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EXPLORING ASSOCIATIONS BETWEEN ALCOHOL USE, STRESS, AND STUDENTS' ATTITUDE TOWARDS STATISTICS

Zachary J. Kunicki
University of Rhode Island, zachary_kunicki@uri.edu

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ZACHARY J. KUNICKI

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ZACHARY J. KUNICKI

APPROVED:

Thesis Committee:

Major Professor Prabhani Kuruppumullage Don

Jing Wu

Lisa L. Harlow

Ashley L. Buchanan

Nasser H. Zawia

DEAN OF THE GRADUATE SCHOOL

UNIVERSITY OF RHODE ISLAND

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ABSTRACT

Statistics, and other quantitative courses, are an essential part of general education and training in many fields. However, these courses routinely lead to stress and anxiety in many students. Students often turn to substance use to manage feelings of stress and anxiety, which has major public health concerns due to the short-term and long-term risks of substance use. This thesis explored the relationship between quantitative anxiety, general forms of anxiety, and alcohol use during the semester in which students were enrolled in an introductory quantitative methods course. Model training using the Spring 2018 data ($n = 119$) suggested a final model of general anxiety, quantitative anxiety, time, an anxiety by time interaction, and random intercepts, where quantitative anxiety and general anxiety were both positive predictors of alcohol use. The R^2 value for the fixed effects was 0.12, and for the fixed and random effects was 0.65. The model was tested on a second independent sample (from Fall 2017, $n = 19$) where the mean squared error was 0.38, suggesting the model performed well in a second sample as the error term was close to zero. Examination of mean trajectory plots of the predicted versus actual values for alcohol use in the Fall 2017 dataset showed the model did well predicting some but not all patterns of change. These findings were further confirmed by fitting a piecewise latent growth curve model to the Spring 2018 dataset, which showed great fit to the data. The results of this study suggest that quantitative anxiety is positive predictor of alcohol use even when taking into account general forms of anxiety. While this study does have several limitations, the results merit further investigation to explore the relationship between quantitative attitudes and substance use. Future studies should aim to replicate the findings of the current study while addressing the limitations, and assess if quantitative attitudes are related to the use of other substances common on college campuses.

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Background and Motivation

1.1 Substance Use on College Campuses

Substance use, to put it mildly, is ubiquitous on college campuses. While students may experiment with multiple difference substances, recent research suggests that alcohol, marijuana, tobacco, and non-prescription amphetamines are among the most commonly used substances on college campuses [1, 2, 3, 4, 5, 6, 7, 8]. According to the Monitoring the Future study, which is a national survey on substance use, a majority of college students (66.7%) reported drinking enough alcohol to get drunk at least once in their lifetime, and 40.8% reported being drunk in the past 30 days [8]. Additionally, 32.4% stated they had an incidence of binge drinking (defined as 4+ drinks in an hour for women or 5+ drinks in an hour for men) in the past 30 days [8]. Concerning marijuana, a study of 11 different universities throughout the four regions of the United States (n = 8,141) found that 53.3% of students had used marijuana at least once in their life, and 26.2% had in the last month [1]. Tobacco use has dropped in recent years, but 8.9% of college students reported smoking cigarettes in the past 30 days, and 6.9% reported the use of an electronic cigarette (e-cigarettes) [8]. Non-prescription amphetamine use is on the rise, with the Monitoring the Future study reporting 3.8% of college students reporting use [8]. However, another study of 9 different universities ranging in size and location within the United States (n = 6962) found 11.2% reported using non-prescription amphetamines within the last six months [9]. There is also research to suggest that obtaining non-prescription amphetamines is easy on college campuses, and many students know someone who misuses these medications [10, 11]. Given that substance use is related to a myriad of health problems, both short-term (e.g. risky sexual behavior) and long-term (e.g. cirrhosis, cancer), these

high rates of use among college students are problematic and of high public health concern [12, 13, 14, 15].

1.2 Reasons College Students Use Substances

Since the substance use rates are high on college campuses, research has explored the reasons students engage in substance use [16]. While there are numerous reasons for substance use that are beyond the scope of this thesis, one of the common reasons students engage in substance use is to cope with feelings of stress and anxiety [2, 3, 4, 17, 18]. In this sense, substance use is a form of self-medication which can provide relief from the unpleasant feelings which accompany stress and anxiety. Research suggests that alcohol, marijuana, and tobacco are three of the top substances used for self-medication [5, 6, 7, 17, 18]. Non-prescription amphetamines, on the other hand, seem to be used because students assume it may help with their academic performance [9]. About 29% of the sample ($n = 6962$) believed the non-prescription amphetamines could improve performance, and other research has shown a link between non-prescription amphetamine use and psychological distress [10, 11, 16]. Arria and colleagues also found that students who believed non-prescription amphetamines could improve academic performance were more likely to engage in non-prescription amphetamine use (Odds Ratio = 2.17), and students who were heavier users of alcohol (Odds Ratio = 1.08) and marijuana (Odds Ratio = 1.01) were also more likely to engage in non-prescription amphetamine use [16].

1.3 Statistics Attitudes and Substance Use

While there is a vast body of literature on reasons students engage in substance use, as stated above one of the main reasons is to cope with feelings of stress and anxiety [2, 3, 4, 17, 18]. This naturally leads one to ask; what is causing all

of this stress and anxiety in college students? There are, of course, numerous reasons which could range anywhere from homesickness [19], workload and exam anxiety [20], and other various forms of interpersonal (e.g. issues with roommates or significant others), intrapersonal (e.g. death of a family member, changes in habits), academic (e.g. poor grades), or environmental (e.g. car trouble, computer crashing) reasons [21].

While it is difficult to explore all of the possible stresses a student may endure, there are certain experiences which a majority of students need to complete, and will cause stress or anxiety in a majority of students. One of these experiences is taking a statistics, or other quantitatively-based course [22, 23, 24, 25, 26, 27, 28]. Research consistently shows that many students find statistics courses to be anxiety or stress provoking, but many students will have to take at least one statistics course during their undergraduate education. A course in statistics is a general education requirement in many universities and training in understanding and conducting statistics is also essential for success in many fields, such as psychology [29] and public health [30]. There are multiple theoretical reasons why students may find statistics classes stressful. It could be because students see statistical skills as fixed, and therefore unable to be improved [31]. It could also be due to previous negative experiences with anything involving math [32], having teachers who viewed math negatively [33], stereotype threat (i.e. performing in a manner consistent with a stereotype based on one's identity) [34, 35], and others [36]. Regardless of the reason for having statistics-specific anxiety, research also suggests that negative attitudes associated with statistics are an issue for course performance since attitudes are of nearly equal importance with quantitative abilities when predicting final course grades [24, 25, 33, 37, 38, 39, 40, 41]. Regardless of the reason why statistics cause stress or anxiety in students, it may well be that

statistics anxiety could be one of the stressors which leads students to engage in substance use. No known study has explored this possible link between statistics attitudes, stress and anxiety, and substance use which is the main focus of this thesis.

1.4 The Current Study

Considering the health risks associated with substance use [12, 13, 14], that many college students turn to substance use to cope with stress [5, 6, 7, 17, 18], and that statistics courses can be stress-inducing in many students [22, 23, 24, 25, 26, 27, 28, 36], it may well be that students with strong negative attitudes towards statistics are at increased risk for substance use. No known study has explored the relationships between statistics attitudes and substance use, so the purpose of the current study is to address this gap in the literature. For the purposes of this thesis, only alcohol use was examined, but data on other commonly used substances on college campuses (e.g. marijuana, cigarettes, e-cigarettes, non-prescription amphetamines) were gathered for future studies based on the results of the current thesis. Thus, the specific aims of this thesis are as follows:

1. Examine if there is a relationship between statistics attitudes and alcohol use throughout the semester (beginning, middle, and end).

2. Examine if a specific growth pattern of alcohol use can be identified over the semester, and if statistics attitudes have a relationship with alcohol use as time-varying covariate.

1.5 Data Collection Procedures

Data were gathered in two stages during the Fall 2017-Spring 2018 academic year. Data collection procedures varied slightly between the Fall 2017 and Spring 2018 semesters. Description of how the data were gathered, demographics of the

samples, and differences in the collection procedures are described below. Institutional Review Board approval was obtained for data collection prior to both the Fall 2017 and Spring 2018 semesters due to the differences in collection procedures.

1.5.1 Data Collection (Fall 2017)

Data were gathered during the Fall 2017 semester from three sections of PSY 200: Quantitative Methods in Psychology. Students were asked to complete measures of statistics attitudes and substance use at three time points throughout the semester. 134 students out of a total of 153 students chose to participants in at least one of the six available surveys, for a participation rate of 87.58%. However, the rate of complete cases, defined as students who completed all six available surveys, was only 19 out of 134 or about 14%. This sample was predominantly female (n = 105, 75.54%) and white (n = 92, 84.40%) with an average age of 21 years (SD = 2.89 years).

Data on statistics attitudes and substances use were gathered separately using two different surveys developed through Google Forms. Students who chose to participate did so on-line, where they first were asked to complete an informed consent before completing the surveys. Data were gathered at three time points over the semester. The first time point was considered the beginning of the semester, and was available for completion during the first three weeks of the semester. The second time point was considered the middle of the semester, and was available for completion during the fifth through seventh weeks of the semester. The third time point was considered the end of the semester, and was available during the final two weeks of the semester and the first week of final exams. Participants were compensated with one extra credit point per survey completed, for a possible total of six extra credit points.

1.5.2 Data Collection (Spring 2018)

Data were gathered in a similar fashion to the Fall 2017 data, but collection was expanded to multiple different statistics courses during Spring 2018. Participants were recruited from three sections of STA 220: Statistics in Modern Society, four sections of STA 308: Introductory Statistics, and three sections of PSY 200: Quantitative Methods in Psychology. Efforts were made to gather data from every introductory statistics course offered on campus, but the instructors of one section of STA 220, one section of PSY 200, and one section of STA 307: Introductory Biostatistics did not participate in the study. Out of the 716 students enrolled in participating sections of STA 220, STA 308, or PSY 200, a total of 456 students participated in at least one of the three time points, which was a participation rate of 64%. The rate of complete cases was 119 out of 456, or 26%. This sample was predominantly female (n = 323, 70.83%) and white (n = 333, 73.03%) with an average age of 20 years (SD = 4.80 years).

When gathering data in Spring 2018, the statistics attitudes and substance use measures were merged into one survey created with Qualtrics. Participation was again done on-line over three time points: beginning, middle, and end of semester. Participants were compensated with one extra credit point per survey completed, for a possible total of three extra credit points at the discretion of the individual course instructors (i.e. on their final grade, on an exam, etc.). All of the measures from the preliminary data were gathered again, but several additional measures and demographic questions were added as part of the data collection for the Spring 2018 sample.

1.6 Standardized Instruments Used

Measures of quantitative attitudes, stress, anxiety, substance use, and demographics were gathered from the students. The names and brief descriptions of the

measures used in this thesis are below. Internal consistency estimates for these measures are calculated as part of the results and provided in section 3.3 of this thesis.

1.6.1 Quantitative Anxiety

Quantitative anxiety was a 4 item measure on a 1 to 5 point Likert scale where higher scores indicated more anxiety. The measure assessed feelings of discomfort towards situations involving quantitative methods. A sample item is "Reading a math or statistics formula." Previous studies suggest this measure meets acceptable internal consistency reliability criteria in a college student sample [37]. Quantitative anxiety was reduced to a single overall factor score using factor analysis for the main analyses [42]. Please refer to Appendix A.1 for the full measure.

1.6.2 Perceived Stress Scale

The Perceived Stress Scale (PSS) was a 14 item measure on a 5 point Likert scale ranging from 0 (never) to 4 (very often). The PSS is designed to measure if an individual views his or her life as stressful. A sample item is "In the last month, how often have you felt that you were on top of things?" Previous research suggests that the PSS has evidence for internal consistency reliability and convergent validity with the impact of life events measure in a college student sample [43]. PSS was reduced to a single overall factor score using factor analysis for the main analyses [42]. Please refer to Appendix A.2 for the full measure.

1.6.3 Depression Anxiety and Stress Scales (DASS-21)

The DASS-21 is a 21 item measure on a 4 point Likert scale ranging from 0 (Did Not Apply to me At All) to 3 (Applied to me Very Much) [44]. The DASS-21 has three subscales of seven items each, and the three different subscales are for depression, anxiety, and stress. A sample item from the anxiety subscale is "I

felt scared without any good reason." Previous research suggests that the DASS-21 subscales have good internal consistency and convergent validity with similar measures [44, 45]. The DASS-21 was reduced to three separate factors for the three subscales for analysis. Please refer to Appendix A.3 for the full measure.

1.6.4 Substance Use

Following the procedures of the Monitoring the Future study, the substance use measures asks if a student has ever used a substance, and the number of days the student has used the substance in the past month [8]. The substances asked about include: alcohol, binge drinking, cigarettes, e-cigarettes, other tobacco products, marijuana, inhalants, hallucinogens, cocaine, non-prescription amphetamine use (e.g. Adderall, Ritalin), methamphetamine, non-prescription pain medication (e.g. Vicodin, Percocet), heroin, sedatives, tranquilizers, and steroids. An additional question of smoking more than 100 cigarettes (yes or no) is also included to assess long-term smoking. Please refer to Appendix A.4 for the full measure.

1.6.5 Student Attitudes Towards Statistics (SATS-36)

The SATS-36 was a 36 item measure, assessed on a 7 point Likert scale, where higher scores indicated more favorable attitudes. The SATS-36 contains four subscales which are: affect, cognitive competence, value, and difficulty. A sample item is "Statistics is a complicated subject." Previous research suggests that the SATS-36 has shown evidence for great internal consistency reliability and convergent validity with the Attitude Towards Statistics measure in a college sample [46]. The SATS-36 was not collected in the Fall 2017 data set, but was gathered as part of the Spring 2018 dataset. The SATS-36 was reduced to a single overall factor for analysis [42]. Please refer to Appendix A.5 for the full measure.

1.6.6 Demographics

The demographics portion of the survey asked students for their gender identity, racial/ethnic identity, if he or she is currently receiving a Pell Grant as a measure of socioeconomic status, age, current relationship status, which statistics course he or she is taking, major, and student status. Student ID numbers were also requested to link the participant's data over time, but new ID numbers were assigned and Student ID numbers destroyed from the dataset before analysis to ensure confidentiality. Please refer Appendix A.6 for all the demographic questions.

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CHAPTER 2

Methods

Throughout this chapter the statistical methods used to assess the relationship between statistics attitudes and alcohol use over time are discussed. Four main methodologies are described. The first is a linear mixed effect model, the second is a latent growth curve model (LGCM), the third is exploratory factor analysis, and the fourth and final is coefficient ω (omega) for internal consistency.

2.1 Linear Mixed Effect Models

Linear mixed effect models are a flexible framework which allow for trends over time to be analyzed via a mean response profile and a covariance structure [1]. An added benefit of linear mixed effect models is the ability to examine both fixed effects and random effects [1]. A fixed effect can be thought of as a population average, denoted by β, or the average amount of change in Y as X changes by one unit. A random effect is any individual differences which distinguishes the trajectory of a single subject from the average trajectory, denoted by b. Thus, the mean trajectory in a linear mixed effect model can be stated as:

$$Y_i = X_i\beta + Z_i b_i + \epsilon_i \tag{1}$$

Where β is a p x 1 vector of the fixed effects and p refers to the number of covariates. b_i is a q x 1 vector of the random effects for every individual i, and q refers to a covariance parameter for the the individual i for the total number of individuals n. X_i is a n_i x p matrix of the covariates, where n refers to the number of participants in the data set. Z_i is a n_i x q matrix, where $q \leq p$. Finally, Y_i is the dependent variable of interest.

Since random effects are being incorporated into the mean trajectory, the covariance structure must also take into account the random effects [1]. Specifically, the covariance structure must take into account both between-subject and within-subject variation. For the between-subject variation, or the fixed effects, it is assumed that the fixed effects follow a multivariate normal distribution with a mean of zero and a covariance structure R_i. R_i is a diagonal matrix equal to $\sigma^2 I_{ni}$ where I_{ni} is a n_i x n_i identity matrix and σ^2 is the matrix of error variances. For within-subject variation, or the random effects, it is assumed that the random effects b_i follow a multivariate normal distribution with a mean of 0 and a covariance matrix G. The covariance matrix G has three components: the variance of the random intercepts (b_{1i}), the variance of the random slopes (b_{2i}) and the covariance between the random intercepts and slopes (b_{1i}, b_{2i}) making it a parsimonious structure with only three components. When putting the fixed and random effects covariance structures together, the covariance structure for a mixed effects model can be stated as:

$$Cov(Y_i) = Z_i G Z_i' + \sigma^2 I_{ni} \tag{2}$$

With the covariance structure taking into account both the within and between subject variation, it is then possible to identify the two different forms of variance and determine through model comparison if a random intercepts, random slopes, or a fully random (intercepts and slopes) model best represents the data for further interpretation [1].

2.1.1 Random Intercepts, Random Slopes, and Fully Random Models

When building a linear mixed effects model researchers can choose to have models with random intercepts, random slopes, or both random intercepts and random slopes (i.e. fully random) [1]. The following model is considered a random

intercepts model, where j refers to the number of time points running from 1 to j:

$$Y_{ij} = X'_{ij}\beta + b_i + \epsilon_{ij} \tag{3}$$

In vector notation as shown above, it is difficult to see how b_i is expressed as the random intercepts, but when broken down further it is easier to see:

$$Y_{ij} = (\beta_1 + b_i) + \beta_2 X_{ij2} + ... + \beta_p X_{ijp} + \epsilon_{ij} \tag{4}$$

As shown above, β_1 is the fixed intercept, or the average intercept term for the entire sample [1]. b_i are the random intercepts for individuals i, which represent the individual deviations away from the average intercept for each subject. Extending this idea to random slopes or random intercepts and slopes is relatively simple. Consider the following model where t refers to the covariate of time:

$$Y_{ij} = (\beta_1 + b_{1i}) + (\beta_2 t_{ij} + b_{2i} t_{ij}) + \beta_3 X_{ij3} + ... + \beta_p X_{ijp} + \epsilon_{ij} \tag{5}$$

In this model, $\beta_1 + b_{1i}$ refers to the fixed intercept (β_1) and the individual deviations b_{1i}, or random effects, away from the intercept [1]. $\beta_2 t_{ij} + b_{2i} t_{ij}$ refers to the average regression estimate over time (β_2) and the random effects away from the average slope, b_{2i}. β_3 through β_p are the other covariates besides time and covariates without random effects included in the model. Conceptually, the same idea is happening where the random effects show individual differences away from the fixed, or average, effect. The only change is the deviation away from both the intercept and the slope, instead of only the intercept.

When building a linear mixed effects model, the researcher needs to choose the covariates of interests, determine if a random intercept, random slopes, or fully random model is appropriate, and also specify a covariance structure [1]. Choosing covariates of interest should be done both theoretically (i.e. based on substantive

knowledge) and statistically, following the same procedures a researcher would use in multiple linear regression or other cross-sectional data analysis. Determining if a random intercept, random slopes, or fully random model is most appropriate can be done through likelihood ratio tests and comparison with model fit criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). If there is no significant difference between a "fully random" (i.e. both random intercepts and random slopes) model and a model with solely random intercepts or random slopes, than the more parsimonious model would be preferred for analysis. When using likelihood ratio tests, the researcher must make sure to use maximum likelihood estimation instead of restricted maximum likelihood estimation (REML). REML estimates are often used to estimate linear mixed effects models, but REML results are not directly comparable using likelihood ratio tests or AIC and BIC values [1].

2.1.2 Assumptions

Additional assumptions beyond the distribution of the fixed and random effects as previously stated include the observations for different participants are independent, and any missing data are considered missing at random or missing completely at random [1].

2.2 Latent Growth Curve Modeling (LGCM)

An alternate approach to modeling change over time is using a latent growth curve model (LGCM). LGCMs are a type of a latent variable model, but the latent variables are not shared response profiles on a questionnaire as latent variables are usually conceptualized, but instead are growth terms [2, 3, 4, 5, 6]. The researcher can specify how many growth terms exist, but usually both a latent intercept and latent slope are specified. It is possible to specify only a latent intercept, or to

specify more than one slope to look at non-linear effects (e.g. piecewise, quadratic) [2].

2.2.1 Latent Growth Curve Modeling Equations

The overall latent growth curve model is expressed as:

$$Y = \tau_y + \Lambda_y \eta + \epsilon \tag{6}$$

where Y is a p x 1 vector, and is predicted by a linear combination of the intercept, τ_y (p x 1) plus the Λ_y design matrix and latent variables, η, and error, ϵ. p is a vector of all scores for an individual i at time t. η refers to the (m x 1) vector of latent variables, and the number of latent variables is determined by the number of growth terms specified by the researcher in the Λ_y design matrix. Finally, the error (also called disturbances) terms ϵ are also p x 1. Λ_y (p x m) are interpreted as regression coefficients, but are actually factor loadings. Since the research is identifying an intercept as one of the latent growth terms, the intercept, τ_y, is often fixed at 0 to identify the model [2]. Thus, the model often looks like the following for every individual i at time t when $m = 2$:

$$y_{it} = \lambda_{1t}\eta_{1i} + \lambda_{2t}\eta_{2i} + \epsilon_{it} \tag{7}$$

The latent variables η_{1i} and η_{2i} represent the intercept and slope, and are expressed as:

$$\eta_{1i} = \mu_1 + \zeta_{1i} \tag{8}$$

$$\eta_{2i} = \mu_2 + \zeta_{2i} \tag{9}$$

$$\psi = \begin{Bmatrix} \psi_1 & \\ \psi_{12} & \psi_2 \end{Bmatrix} \tag{10}$$

The two latent variables are made up of the average intercept (μ_1) and average slope (μ_2), and the residuals ζ_{1i} and ζ_{2i} which represent individual differences from the means of the intercept and slope, respectively. In other words, μ are the fixed effects, whereas ζ are the random effects. ζ_{1i} and ζ_{2i} refer to the error of the estimated intercept μ_1 and μ_2 respectively, which are assumed to be normally distributed with mean 0 and variance ψ_1 for the intercept and ψ_2 for the slope. Finally, ψ_{12} refers to the covariance between the estimated slope and intercept.

Using these equations, both a covariance and a mean structure can be assessed and analyzed. The mean structure is the expectation of the model, where the means of the observed variables π_y (p x 1) are a function of the intercepts τ_y (p x 1), usually constrained to 0 for model identification as stated above, the design matrix Λ_y (p x m), and mean of the latent variables η (m x 1). The equation follows as:

$$\pi_y = \tau_y + \Lambda_y \eta \tag{11}$$

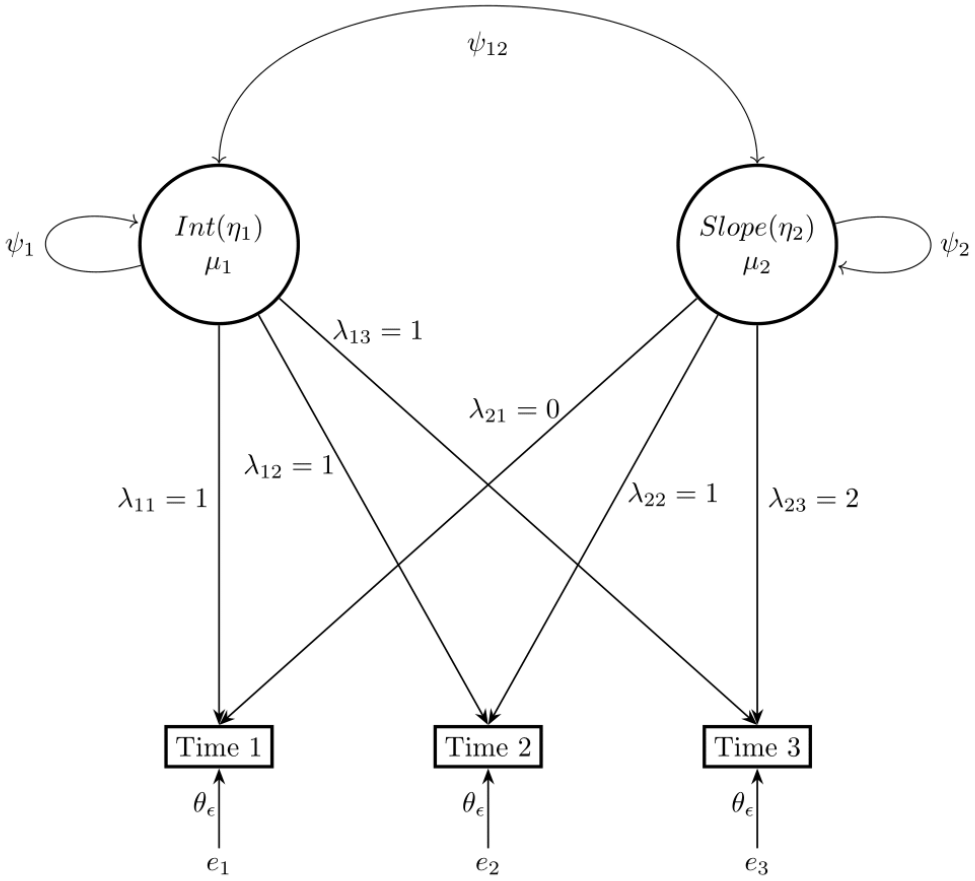
In these equations, the researcher needs to specify the Λ_y matrix to model growth over time the points. Typically, the intercept values are all set to 1 to show the individual intercept is constant over time, and the slope values are then set to test the expected type of growth. For example, if a research had three time points and was assuming a linear growth pattern, the Λ_y matrix would look like:

$$\Lambda_y = \begin{Bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \end{Bmatrix} \tag{12}$$

Below is a figure depicting a latent growth curve model with two latent variables (intercept and linear slope) and three time points as has been discussed so

far.

Figure 1. Sample Latent Growth Curve Model



If a researcher wanted to build a latent growth curve model with an additional growth term, it is as simple as adding a third latent variable, η_{3i}, which has a mean (μ_3), residual (ζ_{3i}), and a third vector in the Λ_y matrix specifying the growth pattern for the third term [2]. The ψ matrix would also need to be updated with a variance, ψ_3 and covariances with the other two latent variables. Additional growth terms are added if a researcher wants to test for non-linear growth patterns. For example, if a research was testing for quadratic effects, the third vector in the Λ_y matrix would be the squared linear terms. Other possible polynomial or non-linear terms are specified in a similar fashion. While specifying the third latent variable is relatively simple from a methodological stand point, researchers should keep in mind that examining polynomial patterns of change requires multiple time points (usually at least 4, although some researchers prefer 6 or more) and a larger sample size to properly identify the model [2, 5, 6].

With the Λ_y matrix specified, the covariance structure can be assessed [2]. The equation for the covariance structure is:

$$\Sigma = \Lambda_y \Psi \Lambda_y' + \Phi_E \tag{13}$$

Where Σ is a p x p matrix, Λ_y are the factor loadings, Ψ is the m x m matrix of factor variances and covariances, and Φ_E is a p x p matrix of the residual variances and covariances (i.e. the deviations away from the average factor scores) [2, 5].

2.2.2 Assumptions

LGCMs have several key assumptions [2, 5, 7]. First, it is assumed that all participants come from a single homogeneous group [7]. Second, it is assumed the error terms ϵ_{it} have a mean of zero and are independent of any of the latent variables η [5]. Third, it is assumed that the residuals for different subjects are independent [5]. Fourth, it is assumed that the variance of the errors are constant over time,

and a stricter assumption of the error variances being constant over time and over cases is sometimes introduced for model identification [5]. Other assumptions may be introduced depending on the needs of the different researchers depending on the topic of study or structure of the data [2, 5, 6]. These assumptions may or not be plausible in every situation in which LGCMs are applied. For example, the fourth assumption of error variances being constant over time and over cases could easily be violated if a group of friends all participated in the current study, and mutually agreed to reduce their alcohol use habits together. Thus, researchers must keep in mind these assumptions while interpreting their findings.

2.2.3 Parameter Estimation

As with most forms of structural equation modeling, parameter estimates are most often calculated using maximum likelihood (ML) estimation [2, 5]. The parameters which need to be estimated are the average of the intercept and the slope (μ_1 and μ_2), the disturbances or error around the intercept and the slope (ζ_{1i} and ζ_{2i}) and the variance-covariance structure ψ which has the error variance of the intercept (ψ_1), the error variance of the slope (ψ_2), and the covariance between the intercept and slope (ψ_{12}) [2, 5].

2.2.4 Assessing Model Fit

To determine if a LGCM is considered a "good fit," or in other words is appropriate for the observed data, a variety of strategies are used. The main hypotheses under consideration are:

$$\begin{aligned} H_0 &: \mu = \mu(\theta); \Sigma = \Sigma(\theta) \\ H_1 &: \mu \neq \mu(\theta); \Sigma \neq \Sigma(\theta) \end{aligned} \tag{14}$$

What these hypotheses are stating is that the mean structure of the model ($\mu(\theta)$) is not significantly different from the mean structure of the data (μ), and

simultaneously the covariance structure of the model ($\Sigma(\theta)$) is not significantly different from the covariance structure of the data (Σ). In this case, retaining the null hypothesis is desirable as the model structure is a good fit for the observed data. In addition to the hypothesis test, assessing model fit is done with a series of statistics referred to as fit indices [2, 4, 6, 8]. Most fit indices are based off the degrees of freedom for the model which in LGCMs are calculated as:

$$df = [p(p+3)/2] - q \tag{15}$$

Where p is the number of variables and q is the number of free parameters [2]. It is recommended that at least three fit indices be provided: the χ^2 test, at least one measure of incremental fit, and at least one measure of absolute fit [9]. An incremental fit index compares the degrees of freedom of the null model, or the worst possible fitting model, to the model specified by the researcher [2, 9]. Examples of incremental fit indices are the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI), also known as the Non-Normed Fit Index [9]. With an incremental fit index, values closer to 1 are indicative of better fit. An absolute fit index assumes the best possible model for the data has a fit of 0, and then determines how far away the specified model is from the perfect model [9]. Examples of absolute fit indices include the Root Mean Square Error of Approximation (RMSEA) and the Standardized Root Mean Square Residual (SRMR) [2, 9]. For the purposes of this study, all five fit indices discussed below will be interpreted for model fit as there is controversy over which fit indices are the most appropriate to use [2, 8, 9].

χ^2 Test

The χ^2 test for LGCM is calculated as:

$$\chi^2 = (N-1)F_{ML} \tag{16}$$

Where N is the sample size and F_{ML} is the maximum likelihood function found from fitting the hypothesized model [2, 8, 9, 10] and is calculated as:

$$F_{ML} = log|\Sigma| - log|\Sigma(\theta)| + Tr(\Sigma(\theta)\Sigma') - (p+q) \tag{17}$$

Conceptually, the χ^2 is testing the difference between the hypothesized model and the variance-covariance matrix of the actual data [2, 8, 9, 10]. Good fit is indicated by having a non-significant finding (using $\alpha = .05$). However, it is well established that the χ^2 test is incredibly sensitive, especially with large samples sizes [2, 8, 9, 10, 11]. A significant difference between the hypothesized model and the matrix of actual data may mean only that a difference exists, which could be due to high statistical power or strong correlations among constructs in the model, both of which can lead to a significant finding [4, 8]. This is why it is recommended other supplemental fit indices be calculated, such as the ones described in the following sections.

Comparative Fit Index (CFI)

The formula for CFI is:

$$CFI = \frac{(\chi^2 - df_{null}) - (\chi^2 - df_{\theta})}{\chi^2 - df_{null}} \tag{18}$$

df_{null} refers to the degrees of freedom of the worst possible or null model, which typically evaluates only variances and assumes no covariance [12]. and df_{θ} refers to the degrees of freedom of the hypothesized model [9, 12]. It is possible for CFI values to fall outside 0 or 1, but if a CFI value falls below 0 it is set to 0 and above 1 it is set to 1 [12]. CFI values closer to 1 are desirable, and values of at least 0.90 are considered good fit, and 0.95 or above great fit [9, 12].

Tucker-Lewis Index (TLI)

The formula for the TLI (or NNFI) is:

$$TLI = \frac{R_{null} - R_\theta}{R_{null} - 1} \tag{19}$$

Where R is a ratio of the χ^2 value divided by the degrees of freedom for the null model and hypothesized model respectively [13]. Similar to CFI, it is possible for TLI values to be above 1 in which case the TLI value is fixed to 1 [9, 13]. TLI values of at least 0.90 are considered good fit, and 0.95 or above great fit [9].

Root Mean Square Error of Approximation (RMSEA)

The formula for the RMSEA is:

$$RMSEA = \frac{\sqrt{\chi^2 - df_\theta}}{\sqrt{(df_\theta N - 1)}} \tag{20}$$

Where the χ^2 value is from the hypothesized model, as are the degrees of freedom, and N refers to the sample size [14]. RMSEA values equal to or below 0.05 suggest great fit, 0.08 or below good fit, and 0.10 or below acceptable fit [9, 15], but these criteria are not universal. For example, other criteria suggest 0.01 or below for great fit, 0.05 or below for good fit, and 0.08 or below for acceptable fit [16]. It is also common to provide the 90% confidence interval surrounding the RMSEA value, where ideally the upper bound does not exceed 0.10 and the lower bound is equal to 0.

Standardized Root Mean Square Residual (SRMR)

The formula for the SRMR is:

$$SRMR = \sqrt{\frac{\sum_{i=1}^{p} \sum_{j=1}^{i} [(s_{ij} - \hat{\sigma}_{ij})/s_{ii}s_{jj}]^2}{p(p+1)/2}} \tag{21}$$

Where s_{ii} and s_{jj} are the observed standard deviations, s_{ij} is the observed covariance, and $\hat{\sigma}_{ij}$ is the estimated covariances. p is the number of observed

variables and both j are i observed variables [17]. Conceptually, the SRMR is comparing the average standardized residuals between the hypothesized model and the observed data [17, 18]. SRMR values equal to or below .05 indicate great fit, and equal to or below .08 indicate acceptable fit [9, 17, 18].

2.2.5 Extensions to Latent Growth Curve Modeling (LGCM)

Due to the flexible nature of LGCM, it is very easy to adjust the model to incorporate other variables or model multiple patterns of growth. For example, if a researcher wanted to include a time-invariant covariate as part of the model, sometimes referred to as a conditional LGCM, it is as simple as introducing the time-invariant covariate as a predictor of the latent variables of the intercept and slope [2, 6]. The equations would change to look like:

$$\eta_{1i} = \mu_1 + \beta_{11} x_{1i} + \zeta_{1i} \tag{22}$$

$$\eta_{2i} = \mu_2 + \beta_{21} x_{2i} + \zeta_{2i} \tag{23}$$

Where β is the coefficient for the time-invariant covariate [2, 6]. The covariate x is only measured once since it is assumed to be constant over the time points (i.e. invariant) so it does not have a subscript for time.

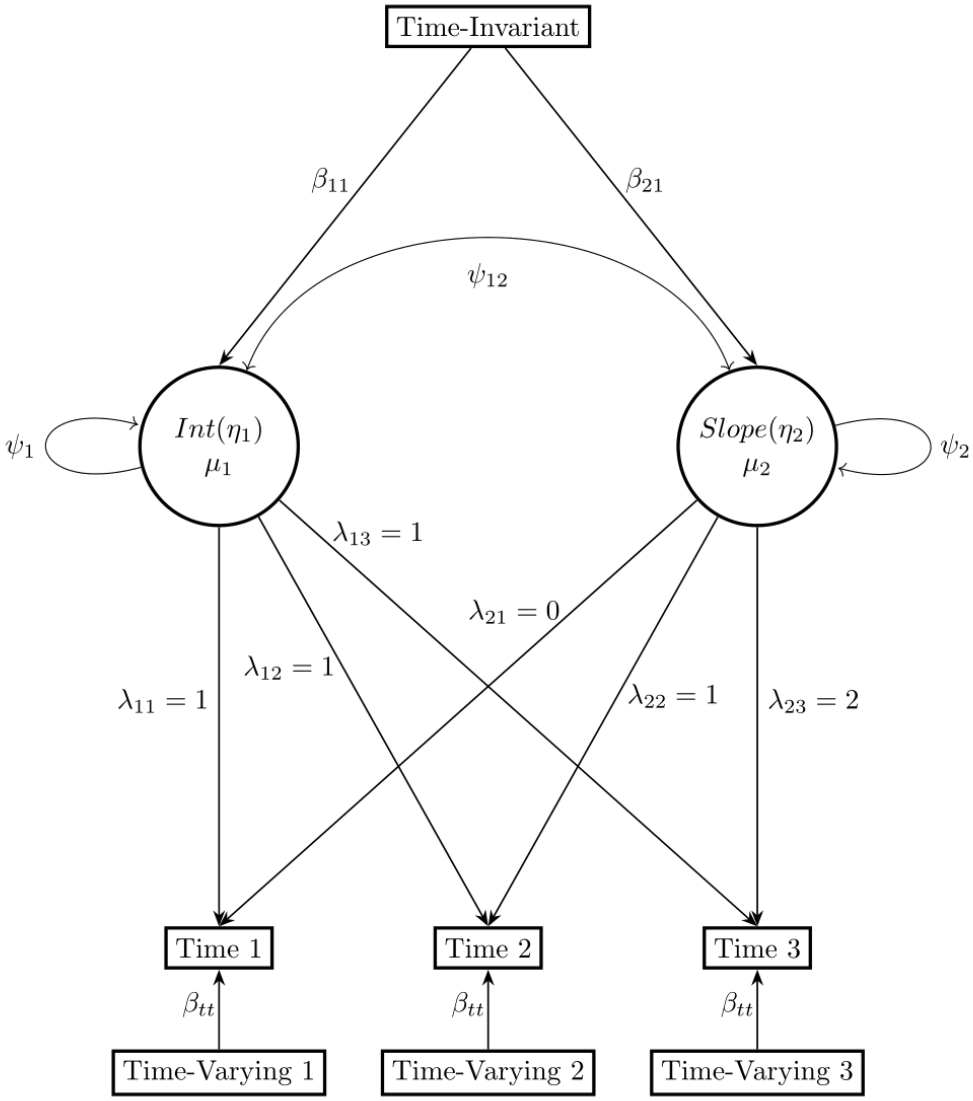
Including a time-varying covariate is also simple, but the covariate is added into the overall LGCM model as follows:

$$y_{it} = \lambda_{1t}\eta_{1i} + \lambda_{2t}\eta_{2i} + \beta_{tti} x_{ti} + \epsilon_{it} \tag{24}$$

Where β_{tti} is the regression coefficient, with two subscripts of t to show that y_t is predicted by x_t at each time point t [6]. Please see the figure below depicting what a latent growth curve model would look like with both time-invariant and

time-varying covariates, where β_{11} and β_{21} are the conditional effects on the latent variables and β_{tt} are the time-varying effects on the response variable.

Figure 2. Latent Growth Curve Model with Covariates. Note: Error variances omitted for simplicity of figure.



Non-Linear Latent Growth Curve Modeling

Other extensions in LGCM can include modeling non-linear patterns of change [2, 6]. As started earlier, this is done simply by modifying the design matrix Λ_y and adding another latent variable representing the new pattern of change. How the design matrix is specified determines what type of non-linear growth is modeled. Consider the design matrix below:

$$\Lambda = \begin{Bmatrix} 1 & 0 & 0 \\ 1 & 1 & 1 \\ 1 & 2 & 4 \end{Bmatrix} \tag{25}$$

The additional third column would then be modeling quadratic growth, since it is the squared linear terms [2, 6]. However, it is difficult to justify quadratic growth in the current study because only having three time points makes it difficult to observe any type of quadratic change. Instead, another non-linear extension to LGCM could be used called piecewise growth curves. In a piecewise growth curve, the researcher is modeling two different linear growth terms similar to spline regression [1, 2, 6]. This adjustment is again done in the design matrix, and an example would look like:

$$\Lambda = \begin{Bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{Bmatrix} \tag{26}$$

Here, the first column is still modeling the constant intercept. The second column is modeling the linear change from time 1 (coded as 0) and time 2 (coded as 1). Since the time 3 is still coded as 1, showing that the linear change from time 1 to time 2 is no longer changing. The third column is modeling the linear change from time 2 (coded as 0) to time 3 (coded as 1), functioning as the second linear term [2, 6].

2.3 Factor Analysis

Factor analysis is a dimension reduction technique which allows researchers to reduce a series of related items into one or more factors [19, 20, 21]. Using factor analysis (or a similar technique, principal components analysis) is appropriate in the context of psychological measures, because the researcher can take the different items on the scale and reduce the multiple items into one or more factor scores to use in analysis. An advantage of using factor analysis for dimension reduction instead of another technique, like summing the participant's scores or taking the average of the items, is that factor analysis can partial out measurement error when calculating the factor scores [22, 23].

The model for factor analysis is:

$$Y = LF + E \tag{27}$$

Where Y is a p x 1 vector of the variables to be reduced, F is a q x 1 vector of factors, L is a p x q matrix of factor loadings for the variables p and factors q and E is a p x 1 vector of measurement error (also called uniqueness) for the p Y variables [10]. Note that the L matrix is commonly referred to as the Λ matrix in the extant literature, but was referred to as L in this thesis to distinguish the factor loadings in factor analysis from the design matrix in latent growth curve modeling.

The variance-covariance matrix for factor analysis is:

$$S_Y = L\phi L' + \Theta \tag{28}$$

Where S_Y is a p x p variance-covariance matrix, L is the same p x q factor loading matrix and L' is the transpose of L, ϕ is a q x q matrix of variances and covariances among the factors, and Θ is a p x p matrix of the measurement errors

among the variables p. Overall, the goal of factor analysis is to find the values for the factor loadings in the L matrix and factor variances and covariances in the ϕ matrix to estimate the the Y variables and S_Y matrix [10, 24].

There are numerous guidelines for interpreting the results of factor analyses (e.g. proportion of variance explained and strength of the loadings), but for the purposes of this thesis factor analysis is being used to obtain factor scores for analysis, not develop a new measure or determine the relative strength of the loadings so those results are not discussed.

There are several methods which can be used to estimate factor scores, including regression scores, the Bartlett method, and the Anderson-Rubin method [22]. Regression scores was the method chosen to obtain the factor scores as it uses least squares regression to obtain standardized factor scores with a mean of zero and variance equal to the squared multiple correlations between the items and factors [22, 23]. The equation for obtain the regression scores is:

$$\hat{Y} = ZL \tag{29}$$

Where $\hat{Y}$ is a p x 1 vector of the estimated factor scores, Z is a p x 1 vector of the standardized measured variables, and L is the p x q factor loading matrix. While the regression method has some drawbacks if more than one factor score is being obtained (e.g. correlations among the factor scores), in this thesis only one factor score is being obtained per measure so the drawbacks do not need to be highly considered [22]. The sole factor score will be used as a measurement of the construct, similar to how the average score of a measure can be used as the operational definition of a construct.

2.4 Coefficient ω

Coefficient ω is a measure of internal consistency reliability, which in psychometrics means the different items of the same scale are measuring the same construct of interest [25, 26, 27, 28]. While Cronbach's α is undoubtedly the more common measure of internal consistency, there is ample research to suggest that coefficient ω is less biased than α, and that ω is a more appropriate measure for internal consistency [25, 26, 27, 28]. The formula for ω is:

$$\omega = 1 - \frac{\sum_{i=1}^{k} \mu^2}{Var_X} \tag{30}$$

where $\Sigma\mu^2$ is the unique variance of a single item on the measure summed over the k items of the measure, and Var_X is the variance of the communality of the item [27, 28]. The communality is obtained via factor analysis, such that the communality (x) is a linear combination of a general factor (g), factors that some but not all items share (f), item-specific factors (s) and measurement error (e) [26, 27, 28]. This is the equation for what is known as the "total" ω, sometimes notated as ω_t. The total ω is recommended for use when a single factor is being assessed for reliability, as is being done in this thesis, but it is recommended to use another form of ω, called hierarchical ω (or ω_h) when three or more factors are obtained from a single measure [26, 27, 28]. A measure has acceptable internal consistency if ω values are higher than .70, and higher than .80 is considered good internal consistency [25].

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CHAPTER 3

Results

Analyses were conducted in R version 3.5.1, using the *BaylorEdPsych*, *lavaan*, *lme4*, *lmerTest*, *mice*, *mitools MissMech*, *MuMIn*, *psych readxl*, and *semTools* packages [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12]. R and the R packages *stargazer*, *effects*, *ggplot2* and the LaTeXpackage *TikZ* were used to create figures and tables [1, 13, 14, 15, 16]. The Spring 2018 dataset was used to train the linear mixed effects model, and the Fall 2017 dataset was reserved for model validation. The datasets were not merged for any analysis as it was not possible to determine if a student from one of the three sections of PSY 200 in Fall 2017 was enrolled in a section of PSY 200, STA 220, or STA 308 in Spring 2018.

3.1 Variable Selection

The specific aims of this study were to determine if quantitative attitudes predicted alcohol use over time, even in the context of other variables known to predict alcohol use (e.g. gender, generic forms of anxiety). To best answer this question, the quantitative anxiety and DASS-21 anxiety subscale were chosen to be the main covariates of interest. Other covariates which were included in the analysis were gender, due to the known gender effects on quantitative attitudes and alcohol use [17, 18], time point, and quantitative course to test for any class-based differences.

3.2 Missing Data and Multivariate Normality Testing

The first step of the analyses was to test if the data were Missing Completely at Random (MCAR) versus Missing at Random (MAR) or Missing Not At Random (MNAR). In the Spring 2018 dataset, a modified Hawkins test was used to

test if the data were MCAR or not and if the data were multivariate normal. The modified Hawkins test imputes all missing data, and then tests if the data are multivariate normal [8]. If the results are non-significant, the researcher can assume both multivariate normality and MCAR. However, the results for the Spring 2018 were significant ($p < .001$), suggesting the data were either MAR or MNAR and were not multivariate normal [8, 19]. The results for the Fall 2017 dataset could not be calculated due to issues of linear dependency in the data [8]. Based on these initial findings, further exploration of the type of missing data and multivariate normality were conducted. First, the datasets were reduced to only the selected variables under consideration in the models (anxiety factor scores, quantitative anxiety factor scores, and alcohol use at all three time points. Gender was excluded from this testing as it was coded as binary variable and is therefore inherently not multivariate normal). When testing for MCAR versus MAR or MNAR, on the dataset with selected variables, the results of the modified Hawkins test suggested that the data were MCAR ($p = 0.20$), but not multivariate normal ($p < .001$). Little's MCAR test provided additional evidence that the data were MCAR, $\chi^2 = 25.56$, df $= 27$, $p = 0.54$, but further multivariate normality testing could not be done due to the missing data. Based on these results, two approaches were taken to handle the missing data in the analyses. First, a conservative approach used listwise deletion, or complete case analysis. Complete case analysis was chosen because it is considered the least biased of non-imputation methods for handling missing data [20] and linear mixed effects models assume the data are MAR or MCAR so the results should not be affected using this approach [29]. The complete case analysis approach brought the sample size for the Spring 2018 dataset down to 119 from 456, and the Fall 2017 dataset down to 19 from 134. Second, because the data were MCAR when using the dataset with selected variables,

full-information maximum likelihood imputation (FIML) was used to impute the data when conducting the latent growth curve model portion of the analyses as FIML is considered the ideal method for missing data imputation in structural equation modeling [20, 21]. However, FIML assumes multivariate normality which was not met with these data [22, 23], although research suggests FIML still performs well when data are not multivariate normal [21]. To summarize, for the factor analysis, coefficient omega, and linear mixed effects model, complete case analysis was used to handle the missing data. For the latent growth curve model, two approaches were taken to handle the missing data: complete case analysis and FIML imputation.

3.3 Factor Analysis and Reliability Results

3.3.1 Quantitative Anxiety

The quantitative anxiety measure showed good internal consistency at all three time points $\omega = 0.96$, 0.96, and 0.96. Factor analysis suggested the proportion of variance explained at 80%, 82%, 80% for beginning, middle, and end of the semester respectively.

3.3.2 DASS-21 Anxiety

The DASS-21 anxiety measure, used as a measure of general anxiety, had good internal consistency, $\omega = 0.93$, 0.96, and 0.96. The single factor scores explained 58%, 70%, and 70% of the variance at the beginning, middle, and end time points respectively.

3.4 Summary Statistics

Descriptive statistics were checked for all covariates and for alcohol use in both datasets. In the Spring 2018 dataset, the sample size distribution of gender was 103 women and 16 men. Nine students were enrolled in the STA 220 section

1, 14 enrolled in STA 220 section 2, 14 students in STA 308 section 1, 26 in STA 308 section 2, 13 in STA 308 section 13, 18 in PSY 200 section 1, 16 in PSY 200 section 2, and 9 in PSY 200 section 3. Summary statistics of the alcohol use variables showed a mean of between 3 and 4 days of drinking alcohol in the past 30 days, but the range of values went between 0 to up to 24 days in the last 30. Alcohol use was transformed by adding 1 to remove any 0s and using a log10 transformation [26]. The mean of all factor scores was 0, as calculation of the regression factor scores results in a standardized score [27, 28]. For a summary of the covariates used in the analyses, please see tables 1 and 2 below.

Table 1. Demographics (Spring 2018, $n = 119$)

Variable	n
Gender Identity	
Female	103
Male	16
Statistics Course	
STA 220-0001	9
STA 220-0002	14
STA 308-0001	14
STA 308-0002	26
STA 308-0003	13
PSY 200-0001	18
PSY 200-0002	16
PSY 200-0003	9

3.5 Linear Mixed-Effects Model Building

As a starting point for the analysis a linear mixed effects model was trained on the Spring 2018 dataset, and included quantitative class, gender, time, anxiety, quantitative anxiety, and interaction terms of gender by time, anxiety by time, quantitative anxiety by time, gender by anxiety, and gender by quantitative anxiety based on the theory posited in this study and the known relationships between

Table 2. Summary Statistics (Spring 2018, $n = 119$)

Variable	Mean	SD	Min	Max	Skew.	Kurt.
Alcohol Use (B)	3.48	3.73	0	16	1.15	0.76
Alcohol Use (M)	3.29	4.19	0	24	1.82	4.33
Alcohol Use (E)	3.84	3.98	0	20	1.34	2.00
Log of Alcohol Use (B)	1.13	0.90	0.00	2.83	−0.02	−1.36
Log of Alcohol Use (M)	1.03	0.93	0.00	3.22	0.26	−1.27
Log of Alcohol Use (E)	1.22	0.89	0.00	3.04	−0.13	−1.22
Quant. Anxiety (B)	0.00	0.97	−2.00	2.13	0.24	−0.41
Quant. Anxiety (M)	0.00	0.98	−1.85	2.27	0.15	−0.32
Quant. Anxiety (E)	0.00	0.97	−2.22	2.23	0.41	−0.38
Anxiety (B)	0.00	0.96	−0.70	2.91	1.28	0.53
Anxiety (M)	0.00	0.98	−0.64	3.36	1.56	1.65
Anxiety (E)	0.00	0.97	−0.77	2.91	1.09	0.15

Note:
B = Beginning
M = Middle
E = End

gender and alcohol use as well as gender and quantitative anxiety. Random intercepts were also included in the base model, which will be referred to as the full model hereafter. Time was treated as a categorical variable in the model because students were given a three-week window to complete the survey at each time point so it could not be assumed that there was a linear relationship between time and alcohol use [29]. The full model was defined as:

$$\begin{aligned} E(Y_{ij}|b_i) = {} & \beta_1 + b_i + \beta_2\{Quantitive\ Class\}_{ij} + \beta_3\{Gender\}_{ij} + \beta_4\{Time\}_{ij} \\ & + \beta_5\{Anxiety\}_{ij} + \beta_6\{Quant.\ Anxiety\}_{ij} + \beta_7\{Gender\ \times\ Time\}_{ij} \\ & + \beta_8\{Anxiety\ \times\ Time\}_{ij} + \beta_9\{Quant.\ Anxiety\ \times\ Time\}_{ij} \\ & + \beta_{10}\{Gender\ \times\ Time\}_{ij} + \beta_{11}\{Gender\ \times\ Quant.\ Anxiety\}_{ij} \\ & + \beta_{12}\{Gender\ \times\ Anxiety\} \end{aligned} \tag{31}$$

Where Y_{ij} was the response variable of log of alcohol use in the last 30 days, β_1 was the intercept, and b_i were the random intercepts for the i individuals at j time points.

In order to select a more parsimonious model backwards elimination was conducted on the full model. The results of the backwards elimination testing suggested that the time by quantitative anxiety, gender by anxiety, gender by quantitative anxiety, and gender by time interactions be removed. It was also suggested that quantitative course and gender be removed from the model, but there was a marginal effect of gender, $p = 0.08$. Thus, the chosen model was alcohol use predicted by time, anxiety, quantitative anxiety, an anxiety by time interaction, and the random intercepts.

The chosen model was then tested for random slopes for quantitative anxiety, and a fully random model with random intercepts and random slopes for quantitative anxiety. These three models were compared using maximum likelihood estimation since REML models are not directly comparable [29]. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) indices were consulted to determine the best fitting model, and the AIC/BIC indices were calculated so that the lowest value indicated the best fit [5]. The AIC and BIC values were lowest for the random intercept model, so it was retained as the final model for analysis. Please see table 3 below for a summary of the AIC and BIC results. Based on these findings, the final model was stated as:

$$\begin{aligned} E(Y_{ij}|b_i) = \beta_1 + b_i + \beta_2\{Time\}_{ij} + \beta_3\{Anxiety\}_{ij} \\ + \beta_4\{Quant.\ Anxiety\}_{ij} + \beta_5\{Anxiety\ \times\ Time\}_{ij} \end{aligned} \tag{32}$$

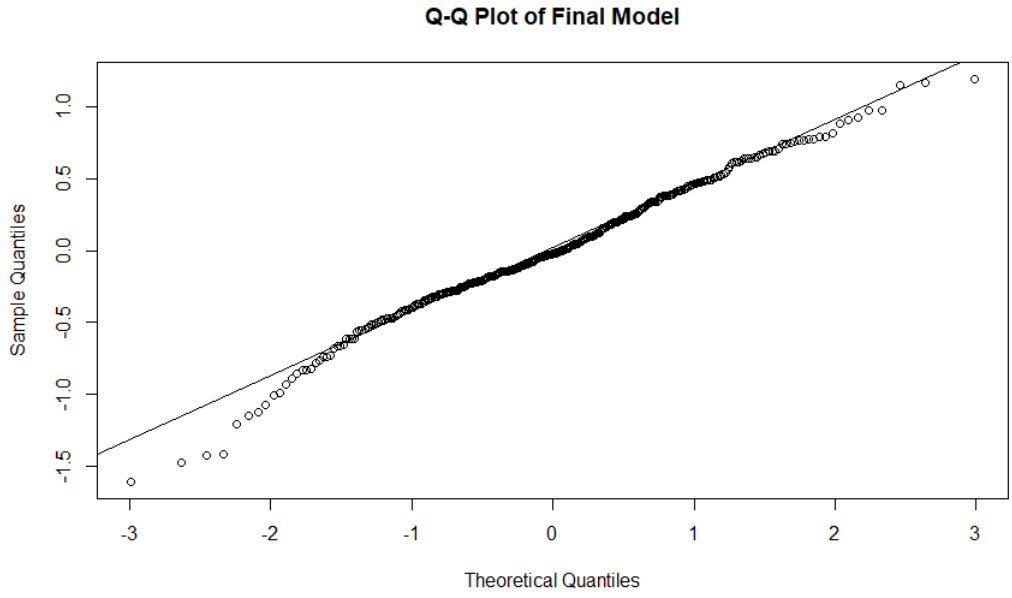
Table 3. AIC and BIC Values for Comparing Linear Mixed Effects Models

Model	AIC	BIC
Random Intercepts	783.36	822.14
Random Slopes	903.27	938.17
Fully Random	790.64	833.29

3.5.1 Model Diagnostics

Model diagnostics were conducted to determine if the final model met the linear mixed effects model assumptions of homogeneity of variance and normally distributed residuals [29]. The Q-Q plot of the residuals, shown in figure 3 below, showed that there were some issues of heavy tails at either end of the residuals but that there were no major violations of normality.

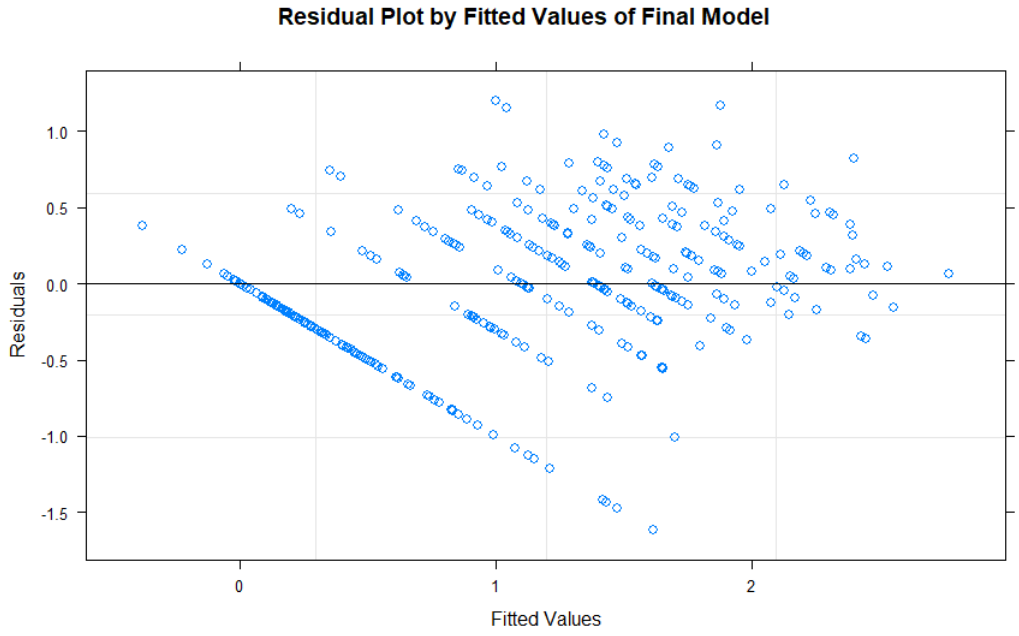
Figure 3. Q-Q Plot of Final Model



Examining of a residual by fitted values plot, shown in figure 4 below, suggested that there may be some issues of heterogeneity of variance as there appeared to be a diagonal pattern in the plot. To further explore these possible issues of

heterogeneity, several other residual plots were conducted. First, a residual plot by the subject ID numbers showed no discernible residual pattern by subject (shown in figure 5). Second, scatter plots with lowess smoothed curves were constructed to better identify any patterns in the residuals. Scatter plots were constructed of residuals by fitted values (figure 6), residuals by outcome variable (log of alcohol use in last 30 days; figure 7), residuals by anxiety factor score (figure 8), and residuals by quantitative anxiety factor score (figure 9).

Figure 4. Residual Plot by Fitted Values of Final Model



Examination of the residual by fitted values plot with the lowess curve suggests that even though there is a diagonal pattern appearing, the lowess curve is relatively unaffected. Therefore, the suspected heterogeneity does not appear to be of large concern [29]. The residual by log of alcohol use plot shows a definitive pattern based on the lowess curve, but since the residuals were contained within a range of -1.5 to 1.0, and the lowess curve line stayed between -0.5 and 0.5, the amount of heterogeneity is relatively little and is also not of large concern [29]. It may well be that the heterogeneity which is occurring is a natural result of com-

Figure 5. Residual Plot by Subject ID of Final Model

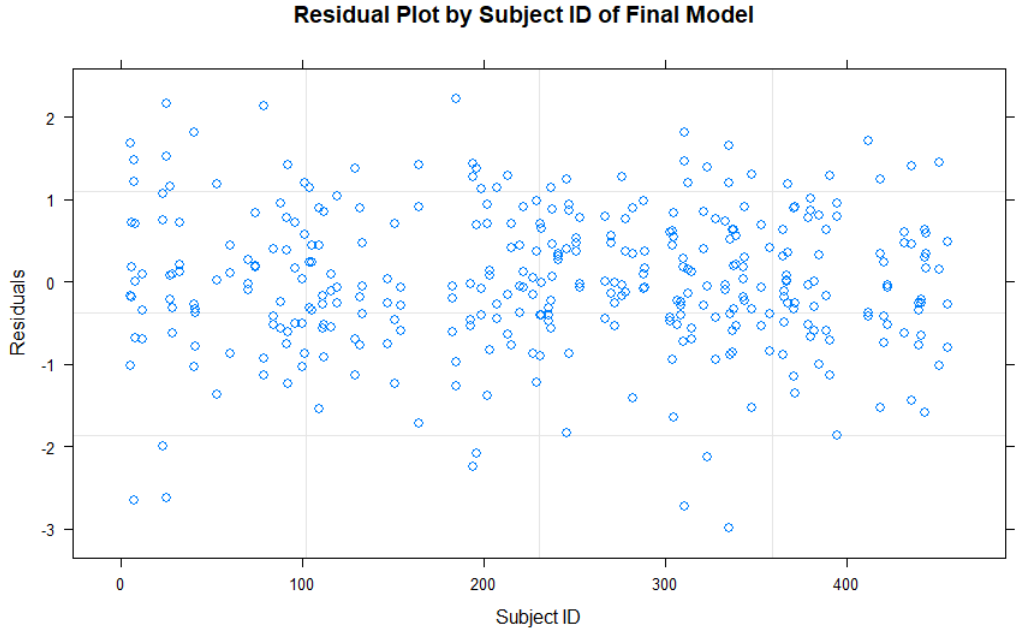


Figure 6. Scatter Plot of Residuals by Fitted Values with Lowess Curve

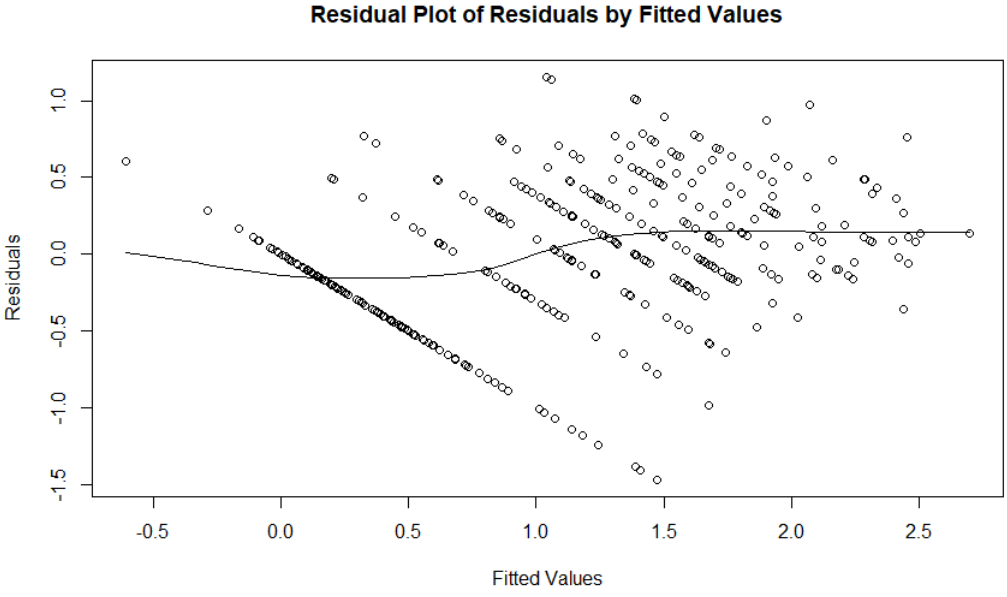


Figure 7. Scatter Plot of Residuals by Log of Alcohol Use with Lowess Curve

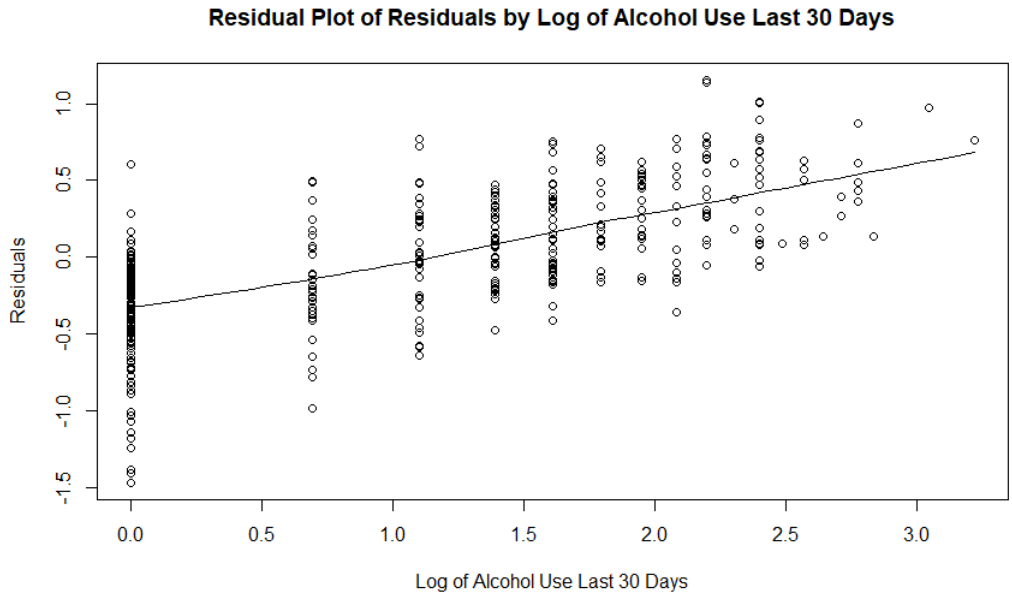


Figure 8. Scatter Plot of Residuals by Anxiety with Lowess Curve

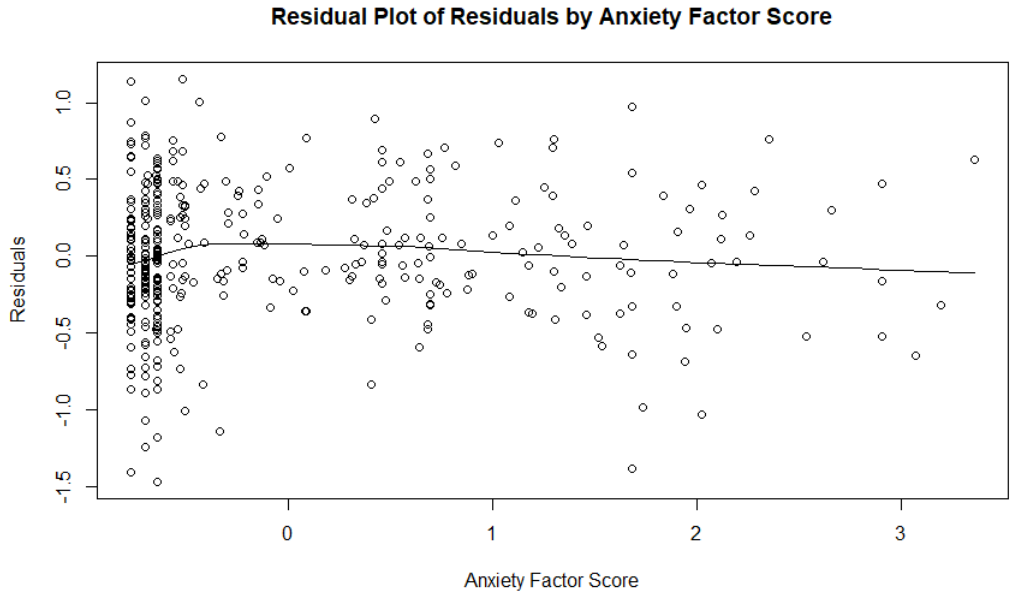
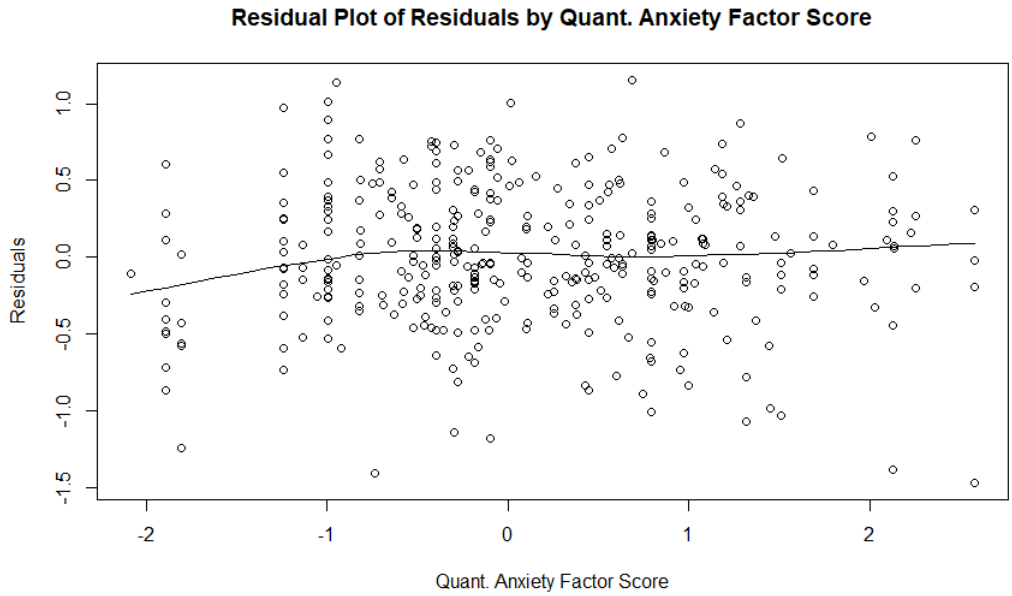


Figure 9. Scatter Plot of Residuals by Quant. Anxiety with Lowess Curve



paring non-alcohol users and alcohol users because differing levels of variability between these two groups are to be expected when comparing both groups in a single model. In other words, non-alcohol users have different variability in alcohol use than alcohol users. The final two scatter plots of residuals by anxiety and residuals by quantitative anxiety also showed no major cause for concern based on the scatter plots and lowess curves. Thus, the model diagnostics suggested that the final model was satisfactory in terms of the assumptions of homogeneity of variance and normality despite the issues discussed above.

3.6 Interpretation of Final Model

3.6.1 Spring 2018 Dataset

The results of the linear mixed effects model suggested significant interactions between anxiety and the end-semester time point and significant main effects of quantitative anxiety and anxiety. To determine the amount of variance explained by the model, Nakagawa and Schielzeth recommend reporting the marginal and conditional R^2 [30]. The formula for the marginal R^2 (R^2_m) is:

$$R_m^2 = \frac{\sigma_f^2}{\sigma_f^2 + \sigma_\gamma^2 + \sigma_\alpha^2 + \sigma_\epsilon^2} \tag{33}$$

where σ_f^2 is is the variance calculated from the fixed effects, σ_γ^2 is the variance of group-specific effects, such that individuals are assigned uniquely to groups, σ_α^2 is the subject-specific variance based on multiple observations of the same individual, and σ_ϵ^2 is the residual variance [30]. The conditional R^2 (R_c^2) includes variation of the random intercepts in the equation such that:

$$R_c^2 = \frac{\sigma_f^2 + \sum_{i=1}^{n} \sigma_i^2}{\sigma_f^2 + \sum_{i=1}^{n} \sigma_i^2 + \sigma_\gamma^2 + \sigma_\alpha^2 + \sigma_\epsilon^2} \tag{34}$$

where σ_i^2 refers to the variance of the i to n random effects [30].

The marginal R_m^2 value was 0.12, suggesting 12% of the variance in alcohol use was explained by the fixed effects and the conditional R_c^2 value was 0.65, suggesting that the fixed and random effects together explained 65% of the variance [30, 31]. The results are displayed in table 4 below, along with the 95% confidence intervals.

Table 4. Linear Mixed Effects Models Results (Spring 2018)

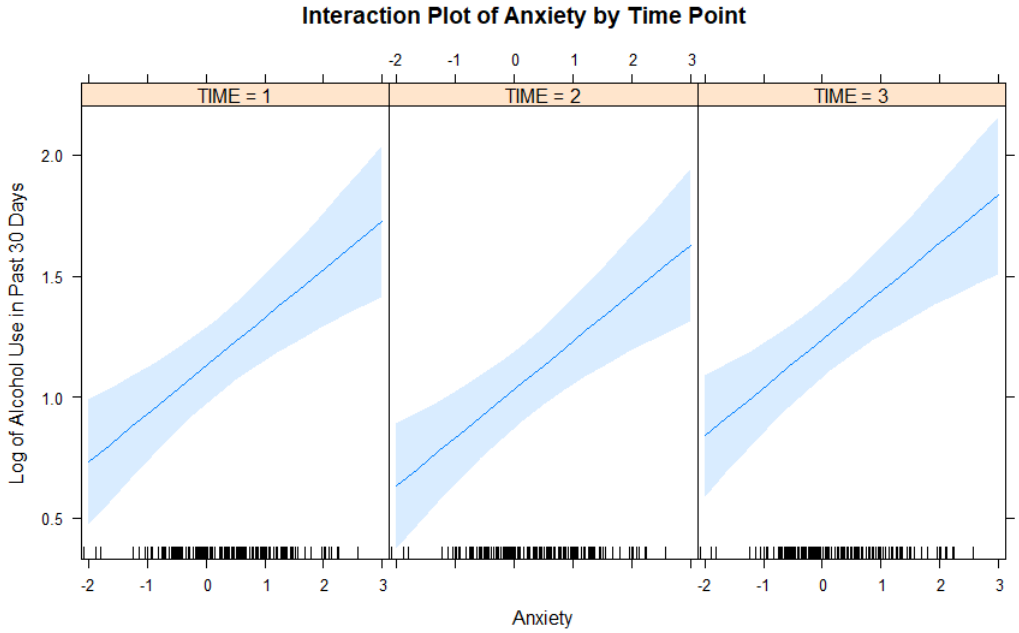
Variable	β	p	Upper 95% CI	Lower 95% CI
Intercept	1.10	<0.001	0.94	1.25
Time (Mid)	-0.10	0.16	-0.23	0.04
Time (End)	0.12	0.09	-0.02	0.26
Anxiety	0.22	0.001	0.10	0.35
Quantitative Anxiety	0.21	<0.001	0.12	0.30
Anxiety x Time (Mid)	0.01	0.87	-0.14	0.16
Anxiety x Time (End)	-0.19	0.02	-0.33	-0.03
Random Intercepts σ	0.66		0.56	0.77
AIC	783.36			
BIC	822.14			

Interpretation of the final model from the Spring 2018 datasets suggests a positive relationship between quantitative anxiety and alcohol use and a positive

relationship between anxiety and alcohol use. The estimated coefficient for anxiety of 0.22 , when exponentiated is $e^{0.22} = 1.25$, or a 25% relative increase in alcohol use when all other variables are held constant [29]. For quantitative anxiety, $e^{0.21} = 1.23$, or a 23% relative increase in alcohol use.

The interaction between anxiety and time was only at the third time point, and was $e^{-0.19} = 0.83$. The exponentiated value below 1.0 suggests a relative decrease in alcohol use when all other variables are held constant. In context of the time by anxiety interaction, the finding suggests that the relationship between anxiety and alcohol use was relatively weaker at the third time point. Looking at the interaction plot below (figure 10), it is difficult to see exactly how the interaction is taking place since there are three parallel lines which all appear to have parallel slopes. While this interaction plot was relatively inconclusive, the time by anxiety interaction was further explored in the latent growth curve modeling section (3.7).

Figure 10. Interaction Plot (Anxiety by Time) Note: 1 = Beginning, 2 = Middle, 3 = End



3.6.2 Fall 2017 Dataset

For model validation, the regression coefficients from the Spring 2018 final model were used to predict the log of alcohol use in the Fall 2017 dataset ($n = 19$). The mean squared error of predicting the alcohol use values was 0.38 and the root mean squared error was 0.62. Since the mean squared error terms were both close to zero, the results suggest that the Spring 2018 model performed well when predicting the Fall 2017 values. Further exploration of the model validation was done using mean trajectory plots to compare the actual values to the predicted values. It appears that the Spring 2018 model did well when predicting patterns of stable alcohol use, or patterns showing a decrease from beginning to mid semester, and then an increase from mid to end semester. However, the model did not do as well predicting patterns of drinking behavior which increased from beginning to mid semester and decreased from mid to end semester. For two specific examples, when comparing actual verses fitted values for participant ID number 30 (figure 11), it can be see that the model did a good job predicting the pattern of change in alcohol use across the three time points. However, for participant ID number 28 (figure 12), the model did a relatively poor job predicting both the actual values and pattern of change.

Figure 11. Fall 2017 Model Validation Plot for Participant ID 30

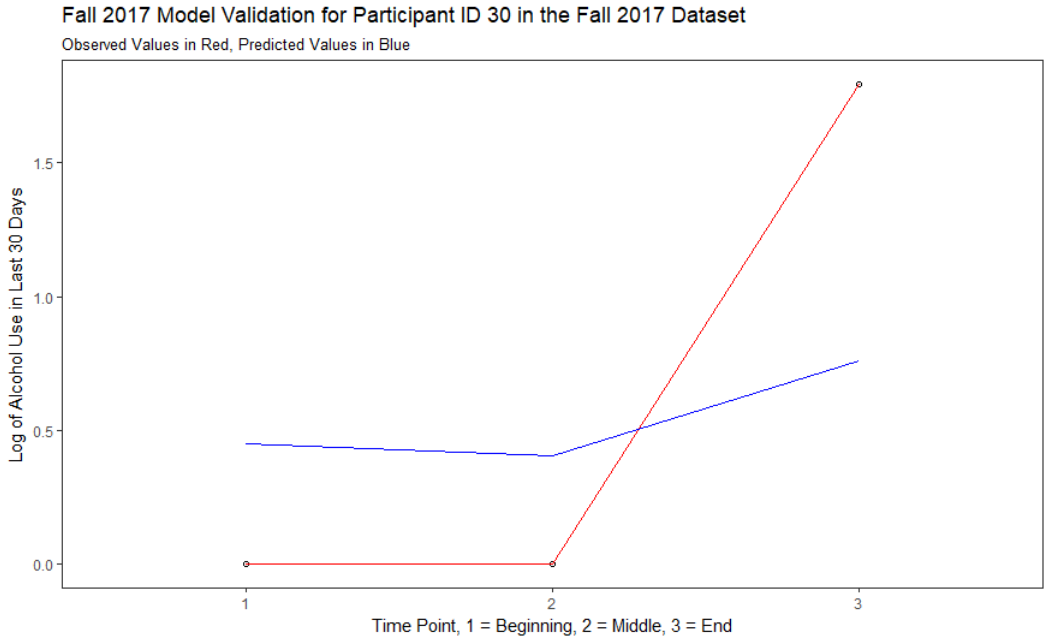
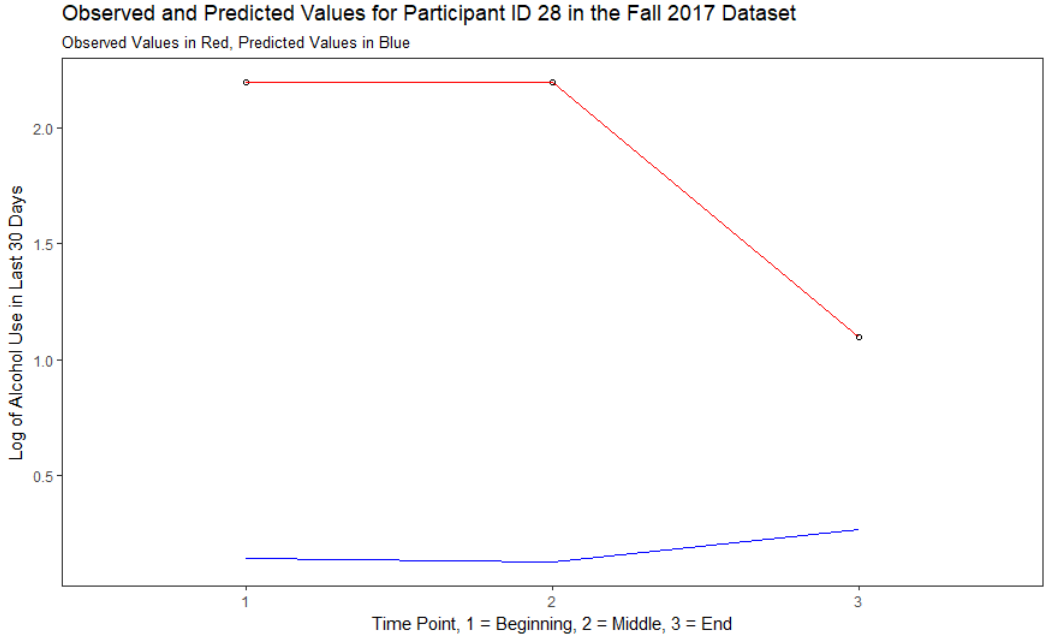


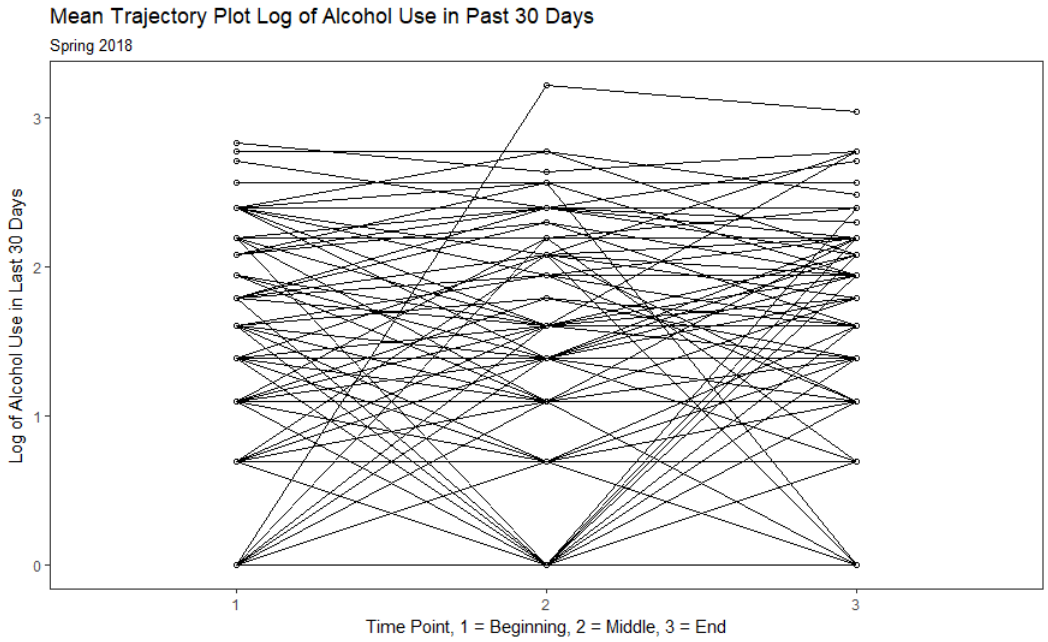
Figure 12. Fall 2017 Model Validation Plot for Participant ID 28



3.7 Latent Growth Curve Model

The final step of the analyses was to further confirm the linear mixed effect model with a latent growth curve analysis. Before building the latent growth curve model (LGCM), mean trajectory plots of alcohol use by time point were consulted to determine what growth pattern would be most appropriate for the data.

Figure 13. Mean Trajectory Plot (Spring 2018)

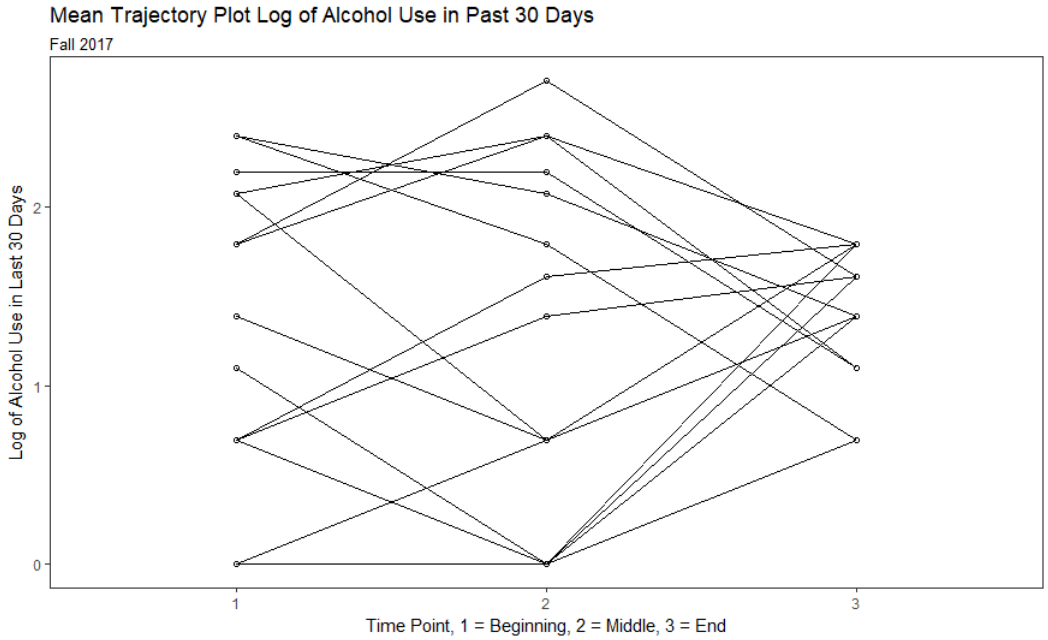


The Spring 2018 mean trajectory plot (figure 13, above) showed both linear and non-linear patterns of change. Since it was not feasible to test for quadratic effects with only three time points [32, 33], a piecewise growth curve model was fit. The piecewise model examined linear changes from beginning to mid semester, and then mid to end semester. The design matrix of loadings was specified as:

$$\Lambda = \begin{Bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{Bmatrix} \tag{35}$$

Examination of the Fall 2017 mean trajectory plot (figure 14, below), further confirmed that there were both linear and non-linear patterns of change and the piecewise model was most appropriate for the data.

Figure 14. Mean Trajectory Plot (Fall 2017)

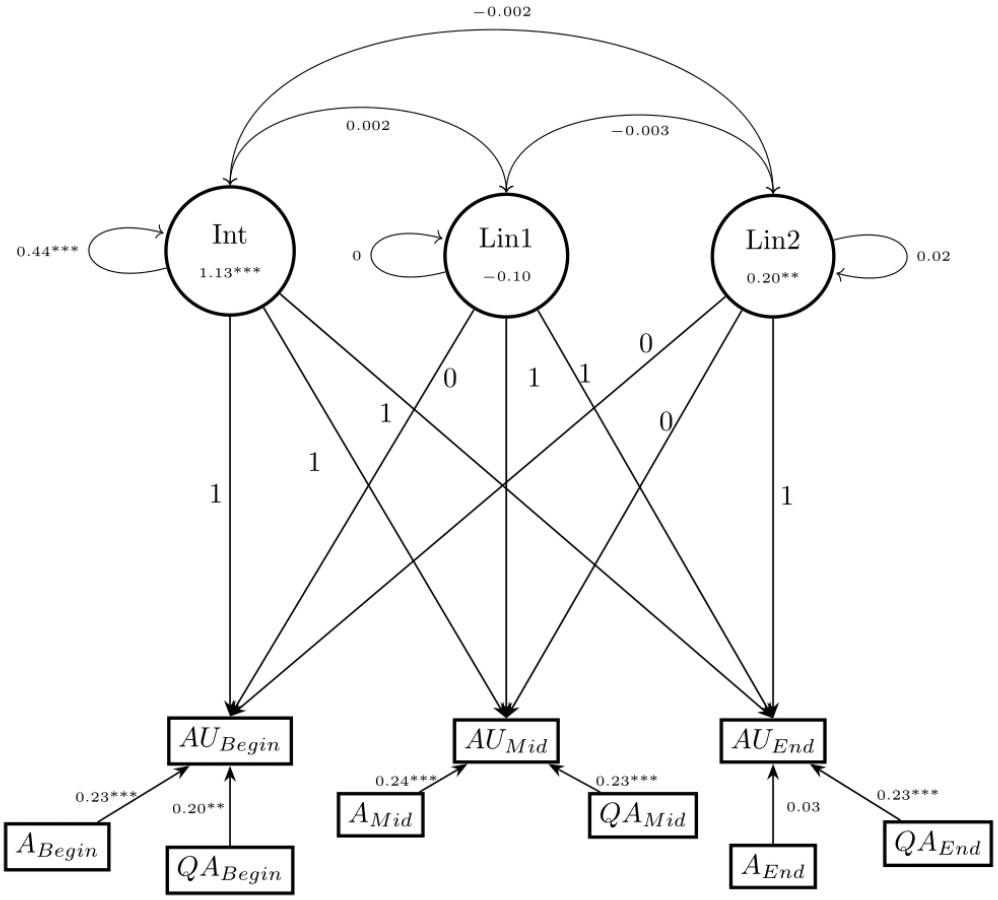


The LGCM had three latent variables (intercept, linear slope 1, and linear slope 2) predicting alcohol use at the three time points. Based on the linear mixed effects model results, quantitative anxiety and anxiety were included as time-varying covariates predicting alcohol use. For model identification purposes, two additional constraints were placed on the model. First, the residual variances for alcohol use at each time point were constrained to be equal and the variance for the first linear slope was constrained to be zero. As mentioned in Section 3.2, this analysis was run twice with different strategies for handling the missing data: complete case analysis and FIML imputation. No LGCM analysis was conducted on the Fall 2017 dataset as the amount of missing data was so high that imputation techniques could not be considered reliable [20, 34].

3.7.1 Complete Case Analysis

The piecewise LGCM showed great fit to the data based on all fit indices used for model evaluation. The χ^2 test was non-significant, $\chi^2 = 7.301$, $p = 0.837$, the CFI value was above 0.95, CFI = 1.000, the TLI value was above 0.95, TLI = 1.000, the RMSEA was below 0.05, RMSEA = 0.000 (90% CI 0.000, 0.055), and the SRMR was below 0.05, SRMR = 0.023 [35]. Quantitative anxiety was a positive predictor of alcohol use at each time point, and generic anxiety was a positive predictor at the beginning and middle semester time point but non-significant at the end of the semester. The mean latent intercept and second mean linear slope were both significant, but only the variance for the latent intercept was significant. These finding were consistent with the linear mixed effects model, as it suggests the only subject-specific deviation from the average value was at the intercepts and the non-significant finding between generic anxiety and alcohol use at the third time point is consistent with the time by anxiety interaction suggesting a weaker relationship between anxiety and alcohol use at the final time point. Please see figure 15 below depicting the LGCM for the Spring 2018 dataset, and table 5 below summarizing the fit indices.

Figure 15. Latent Growth Curve Model with Complete Case Analysis. Note: AU = Alcohol Use, A = Anxiety, QA = Quantitative Anxiety, *p<0.05, **p<0.01, ***p<0.001. Error variances for alcohol use were omitted for simplicity of figure, but all were 0.278*** and constrained to be equal



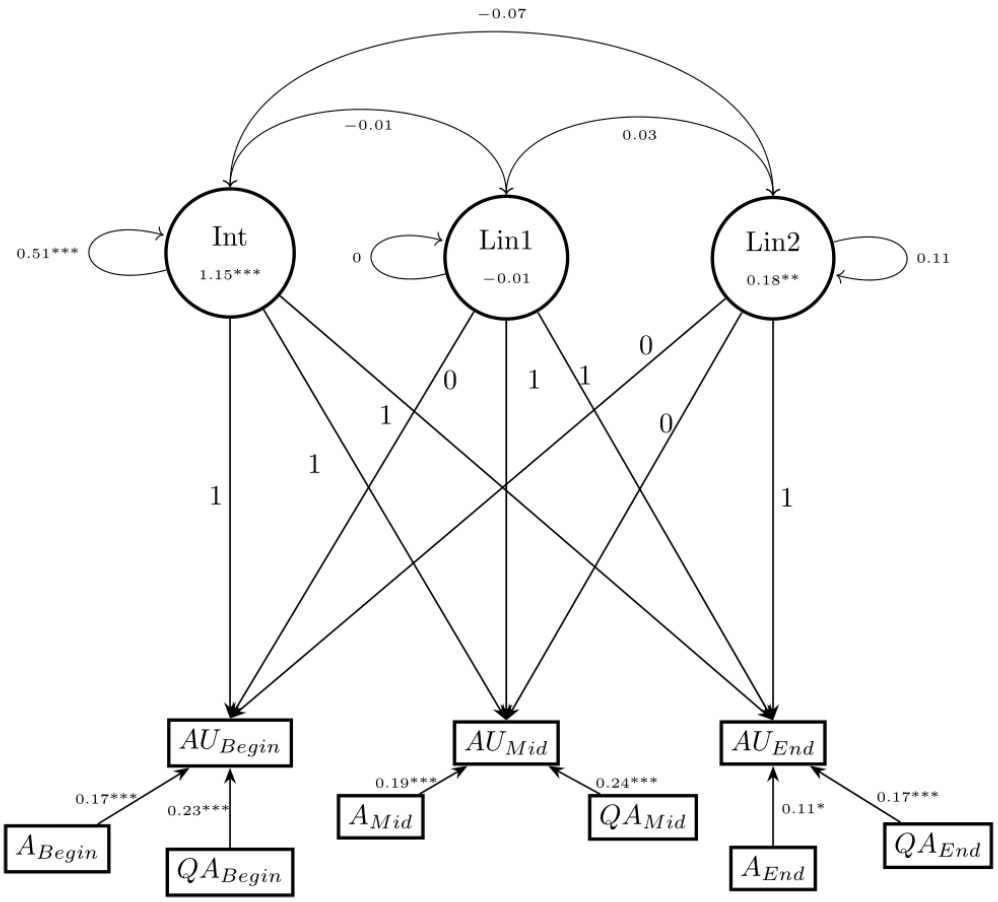
3.7.2 FIML Imputation

When using FIML, the piecewise LGCM still showed great fit to the data based on all fit indices used for model evaluation. The χ^2 test was non-significant, $\chi^2 = 9.386$, $p = 0.950$, the CFI value was above 0.95, CFI = 1.000, the TLI value was above 0.95, TLI = 1.000, the RMSEA was below 0.05, RMSEA = 0.000 (90% CI 0.000, 0.000), and the SRMR was below 0.05, SRMR = 0.023 [35]. Only one qualitatively different interpretation than the complete case analysis emerged. At the final time point, anxiety was a significant predictor of alcohol use ($p = 0.017$) while anxiety was non-significant in the complete case analysis at the final time point. Otherwise, quantitative anxiety was still a positive predictor of alcohol use at each time point, and generic anxiety was still a positive predictor at the beginning and middle semester time points, the mean latent intercept and second mean linear slope were both significant, and only the variance for the latent intercept was significant. These finding were consistent with the linear mixed effects model, as it suggests the only subject-specific deviation from the average value was at the intercepts and the finding between generic anxiety and alcohol use at the third time point was weaker than the other two time points. Please see figure 16 below depicting the LGCM with FIML imputation, and table 5 below summarizing the fit indices.

Table 5. Summary of Fit Indices for the LGCMs by Missing Data Technique

Fit Index	Complete Case	FIML Imputation
χ^2	7.301	9.386
χ^2 p-value	0.837	0.950
CFI	1.000	1.000
TLI	1.000	1.000
RMSEA	0.000	0.000
RMSEA (Upper 90% CI)	0.055	0.000
RMSEA (Lower 90% CI)	0.000	0.000
SRMR	0.023	0.023

Figure 16. Latent Growth Curve Model for the Spring 2018 Dataset using FIML imputation. Note: AU = Alcohol Use, A = Anxiety, QA = Quantitative Anxiety, *p<0.05, **p<0.01, ***p<0.001. Error variances for alcohol use were omitted for simplicity of figure, but all were 0.282*** and constrained to be equal



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CHAPTER 4

Discussion

The specific aims of this study were to 1) determine if there was an association between quantitative anxiety and alcohol use, 2) determine if quantitative anxiety was a predictor of alcohol use even when taking into account more general forms of anxiety, and 3) determine if there was a specific growth pattern of alcohol use over the semester with quantitative anxiety as a time-varying covariate. Based on the results, there is evidence to suggest quantitative anxiety is a significant, positive predictor of alcohol use even when taking into account generic forms of anxiety supporting specific aims 1 and 2. Concerning specific aim 3, there was no effect of time in the linear mixed effects model and there was no significant latent mean or variance for the first latent slope term in the LGCM. There was a significant latent mean of the second linear slope term in the Spring 2018 dataset, and a significant variance for the second linear slope in the Fall 2017 dataset, but overall there was little evidence to suggest that the rate of alcohol use changed over the semester. Thus, the results of this study suggest that alcohol use rates may be relatively stable and that there was no specific growth pattern.

The results of this study support the extant body of literature which shows that alcohol use is a form of self-medication which college students use to cope with adverse feelings of stress and anxiety [1, 2, 3, 4, 5, 6, 7, 8]. These findings specifically integrate the stress/anxiety-inducing effects of statistics/quantitatively-based courses as a unique predictor of alcohol use, even when taking into account generic forms of anxiety [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]. Thus, the claim can be made that quantitative anxiety is a specific form of anxiety which is related to alcohol use in college students. The results also showed that there was an

interaction between anxiety and the final time point predicting alcohol use. Since the final time point was gathered during the final two weeks of the semester and first week of finals week, it may be that students were focusing on finals during this data collection period and drinking less to focus on their exams. Additionally, previous research suggests that motivations for alcohol use fluctuate over time, so it may well be that the changing relationship is to be expected [16, 17, 18]. While the findings of this one study cannot make any sort of causal claims, the results do merit further investigation to determine to what extent quantitative anxiety can trigger self-medication with alcohol use, or is otherwise associated with substance use behaviors. However, it may be prudent to inform centers on college campuses which provide counseling for at-risk students that quantitative anxiety can be predict alcohol use, and students who are already at-risk may be at higher risk during the semester in which they are enrolled in a course which could cause quantitative anxiety.

4.1 Limitations

The results of this study must take into consideration the study limitations. First, while two approaches to missing data were used, and the results were consistent with both techniques, there were drawbacks to both approaches. Complete case analysis is considered the least biased way non-imputation approach to missing data, but it is biased way of handling missing data [23]. Additionally, the assumption of multivariate normality was not met for the FIML imputation [20, 21]. While there is research to suggest FIML imputation still performs well when the data are not multivariate normal, the results must be interpreted knowing that this assumption was not met [**?**]. Second, including only three time points is very limiting for latent growth curve models [24, 25]. Replications should endeavor to include enough time points to better utilize the flexibility of latent growth curve

modeling and enable the researcher to examine possible polynomial patterns of change. A larger sample size than $n = 456$ will also be needed to evaluate more complex growth curve models [25]. Third, this study was conducted entirely with a population whom were enrolled in a quantitative methods course. This inherently provides a form of bias, as there is no way to compare alcohol use habits between students within and not within a quantitative methods course and the relationship quantitative anxiety has with alcohol use in both situations. Fourth, the participants in this study were predominantly white and female, which limits the generalizablity to other demographics. Fifth, this study used a limited number of covariates, opting for a parsimonious model which included only general anxiety and quantitative anxiety. Previous research suggests that other covariates may influence quantitative anxiety (e.g. gender, racial/ethnic identity [15, 26]), which were not explored in this thesis. Sixth, while the model assumptions for normality and homogeneity of variance were not overtly violated, there were still some issues discussed in section 3.5.1 which could be explored in future studies. Seventh, validation of the final model from Spring 2018 in the Fall 2017 dataset showed that the final model did not predict all patterns of alcohol use well.

4.2 Future Directions

The results of this study suggest that even if rates of alcohol use over the semester remain constant, quantitative anxiety is a predictor of alcohol use. Future studies should attempt to replicate the findings of the current study, and make efforts to address the limitations of this study described above. It would also be worthwhile to explore if quantitative anxiety is related to the use of other substances (e.g. marijuana, tobacco, non-prescription amphetamines) to determine if quantitative anxiety is related to other commonly-used substances on college campuses [3, 4, 5, 6, 7, 8, 27, 28]. If possible, an ideal approach would be to compare

two groups of students before, during, and after a semester in which one group is taking a quantitative course and the other group is not. That would provide stronger evidence to show that the stress/anxiety related to taking a quantitative course could lead to substance use. Based on the findings of the current and suggested future studies, interventions may be developed to mitigate the effects of quantitative anxiety on substance use in an effort to promote health on college campuses.

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APPENDIX

Standardized Instruments Used

A.1 Quantitative Anxiety

For the items below, use the following scale to assess your level of anxiety around the following situations.

1. Not at all anxious 2. Slightly anxious 3. Moderately anxious 4. Quite anxious 5. Extremely anxious

1. Signing up for a course in statistics.

2. Reading a math or statistics formula.

3. Being given a homework assignment involving math or statistics.

4. In my ability to understand the mathematics of statistics.

A.2 Perceived Stress Scale

The questions in this scale ask you about your feelings and thoughts during the last month. In each case, you will be asked to indicate how often you felt or thought a certain way. Although some of the questions are similar, there are differences between them and you should treat each one as a separate question. The best approach is to answer each question fairly quickly. That is, don't try to count up the number of times you felt a particular way, but rather indicate the alternative that seems like a reasonable estimate.

For each question choose from the following alternatives:

0. never 1. almost never 2. sometimes 3. fairly often 4. very often

1. In the last month, how often have you been upset because of something that happened unexpectedly?
2. In the last month, how often have you felt that you were unable to control the important things in your life?
3. In the last month, how often have you felt nervous and "stressed"?
4. In the last month, how often have you dealt successfully with irritating life hassles?
5. In the last month, how often have you felt that you were effectively coping with important changes that were occurring in your life?
6. In the last month, how often have you felt confident about your ability to handle your personal problems?
7. In the last month, how often have you felt that things were going your way?
8. In the last month, how often have you found that you could not cope with all the things that you had to do?

9. In the last month, how often have you been able to control irritations in your life?

10. In the last month, how often have you felt that you were on top of things?

11. In the last month, how often have you been angered because of things that happened that were outside of your control?

12. In the last month, how often have you found yourself thinking about things you have to accomplish?

13. In the last month, how often have you been able to control the way you spend your time?

14. In the last month, how often have you felt difficulties were piling up so high you could not overcome them?

A.3 Depression Anxiety and Stress Scales (DASS-21)

Please answer the following questions using the following scale: 0 = Did Not Apply to me At All 1 = Rarely Applied to me 2 = Somewhat Applied to me 3 = Applied to me Very Much

The following seven items are the stress subscale.

- I was intolerant of anything that kept me from getting on with what I was doing.
- I felt I was rather touchy.
- I found it difficult to relax.
- I found myself getting agitated.
- I felt that I was using a lot of nervous energy.
- I found it hard to wind down.
- I tended to over-react to situations.

The following seven items are the depression subscale.

- I felt that life was meaningless.
- I felt that I had nothing to look forward to.
- I couldn't seem to experience any positive feeling at all.
- I was unable to become enthusiastic about anything.
- I felt that I wasn't worth much as a person.
- I felt down-hearted and blue.

- I found it difficult to work up the initiative to do things.

The following seven items are the anxiety subscale.

- I was aware of the action of my heart in the absence of physical exertion.
- I experienced breathing difficulty.
- I experienced trembling.
- I felt I was close to panic.
- I felt scared without any good reason.
- I was worried about situations in which I might panic and make a fool of myself.
- I was aware of dryness of my mouth.

A.4 Substance Use Measures

For the following items, please answer if you have ever used the listed substance (yes or no). If you have used the listed substance, please answer the second question with a number. If you respond with no to any substance, please leave the second question at 0.

- Have you ever drunk ALCOHOL?
- Have you ever BINGE DRUNK alcohol (4+ drinks in an hour for women, 5+ for men)?
- In the past MONTH, how many DAYS did you drink ALCOHOL?
- Have you ever smoked CIGARETTES?
- Do you think you have smoked OVER 100 CIGARETTES in your lifetime?
- In the past MONTH, how many DAYS did you smoke CIGARETTES?
- Have you ever smoked E-CIGARETTES?
- In the past MONTH, how many DAYS did you smoke E-CIGARTTES?
- Have you ever used OTHER TOBACCO PRODUCTS (e.g. chew, snuff, dip)?
- In the past MONTH, how many DAYS did you use OTHER TOBACCO PRODUCTS?
- Have you ever smoked MARIJUANA?
- In the past MONTH, how many DAYS did you smoke MARIJUANA?
- Have you ever used INHALANTS?

- In the past MONTH, how many DAYS did you use INHALANTS?
- Have you ever used HALLUCINOGENS (e.g. LSD, mushrooms, salvia)?
- In the past MONTH, how many DAYS did you use HALLUCINOGENS?
- Have you ever used COCAINE (powder or crack)?
- In the past MONTH, how many DAYS did you use COCAINE (powder or crack)?
- Have you ever used AMPHETAMINES (e.g. Ritalin, Adderall) WITHOUT A PRESCRIPTION?
- In the past MONTH, how many DAYS did you use AMPHETAMINES WITHOUT A PRESCRIPTION?
- Have you ever used METHAMPHETAMINE?
- In the past MONTH, how many DAYS did you use METHAMPHETAMINE?
- Have you ever used PRESCRIPTION PILLS (e.g. Vicodin, Percocet, oxycontin) WITHOUT A PRESCRIPTION?
- In the past MONTH, how many DAYS did you use PRESCRIPTION PILLS WITHOUT A PRESCRIPTION?
- Have you ever used HEROIN?
- In the past MONTH, how many DAYS did you use HEROIN?
- Have you ever used SEDATIVES (e.g. barbiturates)?
- In the past MONTH, how many DAYS did you use SEDATIVES?
- Have you ever used TRANQUILIZERS?

- In the past MONTH, how many DAYS did you use TRANQUILIZERS?
- Have you ever used STEROIDS?
- In the past MONTH, how many DAYS did you use STEROIDS?

A.5 Student Attitudes Towards Statistics

DIRECTIONS: The statements below are designed to identify your attitudes about statistics. Each item has 7 possible responses. The responses range from 1 (strongly disagree) through 4 (neither disagree nor agree) to 7 (strongly agree). If you have no opinion, choose response 4. Please read each statement. Mark the one response that most clearly represents your degree of agreement or disagreement with that statement. Try not to think too deeply about each response. Record your answer and move quickly to the next item. Please respond to all of the statements.

1. I plan to complete all of my statistics assignments.
2. I plan to work hard in my statistics course.
3. I will like statistics.
4. I will feel insecure when I have to do statistics problems.
5. I will have trouble understanding statistics because of how I think.
6. Statistics formulas are easy to understand.
7. Statistics is worthless.
8. Statistics is a complicated subject.
9. Statistics should be a required part of my professional training.
10. Statistics skills will make me more employable.
11. I will have no idea what‘s going on in this statistics course.
12. I am interested in being able to communicate statistical information to others.
13. Statistics is not useful to the typical professional.

14. I plan to study hard for every statistics test.

15. I will get frustrated going over statistics tests in class.

16. Statistical thinking is not applicable in my life outside my job.

17. I use statistics in my every day life.

18. I will be under stress during statistics class.

19. I will enjoy taking statistics courses.

20. I am interested in using statistics.

21. Statistics conclusions are rarely presented in every day life.

22. Statistics is a subject quickly learned by most people.

23. I am interested in understanding statistical information.

24. Learning statistics required a great deal of discipline.

25. I will have no application for statistics in my profession.

26. I will make a lot of math errors in statistics.

27. I plan to attend every statistics class session.

28. I am scared by statistics.

29. I am interested in learning statistics.

30. Statistics involves massive computations.

31. I can learn statistics.

32. I will understand statistics equations.

33. Statistics is irrelevant in my life.

34. Statistics is highly technical.

35. I will find it difficult to understand statistical concepts.

36. Most people have to learn a new way of thinking to do statistics.

- How well did you do in mathematics courses you have taken in the past?
- How good at mathematics are you?
- In the field in which you hope to be employed when you finish school, how much will you use statistics?
- How confident are you that you can master introductory statistics material?
- Are you required to take this statistics course (or one like it) to complete your degree program?
- If the choice had been yours, how likely is it that you would have chosen to take any course in statistics?

A.6 Demographics

For the following items, please choose from one of the listed options as best you can. Where appropriate, you may fill in a response if the ones listed do not pertain to you.

In which course/section of statistics are you currently enrolled?

All sections of PSY 200, STA 220, STA 307, and STA 308 are listed by section and instructor as response options.

With what gender do you identify?

Response options: Female, Male, Transgender, Gender Non-Conforming, Gender Queer, Not listed please fill in

With which racial/ethnic background do you identify?

Response options: White/European Descent, Black/African American, South/Central American, Other Latino(a), Asian/Pacific Islander, Native American/Alaskan Native, Mixed, Not listed please fill in

What grade do you expect to receive in this course?

Response options: A, B, C, D, F

What is your current class standing?

Response options: Freshman, Sophomore, Junior, Senior, Not listed please

fill in

What is closest to your current GPA?

Response option: 2.0, 2.5, 3.0, 3.5, 4.0, Not listed please fill in

What is your current major?

Response option is a fill in the blank.

textbfAre you currently receiving a Pell Grant?

Response options: Yes, No

What is your current relationship status?

Response options: Single, In a Relationship, Married, Divorced, Widowed, Not listed please fill in

What is your student ID number?

Response option is a fill in the blank.

Are you taking any other quantitative or math-based courses this semester? If so, please fill in the course below.

Response option is a fill in the blank.

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