z. (2018). Relations among math self efficacy, interest, intentions, and achievement: A social cognitive perspective. *Contemporary Educational Psychology*, *53*, 73–86. https://doi.org/10.1016/j.cedpsych.2018.01.007

Guo, J., Marsh, H. W., Morin, A. J. S., Parker, P. D., & Kaur, G. (2015). Directionality of the Associations of High School Expectancy-Value, Aspirations, and Attainment: A Longitudinal Study. *American Educational Research Journal*, *52*(2), 371–402. https://doi.org/10.3102/0002831214565786

Guo, J., Marsh, H. W., Parker, P. D., Morin, A. J. S., & Dicke, T. (2017). Extending expectancy-value theory predictions of achievement and aspirations in science: Dimensional comparison processes and expectancy-by-value interactions. *Learning and Instruction*, *49*, 81–91. https://doi.org/10.1016/j.learninstruc.2016.12.007

Guo, J., Parker, P. D., Marsh, H. W., & Morin, A. J. (2015). Achievement, motivation, and educational choices: A longitudinal study of expectancy and value using a multiplicative perspective. *Developmental Psychology*, *51*(8), 1163.

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. P. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods*, *20*(1), 102–116. https://doi.org/10.1037/a0038889

Harackiewicz, J. M., Canning, E. A., Tibbetts, Y., Priniski, S. J., & Hyde, J. S. (2016). Closing achievement gaps with a utility-value intervention: Disentangling race and social class.

Journal of Personality and Social Psychology, *111*(5), 745–765. https://doi.org/10.1037/pspp0000075

Harackiewicz, J. M., Durik, A. M., Barron, K. E., Linnenbrink-Garcia, L., & Tauer, J. M. (2008). The role of achievement goals in the development of interest: Reciprocal relations between achievement goals, interest, and performance. *Journal of Educational Psychology*, *100*(1), 105–122. https://doi.org/10.1037/0022-0663.100.1.105

Harackiewicz, J. M., & Priniski, S. J. (2018). Improving Student Outcomes in Higher Education: The Science of Targeted Intervention. *Annual Review of Psychology*, *69*(1), 409–435. https://doi.org/10.1146/annurev-psych-122216-011725

Harackiewicz, J. M., Smith, J. L., & Priniski, S. J. (2016). Interest Matters: The Importance of Promoting Interest in Education. *Policy Insights from the Behavioral and Brain Sciences*, *3*(2), 220–227. https://doi.org/10.1177/2372732216655542

Harris, R. C., Rosenberg, L., & Grace O'Rourke, M. E. (2013). Addressing the Challenges of Nursing Student Attrition. *Journal of Nursing Education*. https://doi.org/10.3928/01484834-20131218-03

Haughey, K., Zimmerman, S., & Sanders, M. (2017). Perceived Stressors and Coping in Junior, Senior, and Graduate Occupational Therapy Students: A Qualitative Analysis. *The American Journal of Occupational Therapy*, *71*(4_Supplement_1), 7111505152p1-7111505152p1. https://doi.org/10.5014/ajot.2017.71S1-PO7035

He, S., Guo, X., Bi, T., Zhang, T., & Luo, L. (2023). Developmental trajectories of children's educational expectations in China: Contributions of academic achievement and maternal expectations. *Contemporary Educational Psychology*, *72*, 102144. https://doi.org/10.1016/j.cedpsych.2022.102144

Hong, W., Bernacki, M. L., & Perera, H. N. (2020). A latent profile analysis of undergraduates' achievement motivations and metacognitive behaviors, and their relations to achievement in science. *Journal of Educational Psychology*, *112*(7), 1409–1430. https://doi.org/10.1037/edu0000445

How Much Does Becoming an Occupational Therapist Cost? (n.d.). CostHelper. Retrieved February 14, 2022, from https://education.costhelper.com/occupational-therapist.html

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Hulleman, C. S., Barron, K. E., Kosovich, J. J., & Lazowski, R. A. (2016). Student Motivation: Current Theories, Constructs, and Interventions Within an Expectancy-Value Framework. In A. A. Lipnevich, F. Preckel, & R. D. Roberts (Eds.), *Psychosocial Skills and School Systems in the 21st Century* (pp. 241–278). Springer International Publishing. https://doi.org/10.1007/978-3-319-28606-8_10

Hulleman, C. S., Godes, O., Hendricks, B. L., & Harackiewicz, J. M. (2010). Enhancing interest and performance with a utility value intervention. *Journal of Educational Psychology*, *102*(4), 880–895. https://doi.org/10.1037/a0019506

Hulleman, C. S., & Harackiewicz, J. M. (2009). Promoting Interest and Performance in High School Science Classes. *Science*, *326*(5958), 1410–1412. JSTOR.

Hunt, G., Verstappen, A., Stewart, L., Kool, B., & Slark, J. (2020). Career interests of undergraduate nursing students: A ten-year longitudinal study. *Nurse Education in Practice*, *43*, 102702. https://doi.org/10.1016/j.nepr.2020.102702

Hustinx, P. W. J., Kuyper, H., van der Werf, M. P. C., & Dijkstra, P. (2009). Achievement motivation revisited: New longitudinal data to demonstrate its predictive power. *Educational Psychology*, *29*(5), 561–582. https://doi.org/10.1080/01443410903132128

Jacob, T., Gummesson, C., Nordmark, E., El-Ansary, D., Remedios, L., & Webb, G. (2012). Perceived Stress and Sources of Stress Among Physiotherapy Students From 3 Countries. *Journal of Physical Therapy Education*, *26*(3), 57–65. http://dx.doi.org/10.1097/00001416-201207000-00008

Jacob, T., Itzchak, E. B., & Raz, O. (2013). Stress among healthcare students – A cross disciplinary perspective. *Physiotherapy Theory and Practice*, *29*(5), 401–412. https://doi.org/10.3109/09593985.2012.734011

Jacobs, K. (2019). *Special Task Force February 2019 Summary Report* (pp. 1–38). American Occupational Therapy Association. https://www.aota.org/-/media/Corporate/Files/AboutAOTA/BOD/Special-Task-Force-February-2019-Summary-Report.pdf

Jamshidi, N., Molazem, Z., Sharif, F., Torabizadeh, C., & Najafi Kalyani, M. (2016). The Challenges of Nursing Students in the Clinical Learning Environment: A Qualitative Study. *The Scientific World Journal*, *2016*, e1846178. https://doi.org/10.1155/2016/1846178

Jeffreys, M. R. (2007). Tracking students through program entry, progression, graduation, and licensure: Assessing undergraduate nursing student retention and success. *Nurse Education Today*, *27*(5), 406–419. https://doi.org/10.1016/j.nedt.2006.07.003

Jiang, Y., Kim, S., & Bong, M. (2020). The role of cost in adolescent students' maladaptive academic outcomes. *Journal of School Psychology*, *83*, 1–24. https://doi.org/10.1016/j.jsp.2020.08.004

Jiang, Y., & Rosenzweig, E. Q. (2021). Using cost to improve predictions of adolescent students' future choice intentions, avoidance intentions, and course grades in mathematics and English. *Learning and Individual Differences*, *86*, 101978. https://doi.org/10.1016/j.lindif.2021.101978

Jiang, Y., Rosenzweig, E. Q., & Gaspard, H. (2018). An expectancy-value-cost approach in predicting adolescent students' academic motivation and achievement. *Contemporary Educational Psychology*, *54*, 139–152. https://doi.org/10.1016/j.cedpsych.2018.06.005

Jiang, Y., & Zhang, L. (2023). High school students' expectancy, value, and cost profiles and their relations with engagement and achievement in Math and English. *Learning and Individual Differences*, *101*, 102252. https://doi.org/10.1016/j.lindif.2022.102252

Jimenez, C., Navia-Osorio, P. M., & Diaz, C. V. (2010). Stress and health in novice and experienced nursing students. *Journal of Advanced Nursing*, *66*(2), 442–455. https://doi.org/10.1111/j.1365-2648.2009.05183.x

Jobst, L. J., Bader, M., & Moshagen, M. (2021). A tutorial on assessing statistical power and determining sample size for structural equation models. *Psychological Methods*. https://doi.org/10.1037/met0000423

Johnson, M. L., & Sinatra, G. M. (2013). Use of task-value instructional inductions for facilitating engagement and conceptual change. *Contemporary Educational Psychology*, *38*(1), 51–63. https://doi.org/10.1016/j.cedpsych.2012.09.003

Jones-Schenk, J., Leafman, J., Wallace, L., & Allen, P. (2017). Addressing the Cost, Value, And Student Debt in Nursing Education. *NURSING ECONOMIC*, *35*(1), 8.

Jorgensen, T. D., Rhemtulla, M., Schoemann, A., McPherson, B., Wu, W., & Little, T. D. (2014). Optimal assignment methods in three-form planned missing data designs for longitudinal panel studies. *International Journal of Behavioral Development*, *38*(5), 397–410. https://doi.org/10.1177/0165025414531094

Juraschek, S. P., Zhang, X., Ranganathan, V., & Lin, V. W. (2019). Republished: United States Registered Nurse Workforce Report Card and Shortage Forecast. *American Journal of Medical Quality*, *34*(5), 473–481. https://doi.org/10.1177/1062860619873217

Karaca, A., Yildirim, N., Cangur, S., Acikgoz, F., & Akkus, D. (2019). Relationship between mental health of nursing students and coping, self-esteem and social support. *Nurse Education Today*, *76*, 44–50. https://doi.org/10.1016/j.nedt.2019.01.029

Keith, T. Z. (2014). *Multiple Regression and Beyond: An Introduction to Multiple Regression and Structural Equation Modeling* (2nd ed.). Routledge.

Khalaila, R. (2015). The relationship between academic self-concept, intrinsic motivation, test anxiety, and academic achievement among nursing students: Mediating and moderating effects. *Nurse Education Today*, *35*(3), 432–438. https://doi.org/10.1016/j.nedt.2014.11.001

Kim, Y., Yu, S. L., Koenka, A. C., Lee, H., & Heckler, A. F. (2021). Can Self-Efficacy and Task Values Buffer Perceived Costs? Exploring Introductory- and Upper-Level Physics Courses. *The Journal of Experimental Education*, 1–23. https://doi.org/10.1080/00220973.2021.1878992

Kinsella, E. A., Smith, K., Bhanji, S., Shepley, R., Modor, A., & Bertrim, A. (2020). Mindfulness in allied health and social care professional education: A scoping review. *Disability and Rehabilitation*, *42*(2), 283–295. https://doi.org/10.1080/09638288.2018.1496150

Kjærnsli, M., & Lie, S. (2011). Students' Preference for Science Careers: International comparisons based on PISA 2006. *International Journal of Science Education*, *33*(1), 121–144. https://doi.org/10.1080/09500693.2010.518642

Klem, L. (2000). Structural equation modeling. In *Reading and understanding MORE multivariate statistics* (pp. 227–260). American Psychological Association.

Kline, R. B. (2016). *Principles and Practice of Structural Equation Modeling* (4th ed.). Guilford Press.

Kosovich, J. J., Flake, J. K., & Hulleman, C. S. (2017). Short-term motivation trajectories: A parallel process model of expectancy-value. *Contemporary Educational Psychology*, *49*, 130–139. https://doi.org/10.1016/j.cedpsych.2017.01.004

Kumar, S., & Jejurkar, K. (2005). STUDY OF STRESS LEVEL IN OCCUPATIONAL THERAPY STUDENTS DURING THEIR ACADEMIC CURRICULUM. *The Indian Journal of Occupational Therapy*, *XXXVII*(1), 4.

Lang, K. M., Moore, E. W. G., & Grandfield, E. M. (2020). A novel item-allocation procedure for the three-form planned missing data design. *MethodsX*, *7*, 100941. https://doi.org/10.1016/j.mex.2020.100941

Lauermann, F., Tsai, Y.-M., & Eccles, J. S. (2017). Math-related career aspirations and choices within Eccles et al's expectancy–value theory of achievement-related behaviors. *Developmental Psychology*, *53*(8), 1540–1559. https://doi.org/10.1037/dev0000367

Lee, S. Y., Friedman, S., Christiaans, E., & Robinson, K. A. (2022). Valuable but costly? University students' expectancy-value-cost profiles in introductory chemistry courses. *Contemporary Educational Psychology*, *69*, 102056. https://doi.org/10.1016/j.cedpsych.2022.102056

Lee, Y., Freer, E., Robinson, K. A., Perez, T., Lira, A. K., Briedis, D., Walton, S. P., & Linnenbrink-Garcia, L. (2022). The multiplicative function of expectancy and value in predicting engineering students' choice, persistence, and performance. *Journal of Engineering Education*, jee.20456. https://doi.org/10.1002/jee.20456

Lee, Y., & Seo, E. (2021). Longitudinal relations between South Korean adolescents' academic self-efficacy and values in mathematics and English. *British Journal of Educational Psychology*, *91*(1), 217–236. https://doi.org/10.1111/bjep.12357

Lewis-Kipkulei, P., Dunn, L. S., & Carpenter, A. M. (2021). Implications for Occupational Therapy Student Stress, Well-Being, and Coping: A Scoping Review. *Journal of Occupational Therapy Education*, *5*(1), 1–22. https://doi.org/10.26681/jote.2021.050102

Li, W., Lee, A., & Solmon, M. (2007). The role of perceptions of task difficulty in relation to self-perceptions of ability, intrinsic value, attainment value, and performance. *European Physical Education Review*, *13*(3), 301–318. https://doi.org/10.1177/1356336X07081797

Lin, V., Zhang, X., & Dixon, P. (2015). Occupational Therapy Workforce in the United States: Forecasting Nationwide Shortages. *PM&R*, *7*(9), 946–954. https://doi.org/10.1016/j.pmrj.2015.02.012

Loans for Undergraduate Students (p. 6). (2020). National Center for Education Statistics.

Luo, Y., & Wang, H. (2009). Correlation research on psychological health impact on nursing students against stress, coping way and social support. *Nurse Education Today*, *29*(1), 5–8. https://doi.org/10.1016/j.nedt.2008.05.019

Luttrell, V. R., Callen, B. W., Allen, C. S., Wood, M. D., Deeds, D. G., & Richard, D. C. S. (2010). The Mathematics Value Inventory for General Education Students: Development and Initial Validation. *Educational and Psychological Measurement*, *70*(1), 142–160. https://doi.org/10.1177/0013164409344526

Lysaght, R., Donnelly, C., & Villeneuve, M. (2009). Factors predicting applicant outcomes in occupational therapy education. *Canadian Journal of Occupational Therapy*, *76*(1), 38–48.

Maltese, A. V., & Tai, R. H. (2011). Pipeline persistence: Examining the association of educational experiences with earned degrees in STEM among U.S. students. *Science Education*, *95*(5), 877–907. https://doi.org/10.1002/sce.20441

Marsh, H. W., & Craven, R. G. (2006). Reciprocal Effects of Self-Concept and Performance From a Multidimensional Perspective: Beyond Seductive Pleasure and Unidimensional Perspectives. *Perspectives on Psychological Science*, *1*(2), 133–163. https://doi.org/10.1111/j.1745-6916.2006.00010.x

Marsh, H. W., & Martin, A. J. (2011). Academic self-concept and academic achievement: Relations and causal ordering: Academic self-concept. *British Journal of Educational Psychology*, *81*(1), 59–77. https://doi.org/10.1348/000709910X503501

Marsh, H. W., Pekrun, R., Lichtenfeld, S., Guo, J., Arens, A. K., & Murayama, K. (2016). Breaking the double-edged sword of effort/trying hard: Developmental equilibrium and longitudinal relations among effort, achievement, and academic self-concept. *Developmental Psychology*, *52*(8), 1273–1290. https://doi.org/10.1037/dev0000146

Marsh, H. W., Trautwein, U., Lüdtke, O., Köller, O., & Baumert, J. (2005). Academic Self-Concept, Interest, Grades, and Standardized Test Scores: Reciprocal Effects Models of Causal Ordering. *Child Development*, *76*(2), 397–416. JSTOR.

Martin, A., Papworth, B., Ginns, P., Malmberg, L.-E., Collie, R. J., & Calvo, R. A. (2015). Real-time motivation and engagement during a month at school: Every moment of every day for every student matters. *Learning and Individual Differences*, *38*, 26–35. https://doi.org/10.1016/j.lindif.2015.01.014

Masson, A.-L., Klop, T., & Osseweijer, P. (2016). An analysis of the impact of student–scientist interaction in a technology design activity, using the expectancy-value model of achievement related choice. *International Journal of Technology and Design Education*, *26*(1), 81–104. https://doi.org/10.1007/s10798-014-9296-6

Mayor-Silva, L. I., Romero-Saldaña, M., Moreno-Pimentel, A. G., Álvarez-Melcón, Á., Molina-Luque, R., & Meneses-Monroy, A. (2021). The role of psychological variables in improving resilience: Comparison of an online intervention with a face-to-face intervention. A randomised controlled clinical trial in students of health sciences. *Nurse Education Today*, *99*, 104778. https://doi.org/10.1016/j.nedt.2021.104778

Meade, A., Johnson, E., & Braddy, P. (2008). Power and sensitivity of alternative fit indices in tests of measurement invariance. *Journal of Applied Psychology*, *93*(3), 568–592. https://doi.org/10.1037/0021-9010.93.3.568

Meece, J. L., Wigfield, A., & Eccles, J. S. (1990). Predictors of math anxiety and its influence on young adolescents' course enrollment intentions and performance in mathematics.

Journal of Educational Psychology, *82*(1), 60–70. https://doi.org/10.1037/0022-0663.82.1.60

Merkley, B. R. (2015). *Student nurse attrition: A half century of research*. https://doi.org/10.5430/jnep.v6n3p71

Meyer, G., Shatto, B., & Kuljeerung, O. (2021). The Impact of Student Debt on Professional Satisfaction in Graduate Entry Nurses. *Nursing Economic*, *39*(1), 8.

Millett, C. M. (2016). Dollars and Sense: The Policy Implications of Financing an Accelerated Nursing Degree. *Journal of Professional Nursing*, *32*(5, Supplement), S14–S23. https://doi.org/10.1016/j.profnurs.2016.02.009

Mirzaei, T., Oskouie, F., & Rafii, F. (2012). Nursing students' time management, reducing stress and gaining satisfaction: A grounded theory study. *Nursing & Health Sciences*, *14*(1), 46–51. https://doi.org/10.1111/j.1442-2018.2011.00661.x

Moshagen, M. (2021). *Power Analysis for Structural Equation Models: SemPower Manual*. 26.

Muenks, K., Wigfield, A., & Eccles, J. S. (2018). I can do this! The development and calibration of children's expectations for success and competence beliefs. *Developmental Review*, *48*, 24–39. https://doi.org/10.1016/j.dr.2018.04.001

Mulder, J. D. (2022). Power Analysis for the Random Intercept Cross-Lagged Panel Model Using the powRICLPM R-Package. *Structural Equation Modeling: A Multidisciplinary Journal*, 1–14. https://doi.org/10.1080/10705511.2022.2122467

Musu-Gillette, L. E., Wigfield, A., Harring, J. R., & Eccles, J. S. (2015). Trajectories of change in students' self-concepts of ability and values in math and college major choice. *Educational Research and Evaluation*, *21*(4), 343–370. https://doi.org/10.1080/13803611.2015.1057161

Muthen, L., & Muthen, B. (n.d.). *Mplus User's Guide* (Vol. 8). Muthén & Muthén.

Nagengast, B., Marsh, H. W., Scalas, L. F., Xu, M. K., Hau, K.-T., & Trautwein, U. (2011). Who Took the "×" out of Expectancy-Value Theory?: A Psychological Mystery, a Substantive-Methodological Synergy, and a Cross-National Generalization. *Psychological Science*, *22*(8), 1058–1066. https://doi.org/10.1177/0956797611415540

Nerdrum, P., Rust∅en, T., & Helge R∅nnestad, M. (2009). Psychological Distress Among Nursing, Physiotherapy and Occupational Therapy Students: A Longitudinal and Predictive Study. *Scandinavian Journal of Educational Research*, *53*(4), 363–378. https://doi.org/10.1080/00313830903043133

Newton, S. E., & Moore, G. (2009). Use of Aptitude to Understand Bachelor of Science in Nursing Student Attrition and Readiness for the National Council Licensure Examination-Registered Nurse. *Journal of Professional Nursing*, *25*(5), 273–278. https://doi.org/10.1016/j.profnurs.2009.01.016

Nuutila, K., Tuominen, H., Tapola, A., Vainikainen, M.-P., & Niemivirta, M. (2018). Consistency, longitudinal stability, and predictions of elementary school students' task interest, success expectancy, and performance in mathematics. *Learning and Instruction*, *56*, 73–83. https://doi.org/10.1016/j.learninstruc.2018.04.003

Ohl, A., Schelly, D., Reid, J., & Boolani, A. (2019). Sleep Quality and Quantity of Occupational Therapy and Other Allied Health Students. *Occupational Therapy in Mental Health*, *35*(4), 407–421. https://doi.org/10.1080/0164212X.2019.1581121

Papazisis, G., Tsiga, E., Papanikolaou, N., Vlasiadis, I., & Sapountzi-Krepia, D. (2008). Psychological distress, anxiety and depression among nursing students in Greece. *International Journal of Caring Sciences*, *1*(1), 42–46.

Patall, E. A., Vasquez, A. C., Steingut, R. R., Trimble, S. S., & Pituch, K. A. (2016). Daily interest, engagement, and autonomy support in the high school science classroom. *Contemporary Educational Psychology*, *46*, 180–194. https://doi.org/10.1016/j.cedpsych.2016.06.002

Pekrun, R., & Marsh, H. W. (2022). Research on situated motivation and emotion: Progress and open problems. *Learning and Instruction*, *81*, 101664. https://doi.org/10.1016/j.learninstruc.2022.101664

Perez, T., Cromley, J. G., & Kaplan, A. (2014). The role of identity development, values, and costs in college STEM retention. *Journal of Educational Psychology*, *106*(1), 315–329. https://doi.org/10.1037/a0034027

Perez, T., Dai, T., Kaplan, A., Cromley, J. G., Brooks, W. D., White, A. C., Mara, K. R., & Balsai, M. J. (2019). Interrelations among expectancies, task values, and perceived costs in undergraduate biology achievement. *Learning and Individual Differences*, *72*, 26–38. https://doi.org/10.1016/j.lindif.2019.04.001

Perez, T., Wormington, S. V., Barger, M. M., Schwartz-Bloom, R. D., Lee, Y., & Linnenbrink-Garcia, L. (2019). Science expectancy, value, and cost profiles and their proximal and distal relations to undergraduate science, technology, engineering, and math persistence. *Science Education*, *103*(2), 264–286. https://doi.org/10.1002/sce.21490

Perinelli, E., Pisanu, F., Checchi, D., Scalas, L. F., & Fraccaroli, F. (2022). Academic self-concept change in junior high school students and relationships with academic achievement. *Contemporary Educational Psychology*, *69*, 102071. https://doi.org/10.1016/j.cedpsych.2022.102071

Peter, C. (2005). Learning—Whose Responsibility Is It?: *Nurse Educator*, *30*(4), 159–165. https://doi.org/10.1097/00006223-200507000-00008

Pfeifer, T. A., Kranz, P. L., & Scoggin, A. E. (2008). Perceived stress in occupational therapy students: Perceived stress in occupational therapy students. *Occupational Therapy International*, *15*(4), 221–231. https://doi.org/10.1002/oti.256

Pinxten, M., Marsh, H. W., Fraine, B. D., Noortgate, W. V. D., & Damme, J. V. (2014). Enjoying mathematics or feeling competent in mathematics? Reciprocal effects on mathematics achievement and perceived math effort expenditure. *British Journal of Educational Psychology*, *84*(1), 152–174. https://doi.org/10.1111/bjep.12028

Poleshuck, L., Eckhardt, S., Peck, S., Salce, C., & Valenti, S. (2020). Perceived Stress in Undergraduate OT Students. *AJOT: American Journal of Occupational Therapy*, *74*(S1), NA-NA. https://doi.org/10.5014/ajot.2020.74S1-PO8022

Potolsky, A., Cohen, J., & Saylor, C. (2003). Academic performance of nursing students: Do prerequisite grades and tutoring make a difference? *Nursing Education Perspectives*, *24*(5), 246–250.

Priess-Groben, H. A., & Hyde, J. S. (2017). Implicit Theories, Expectancies, and Values Predict Mathematics Motivation and Behavior across High School and College. *Journal of Youth and Adolescence*, *46*(6), 1318–1332. https://doi.org/10.1007/s10964-016-0579-y

Purcell, K., Elias, P., Ellison, R., Adam, D., & Livanos, I. (2008). *Applying for Higher Education – the diversity of career choices, plans and expectations*. 202.

Putnick, D. L., & Bornstein, M. H. (2016). Measurement Invariance Conventions and Reporting: The State of the Art and Future Directions for Psychological Research. *Developmental Review : DR*, *41*, 71–90. https://doi.org/10.1016/j.dr.2016.06.004

Rach, S., & Heinze, A. (2017). The Transition from School to University in Mathematics: Which Influence Do School-Related Variables Have? *International Journal of Science and Mathematics Education*, *15*(7), 1343–1363. https://doi.org/10.1007/s10763-016-9744-8

Ramsburg, L. (2007). Strive for success: A successful retention program for Associate of Science in Nursing students. *Teaching and Learning in Nursing*, *2*(1), 12–16. https://doi.org/10.1016/j.teln.2006.10.005

Reeve, K. L., Shumaker, C. J., Yearwood, E. L., Crowell, N. A., & Riley, J. B. (2013). Perceived stress and social support in undergraduate nursing students' educational experiences. *Nurse Education Today*, *33*(4), 419–424. https://doi.org/10.1016/j.nedt.2012.11.009

Rhemtulla, M., Brosseau-Liard, P. É., & Savalei, V. (2012). When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. *Psychological Methods*, *17*(3), 354–373. https://doi.org/10.1037/a0029315

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin*, *138*(2), 353–387. https://doi.org/10.1037/a0026838

Rieger, S., Göllner, R., Spengler, M., Trautwein, U., Nagengast, B., & Roberts, B. W. (2022). The persistence of students' academic effort: The unique and combined effects of conscientiousness and individual interest. *Learning and Instruction*, *80*, 101613. https://doi.org/10.1016/j.learninstruc.2022.101613

Robbins, S. B., Lauver, K., Le, H., Davis, D., Langley, R., & Carlstrom, A. (2004). Do Psychosocial and Study Skill Factors Predict College Outcomes? A Meta-Analysis. *Psychological Bulletin*, *130*(2), 261–288. https://doi.org/10.1037/0033-2909.130.2.261

Robinson, K. A., Lee, Y., Bovee, E. A., Perez, T., Walton, S. P., Briedis, D., & Linnenbrink-Garcia, L. (2018). Motivation in transition: Development and roles of expectancy, task values, and costs in early college engineering. *Journal of Educational Psychology*. https://doi.org/10.1037/edu0000331

Robinson, K. A., Perez, T., Nuttall, A. K., Roseth, C. J., & Linnenbrink-Garcia, L. (2018). From science student to scientist: Predictors and outcomes of heterogeneous science identity trajectories in college. *Developmental Psychology*, *54*(10), 1977–1992. https://doi.org/10.1037/dev0000567

Rochford, C., Connolly, M., & Drennan, J. (2009). Paid part-time employment and academic performance of undergraduate nursing students. *Nurse Education Today*, *29*(6), 601–606. https://doi.org/10.1016/j.nedt.2009.01.004

Rosenzweig, E. Q., Wigfield, A., & Eccles, J. S. (2022). Beyond utility value interventions: The why, when, and how for next steps in expectancy-value intervention research. *Educational Psychologist*, *57*(1), 11–30. https://doi.org/10.1080/00461520.2021.1984242

Rosenzweig, E. Q., Wigfield, A., & Hulleman, C. S. (2020). More useful or not so bad? Examining the effects of utility value and cost reduction interventions in college physics. *Journal of Educational Psychology*, *112*(1), 166–182. https://doi.org/10.1037/edu0000370

Rushworth, L., & Happell, B. (2000). ‘Psychiatric nursing was great, but I want to be a “real” nurse’: Is psychiatric nursing a realistic choice for nursing students? *Australian and New Zealand Journal of Mental Health Nursing*, *9*(3), 128–137. https://doi.org/10.1046/j.1440-0979.2000.00174.x

Rutkowski, L., & Svetina, D. (2014). Assessing the Hypothesis of Measurement Invariance in the Context of Large-Scale International Surveys. *Educational and Psychological Measurement*, *74*, 31–57. https://doi.org/10.1177/0013164413498257

Satorra, A., & Bentler, P. (2001). A SCALED DIFFERENCE CHI-SQUARE ’lEST STATISTIC FOR MOMENT STRUCTURE ANALYSIS. *Psychometrika*, *66*(4), 507–514.

Schoor, C. (2016). Utility of reading—Predictor of reading achievement? *Learning and Individual Differences*, *45*, 151–158. https://doi.org/10.1016/j.lindif.2015.11.024

Seymour, E. (1997). *Talking about leaving: Why undergraduates leave the sciences.* Westview Press. http://www-personal.umich.edu/~glarose/dept/teaching/resources/talkingAboutLeavingSeymourHewittOverview.pdf

Seymour, E., & Hunter, A.-B. (Eds.). (2019). *Talking about Leaving Revisited: Persistence, Relocation, and Loss in Undergraduate STEM Education*. Springer International Publishing. https://doi.org/10.1007/978-3-030-25304-2

Shin, D. D., Lee, M., Ha, J. E., Park, J. H., Ahn, H. S., Son, E., Chung, Y., & Bong, M. (2019). Science for all: Boosting the science motivation of elementary school students with utility value intervention. *Learning and Instruction*, *60*, 104–116. https://doi.org/10.1016/j.learninstruc.2018.12.003

Simpkins, S. D., Davis-Kean, P. E., & Eccles, J. S. (2006). *Math and Science Motivation: A Longitudinal Examination of the Links Between Choices and Beliefs*. *42*(1), 70–83.

Simpkins, S. D., Fredricks, J. A., & Eccles, J. S. (2012). Charting the Eccles’ expectancy-value model from mothers’ beliefs in childhood to youths’ activities in adolescence. *Developmental Psychology*, *48*(4), 1019–1032. https://doi.org/10.1037/a0027468

Sopper, D. (2023). *Free A-priori Sample Size Calculator for Structural Equation Models—Free Statistics Calculators*. https://www.danielsoper.com/statcalc/calculator.aspx?id=89

St Omer, S. M., Akungu, O. A., & Chen, S. (2022). Examining the relation among cost, academic emotion, and achievement in mathematics. *Current Psychology*. https://doi.org/10.1007/s12144-022-02839-z

Steiger, J. H. (1998). A note on multiple sample extensions of the RMSEA fit index. *Structural Equation Modeling: A Multidisciplinary Journal*, *5*(4), 411–419. https://doi.org/10.1080/10705519809540115

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics* (5th ed.). Pearson Allyn & Bacon.

Tang, Z., Li, X., Zhang, Y., Li, X., Zhang, X., Hu, M., & Wang, J. (2021). Psychometric analysis of a Chinese version of the Sleep Hygiene Index in nursing students in China: A cross-sectional study. *Sleep Medicine*, *81*, 253–260. https://doi.org/10.1016/j.sleep.2021.02.050

ten Hoeve, Y., Castelein, S., Jansen, G., & Roodbol, P. (2017). Dreams and disappointments regarding nursing: Student nurses' reasons for attrition and retention. A qualitative study design. *Nurse Education Today*, *54*, 28–36. https://doi.org/10.1016/j.nedt.2017.04.013

The future of nursing: Leading change, advancing health. (2011). National Academies Press.

The NCES Fast Facts Tool provides quick answers to many education questions. (n.d.). National Center for Education Statistics. Retrieved February 14, 2022, from https://nces.ed.gov/fastfacts/display.asp?id=900

Tomkin, J. H., & West, M. (2022). STEM courses are harder: Evaluating inter-course grading disparities with a calibrated GPA model. *International Journal of STEM Education*, *9*(1), 27. https://doi.org/10.1186/s40594-022-00343-1

Trautwein, U., Marsh, H. W., Nagengast, B., Lüdtke, O., Nagy, G., & Jonkmann, K. (2012). Probing for the multiplicative term in modern expectancy–value theory: A latent interaction modeling study. *Journal of Educational Psychology*, *104*(3), 763–777. https://doi.org/10.1037/a0027470

Updegraff, K. A., Eccles, J. S., Barber, B. L., & O'brien, K. M. (1996). Course enrollment as self-regulatory behavior: Who takes optional high school math courses? *Learning and Individual Differences*, *8*(3), 239–259. https://doi.org/10.1016/S1041-6080(96)90016-3

Usami, S. (2021). On the Differences between General Cross-Lagged Panel Model and Random-Intercept Cross-Lagged Panel Model: Interpretation of Cross-Lagged Parameters and Model Choice. *Structural Equation Modeling: A Multidisciplinary Journal*, *28*(3), 331–344. https://doi.org/10.1080/10705511.2020.1821690

Uyehara, J., Magnussen, L., Itano, J., & Zhang, S. (2007). Facilitating Program and NCLEX-RN Success in a Generic BSN Program. *Nursing Forum*, *42*(1), 31–38. https://doi.org/10.1111/j.1744-6198.2007.00063.x

Viljaranta, J., Tolvanen, A., Aunola, K., & Nurmi, J.-E. (2014). The Developmental Dynamics between Interest, Self-concept of Ability, and Academic Performance. *Scandinavian Journal of Educational Research*, *58*(6), 734–756. https://doi.org/10.1080/00313831.2014.904419

Volkert, D., Candela, L., & Bernacki, M. (2018). Student motivation, stressors, and intent to leave nursing doctoral study: A national study using path analysis. *Nurse Education Today*, *61*, 210–215. https://doi.org/10.1016/j.nedt.2017.11.033

Wang, Y., & Lewis, S. E. (2022). Efficacy and Insights Gained from a Utility Value Intervention with Inorganic Chemistry Students. *Journal of Chemical Education*, acs.jchemed.2c00045. https://doi.org/10.1021/acs.jchemed.2c00045

Watt, H. M., Shapka, J. D., Morris, Z. A., Durik, A. M., Keating, D. P., & Eccles, J. S. (2012). Gendered motivational processes affecting high school mathematics participation, educational aspirations, and career plans: A comparison of samples from Australia, Canada, and the United States. *Developmental Psychology*, *48*(6), 1594.

Weidinger, A. F., Spinath, B., & Steinmayr, R. (2020). The value of valuing math: Longitudinal links between students' intrinsic, attainment, and utility values and grades in math. *Motivation Science*, *6*(4), 413–422. https://doi.org/10.1037/mot0000179

Wentzel, K. R., & Wigfield, A. (Eds.). (2009). *Handbook of motivation at school*. Routledge.

Westland, C. (2010). Lower bounds on sample size in structural equation modeling. *Electronic Commerce Research and Applications*, *9*(6), 476–487. https://doi.org/10.1016/j.elerap.2010.07.003

Widaman, K. F., Ferrer, E., & Conger, R. D. (2010). Factorial Invariance Within Longitudinal Structural Equation Models: Measuring the Same Construct Across Time. *Child Development Perspectives*, *4*(1), 10–18. https://doi.org/10.1111/j.1750-8606.2009.00110.x

Wigfield, A., & Cambria, J. (2010). Expectancy-value theory: Retrospective and prospective. In *The decade ahead: Theoretical perspectives on motivation and achievement* (pp. 35–70). Emerald Group Publishing Limited.

Wigfield, A., & Eccles, J. S. (2000). Expectancy–Value Theory of Achievement Motivation. *Contemporary Educational Psychology*, *25*(1), 68–81. https://doi.org/10.1006/ceps.1999.1015

Wigfield, A., & Eccles, J. S. (2020). Chapter Five - 35 years of research on students' subjective task values and motivation: A look back and a look forward. In A. J. Elliot (Ed.), *Advances in Motivation Science* (Vol. 7, pp. 161–198). Elsevier. https://doi.org/10.1016/bs.adms.2019.05.002

Wilkes, L., Cowin, L., & Johnson, M. (2015). The reasons students choose to undertake a nursing degree. *Collegian*, *22*(3), 259–265. https://doi.org/10.1016/j.colegn.2014.01.003

Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample Size Requirements for Structural Equation Models: An Evaluation of Power, Bias, and Solution Propriety. *Educational and Psychological Measurement*, *73*(6), 913–934. https://doi.org/10.1177/0013164413495237

Wolf, L., Stidham, A. W., & Ross, R. (2015). Predictors of Stress and Coping Strategies of US Accelerated vs. Generic Baccalaureate Nursing Students: An Embedded Mixed Methods Study. *Nurse Education Today*, *35*(1), 201–205. https://doi.org/10.1016/j.nedt.2014.07.005

Wolkowitz, A. A., & Kelley, J. A. (2010). Academic Predictors of Success in a Nursing Program. *Journal of Nursing Education*, *49*(9), 498–503. https://doi.org/10.3928/01484834-20100524-09

Yeager, D. S., Henderson, M. D., Paunesku, D., Walton, G. M., D'Mello, S., Spitzer, B. J., & Duckworth, A. L. (2014). Boring but important: A self-transcendent purpose for learning fosters academic self-regulation. *Journal of Personality and Social Psychology*, *107*(4), 559–580. https://doi.org/10.1037/a0037637

Yuan, K.-H., & Bentler, P. M. (2000). Three Likelihood-Based Methods for Mean and Covariance Structure Analysis with Nonnormal Missing Data. *Sociological Methodology*, *30*, 165–200.

Zyphur, M. J., Allison, P. D., Tay, L., Voelkle, M. C., Preacher, K. J., Zhang, Z., Hamaker, E. L., Shamsollahi, A., Pierides, D. C., Koval, P., & Diener, E. (2020). From Data to Causes I: Building A General Cross-Lagged Panel Model (GCLM). *Organizational Research Methods*, *23*(4), 651–687. https://doi.org/10.1177/1094428119847278

Zyphur, M. J., Voelkle, M. C., Tay, L., Allison, P. D., Preacher, K. J., Zhang, Z., Hamaker, E. L., Shamsollahi, A., Pierides, D. C., Koval, P., & Diener, E. (2020). From Data to Causes II: Comparing Approaches to Panel Data Analysis. *Organizational Research Methods*, *23*(4), 688–716. https://doi.org/10.1177/1094428119847280

CURRICULUM VITAE

KYLE MEFFERD, MS, PhD(c)
KMefferd@touro.edu

EDUCATION

Ph.D. University of Nevada, Las Vegas – Las Vegas, NV May 2023
Educational Psychology

M.S. University of Nevada, Las Vegas – Las Vegas, NV May 2015
Biomechanical & Kinesiological Sciences

B.S. University of Nevada, Las Vegas – Las Vegas, NV May 2012
Kinesiological Sciences

PROFESSIONAL EXPERIENCE

Assistant Director Mar 2021 - Present
Touro University Nevada: Office of Academic Services and Institutional Support

Senior Learning Specialist Nov 2014 – Mar 2021
Touro University Nevada: Office of Academic Services and Institutional Support

Graduate Assistant - Biomechanics Aug 2012 – May 2014
University of Nevada, Las Vegas

Undergraduate Biomechanics Lab Instructor Aug 2013 – May 2014
University of Nevada, Las Vegas

Sports Injury Research Center, Biomechanics Liaison Aug 2011 - May 2014
University of Nevada, Las Vegas

PUBLICATIONS

Mefferd, K.C., Bernacki, M.L. Tracing Undergraduate Science Learners' Digital Cognitive Strategy Use and Relation to Performance. *J Sci Educ Technol* (2023). https://doi.org/10.1007/s10956-022-10018-9

R. Part, H.N. Perera, **K.C. Mefferd,** C. Miller (2023). Decomposing Trait and State Variability in General and Specific Subjective Task Value Beliefs. *Contemporary Educational Psychology*, 72, doi: 10.1016/j.cedpsych.2022.102112

Masumoto, K., **Mefferd, K. C**., Iyo, R., & Mercer, J. A. (2018). Muscle activity and physiological responses during running in water and on dry land at submaximal and maximal efforts. *Journal of Strength and Conditioning Research*, 32(7), 1960-1967. DOI: 10.1519/JSC.0000000000002107

Dufek, J., Ryan-Wenger, N., Eggleston, J. E., & **Mefferd, K.** (2018). A Novel Approach to Assess Head Injury Severity in Pediatric Patient Falls. *Journal of Pediatric Health Care*, 32(2), e59-e66. DOI: doi.org/10.1016/j.pedhc.2017.09.012

Masumoto, K., **Mefferd, K. C.**, Iyo, R., & Mercer, J. A. (2015). Biomechanical and Physiological Responses during Running in Water and on Dry Land at Maximal Effort. *Medicine and Science in Sports and Exercise*, 47(5S):711. DOI: 10.1249/01.mss.0000478664.80070.33

Mefferd, Kyle, "Comparison of Muscle Latencies for Diabetic Neuropathy Patients Versus Healthy Controls During a Perturbed Balance Task" (2015). *UNLV Theses, Dissertations, Professional Papers, and Capstones.* 2387. http://dx.doi.org/10.34917/7645967

VERIFIED CERTIFICATES

Bayesian for Beginners QuantFish	Mar 2023
Sample Size Planning in Mplus QuantFish	Dec 2022
Longitudinal SEM in Mplus: Latent Growth and Cross-Lagged Models InStats	June 2022
Effective Online Teaching Practices Association Of College and University Educators (ACUE):	SU 2021 – SP 2022
Comprehensive Systematic Review Training Program Joanna Briggs Institute	June 2021
Data Science: R Basics HarvardX – EdX	Aug 2019
Adobe Audition CC Audio Production Course Basics to Expert Mike Russel & UDemy	Apr 2020
Data Science: Visualization HarvardX – EdX	June 2020
SQL for Data Science IBM - EdX	Aug 2020
Data Science: Probability HarvardX – EdX	Dec 2020

SKILLS

Languages/Software: SPSS, Mplus, R, Microsoft Excel

Statistical Analysis and Modeling: Data analysis including longitudinal (e.g., growth modeling, multilevel modeling, dynamic structural equation modeling, cross-lagged panel models) and cross-sectional designs (e.g., parametric, nonparametric, categorial)

Data Visualization: Adobe Illustrator, Inkscape, Tableu, R, Microsoft Excel

Graphic Design: Adobe Photoshop, Adobe After Effects, Adobe Audition, Adobe Premiere Pro

RESEARCH EXPERIENCE

Graduate Research Assistant (Educational Psychology) — Aug 2016 - Present
University of Nevada, Las Vegas

Graduate Research Assistant (Biomechanics) — Aug 2012 – May 2014
University of Nevada, Las Vegas

Undergraduate Research Assistant (Biomechanics) — Aug 2011 – May 2012
University of Nevada, Las Vegas

CONFERENCE PRESENTATIONS, Refereed

Presentation Talk, Trajectories of STEM Students' Motivation and Self-Regulatory Behaviors as Predictors of Academic Outcomes
Nevada State College Faculty Symposium — Jan 2023
K. Mefferd, C. Mefferd

Poster, Decomposing Trait and State Variability in Subjective Task Value Data
2021 APA Annual Convention — May 2021
R. Part, **K.C. Mefferd**, H.N. Perera, C. Miller

Poster, Using Virtual Reality and 3D Technologies to Expand the Health Professions Pipeline in Southern Nevada
Electronic Resources & Libraries Annual Conference — Mar 2020
F. Mazzia, M. De Armond, **K. Mefferd**

Poster, Tracing Science Learners' Digital Distribution of Self-Assessment Quizzes, Lecture Access, and Effects on Achievement
2019 American Educational Research Association Annual Meeting — Apr 2019
K.C. Mefferd, M.L. Bernacki, & W. Hong

Round Table Presentation, Tracing Undergraduate Science Learners' Digital Cognitive Strategy Use and Effects on Achievement

2018 American Educational Research Association Annual Meeting — Apr 2018
K.C. Mefferd, & M.L. Bernacki

Poster, Biomechanical Analysis of Infant Fall Impacts Using HIC to Predict Injury Severity

Computer Methods in Biomechanics & Biomedical Engineering — Apr 2013
Mefferd, K.C., Ryan-Wenger, N.A. & Dufek, J.S.

Poster, Quantify Head Injury Severity Following Pediatric Patient Falls

Southwest American College of Sports Medicine — Nov 2012
J.S. Dufek, N.A. Ryan-Wenger, & **K.C. Mefferd**

CONFERENCE PRESENTATIONS, Non - Refereed

Poster, Biomechanical Analysis of Infant Fall Impacts Using HIC to Predict Injury Severity

University of Nevada, Las Vegas — Nov 2012
NORAXON Symposium
Mefferd, K.C., Ryan-Wenger, N.A., & Dufek, J.S.

Poster, Biomechanical Analysis of Infant Fall Impacts Using HIC to Predict Injury Severity

University of Nevada, Las Vegas — Nov 2012
STEM Summit
Mefferd, K.C., Ryan-Wenger, N.A., & Dufek, J.S.

Poster, Quantifying Head Injury Severity Following Pediatric Patient Falls

University of Nevada, Las Vegas — Nov 2012
STEM Summit
Mefferd, K.C., Ryan-Wenger, N.A. & Dufek, J.S.

Poster, Biomechanical Analysis of Infant Fall Impacts and Modern Approaches to Predict Future Injury

University of Nevada, Las Vegas — Aug 2012
INBRE Symposium
Mefferd, K.C., Ryan-Wenger, N.A. & Dufek, J.S.

PROFESSIONAL TRAININGS

Association on Higher Education and Disability — Feb 2016

Phoenix, AZ
2016 Management & TRiO Institutes

Clery Training — Feb 2016

safeTALK Suicide Awareness Training — Oct 2015

PROFESSIONAL COMMITTEES

Professional Development Committee (Chair)	Mar 2020 – Present
Social Committee (Co-Chair)	Oct 2017 – Mar 2020
Drug and Alcohol Committee	Jan 2016 – Present
Scholarship Committee: TUN General Scholarship Awarding	Apr 2016 – July 2017
Professional Development Committee (Chair)	Aug 2015 – Oct 2017

AWARDS

Nominated: UNLV Graduate College Outstanding Dissertation Award — Mar 2023

Using Virtual Reality & 3D Technologies to Expand the Health Professions Pipeline in Southern Nevada ($10,000)
National Network of Libraries of Medicine Express Outreach Award — Apr 2019 – Apr 2020

UNLV Graduate Access Childcare Scholarship ($3500) — Aug 2021

HONORS AND SCHOLARSHIPS

Nevada IDeA Network of Biomedical Research Excellence Scholarship	Summer 2012
Nevada Millennium Scholarship	2007-2012

PROFESSIONAL AFFILIATIONS

Cognitive Neuroscience Society	Jan 2019 – Present
National Association of Student Personnel Administrators	Jan 2015 – Present
American Psychological Association	May 2017 – Present
American Educational Research Association	May 2017 – Present
Association on Higher Education and Disability	Jan 2015 – Present
American College of Sports Medicine	Jan 2012 – Present
National Strength and Conditioning Association	July 2014 – Present
Knights of Columbus	July 2010 – Present