5-1-2024

TRAJECTORIES OF DEPRESSION SEVERITY IN THE FIRST SEMESTER OF COLLEGE

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by
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A Thesis

Submitted to the
Department of Psychology
College of Science and Mathematics
In partial fulfillment of the requirement
For the degree of
Master of Arts in Clinical Psychology
at
Rowan University
April 25, 2022

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Dedication

I would like to dedicate this thesis to all that have provided me support during graduate school thus far.

Acknowledgment

I would like to take the time to acknowledge the members of my thesis committee, Dr. Young and Dr. Dinzeo, for all their support throughout each aspect of my thesis. This thesis would not have been possible without your assistance and guidance. I would like to thank Dr. Brunwasser for all the consistent support, encouragement, and mentorship in so many areas. My understanding of research, statistics, and deeper critical thinking regarding these areas has grown immensely with your guidance. I am so grateful for your patience and thoughtful mentorship that has allowed me to build upon my skills and knowledge over time. Additionally, I would like to thank the many lab members from the Prevention Science lab who have given me support and feedback throughout this process.

I'd like to take acknowledge my family including my dad, mom, sister, and grandparents for their consistent support. I would also like to thank Jordan for his love and support throughout this process. I am so grateful for my family and partner. I could not have made it this far without each of your support.

Abstract

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TRAJECTORIES OF DEPRESSION SEVERITY IN THE FIRST SEMESTER OF COLLEGE
2021-2022
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Master of Arts in Clinical Psychology

Depression is a major public health concern among students in higher education. Prior work suggests that depressive symptoms increase during the transition to college. Transfer students face unique challenges during the transition to a new academic institution that may make them particularly vulnerable. There is a critical need to expand prevention efforts. Research that improves identification of students at greatest risk for developing impairing depressive symptoms, and etiological processes contributing to depressive symptoms could aid in the provision of limited prevention resources. Furthermore, longitudinal research tracking symptom trajectories during the transition to college could help inform the timing of preventive interventions for new students. We propose to conduct secondary data analysis from a prospective cohort study designed to model mental health symptoms among first-year students and incoming transfer students during their first semester at a large university. Our goal is to model the course and predictors of depression severity as captured by measures of depression-related impairment. We propose two hypotheses: (1) depression severity will follow a nonlinear trajectory with increasing severity in the early part of the semester followed by a plateau in symptom change; (2) transfer students will report higher levels of depression severity throughout the semester relative to first year students.

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Chapter 1

Introduction

Public Health Burden of Depression

Depression affects approximately 20% of the United States (US) population at some point in their lives (Kessler et al., 2007). The World Health Organization estimates depression is the leading cause of disability worldwide (Friedrich, 2017). At the individual level, depression is a major driver of functional impairment that greatly reduces quality of life (Gotlib & Hammen, 2008; Q. Liu et al., 2020). About 80% of adults with depression report having difficulty with work, home, or social activities due to their symptoms of depression (Brody, 2018). At the societal level, depression carries a significant economic burden. Between 2010- 2018, the estimated economic burden of adults with Major Depressive Disorder (MDD) was $326.2 billion (Greenberg et al., 2021). Direct costs, suicide-related costs, and workplace costs all increased during that time period, with the largest growth being in workspace costs (Greenberg et al., 2021).

Although relatively uncommon in childhood, the prevalence of depression increases dramatically during adolescence with a lifetime prevalence rate of approximately 15% by age 18 in the US (Merikangas et al., 2009). More recent research has looked at the impact of COVID-19 on depression rates in adolescence and found adolescent depression is now estimated to effect 25.2% of youth globally (Racine et al., 2021). Thus, it is not surprising that emerging adults of traditional college age (18-25) also have high rates of depression. In 2008, 7% of both college students and their non-college attending peers met criteria for MDD (Blanco et al., 2008). In a recent study assessing depression specifically in undergraduate students, 36% of students reported moderate to severe symptoms of depression (J. Lee et al., 2021). Depression in college is associated with a host of negative outcomes, including poor academic performance, impaired social functioning, lowered life satisfaction, and increased substance use (Begdache et al., 2019; Lardier et al., 2020).

High levels of depression are also associated with less college persistence, which could possibly lead to drop out, though other studies have found conflicting results (Arbona et al., 2018; Eisenberg et al., 2013). Persistence refers to the likelihood of a student returning to any college or institution for their second year, whereas dropout refers to a student that leaves their institution and does not transfer or attend any other college (Sedmak, 2021). Depression may lead college students to perceive their stressors more negatively and can result in difficulty sleeping, unwanted changes in weight, increased suicidal thoughts, and problems with academic learning and retention (Cassady et al., 2019). Furthermore, college students with depression have reported less interest in school, difficulty paying attention, and higher frequency of skipping class (Cassady et al., 2019). In sum, depression among college students is a significant public health problem.

The Transition to College as a Period of Elevated Risk

The transition to college appears to be a uniquely challenging time for many students that may increase vulnerability to depressive symptoms (Kessler et al., 2007). Two prospective cohort studies found that, on average, students making the transition to a new university reported increasing levels of depressive symptoms during the first semester (Brunwasser, 2012) . Additionally, first-semester students tend to present with high levels of stress that often persist over time (Meyer, 2021). There are many stressors accompanying the college transition that could account for the increases in mental health problems, including changing social structures, increases in academic pressure, changes in living and academic environments, worsening health problems, and feelings of loneliness (Guassi Moreira & Telzer, 2015; Pittman & Richmond, 2008).

These stressors can be amplified for students identifying with groups that have been traditionally underrepresented in higher education (Meyer, 2021). Underrepresented college students (i.e. first- generation students, students with financial struggles, students from traditionally underrepresented racial/ethnic groups) at predominantly white institutions may have contrasting backgrounds to the new college environment that can exacerbate the difficulty of the transition to college (Tan et al., 2019). Having less diverse classmates and faculty can also lead to higher distress due to a reduced sense of belonging and discrimination (Tan et al., 2019). It is also common for underrepresented students to belong to more than one marginalized group, which can create compounded and uniquely challenging stressors for these students (Tan et al., 2019). Overall, the transition to college is a time when students face many stressors that may increase their susceptibility to depressive symptoms.

Transfer Students as a High-Risk Population

Transfer students appear to be a particularly vulnerable population, with elevated levels of stress and depression when compared to first year students (Brunwasser, 2012). Transfer students make up a large percentage of students in higher education. Specifically, 28% of students entering higher education in the fall of 2011 transferred within six years (Chin-Newman & Shaw, 2013; Shapiro et al., 2018). Mehr and Daltry (2016) found that when compared with students who had not transferred, transfer students had significantly higher scores on depression, anxiety, academic distress, and family distress assessments. Transfer students also reported less involvement in athletics, campus, and social activities and a higher involvement in outside jobs (Mehr & Daltry, 2016). Transfer students often experience a temporary drop in academic functioning after arriving at a new institution; a phenomenon referred to as "transfer shock" in the education literature (Scott et al., 2017).

There are surprisingly few studies analyzing mental health outcomes among transfer students as they start at a new academic institution. Most existing studies are cross-sectional or measure mental health outcomes infrequently during the transition (Scott et al., 2017). Exceptions to this are two prospective cohort studies that measured depressive symptoms at 8 and 5 time points, respectively, during students' first semester at a large university. These studies found that both on-campus and off-campus transfer students had elevated depressive symptoms relative to first-year students at the outset of the semester and that off-campus transfers continued to report elevated symptoms throughout the first semester (Brunwasser, 2012).

The existing research is also unclear about whether being a transfer student, and the transfer experience itself, contributes causally to mental health difficulties during the transition to college or whether being a transfer student is merely a marker of other, preexisting causal risk processes (e.g., financial distress). This has important implications for prevention. If being a transfer is a non-causal risk marker, it may be prudent to prioritize transfer students in prevention efforts simply because they are at greater than average risk; however, it may not be necessary to target processes that are related to the transfer experience if they are not causal contributors to depression. If the process of transferring plays a causal role (e.g., transfer experiencing inadequate support, transfers having fewer opportunities for social engagement, etc.), then it will be important to tailor interventions to specifically target these processes (Offord & Kraemer, 2000). In sum, knowing whether transfers are at increased risk is important for the allocation of prevention resources regardless of whether transferring contributes causally to depression; but knowing whether the specific stressors or transferring (independent of other stressors not caused by transferring) play a causal role is critical for determining the content of prevention programs.

Prevention of Depression

Despite access to free mental health treatment resources on college campuses, many students with elevated depressive symptoms do not seek help, and those who do are often met with long waitlists or limited sessions (Cuijpers, 2016; Ebert et al., 2019). Over the last two decades, there has been an increase in both use and demand for mental health services, making it difficult for colleges to meet the mental health needs of their students. It is necessary to have something other than treatments for symptomatic students (Eisenberg et al., 2013). Preventive approaches are crucial because a substantial portion of those that receive treatment do not fully recover, and even if they do recover, the consequences of depression can have a lasting impact (i.e. poor grades and social impairment) that persists even after symptom recover (Cuijpers, 2016; Kennard et al., 2006). Efficacious and scalable preventive interventions, in combination with existing treatments, could dramatically reduce the burden of depression. Prioritizing students at the greatest risk for developing impairing depressive symptoms is critical as prevention resources are limited. Therefore, it is crucial to improve the identification of high-risk students and analyze their depressive symptom trajectories over the course of the first semester to strengthen the impact of prevention efforts. In sum, prevention efforts targeting high-risk students during the stressful transition to college have the potential to curb depressive symptoms before they take hold and have an adverse impact on functioning during college.

Existing prevention interventions have generally shown promise in tightly controlled efficacy trials, but it remains unclear whether these interventions can retain their potency when disseminated more broadly (S. M. Brunwasser & Garber, 2016; Ormel et al., 2019). There is also little research on the optimal timing of prevention efforts. Prevention programs might be most efficacious if they were deployed just prior to periods of increasing risk and targeted contributing etiological factors, such as increased stress during exam periods. Longitudinal studies could potentially help identify periods of increasing risk and optimal timing for interventions.

The transition to college may be an important window for prevention efforts. Longitudinal research that elucidates depression trajectories and improves identification of students at greatest risk for developing impairing depressive symptoms is needed to inform preventative efforts. To date, there is little research in the college student or transfer student population assessing trends in depressive severity over the first semester (for exceptions, see Brunwasser, 2012). Prospective longitudinal research during the first semester may facilitate identification of specific time periods during which students experience the greatest levels of distress. This could help us deploy interventions tactically to prepare students for these particularly challenging points of the transition.

Latent Variable Modeling of Depression

In addition to these noted limitations, most studies evaluating depression severity in the college student population rely on questionnaires or interviews yielding composite scores computed by summing or averaging items measuring specific symptoms. Typically, these composite scores are assumed to estimate depression severity as a unidimensional construct using a stable measurement process (i.e., mean changes over time represent true changes in depression severity, not instability in measurement). However, there is compelling evidence against models assuming unidimensional and stable measurement in widely-used depression instruments (Fried et al., 2016). Furthermore, statistical models of depression severity composite scores typically weigh all items equally and do not account for measurement error. Variance in the composite scores is implicitly assumed to reflect only true variation in depression severity with no other sources of variability (e.g., measurement error). The assumption of perfect measurement is implausible and could result in biased model estimates (Bollen, 1989). Fried and Nesse (2016) called for a more widespread use of factory analysis and latent class analysis for the measurement of depression.

Prior to modeling change in depression severity, it is crucial to test whether there is evidence against the assumption of measurement invariance across time points (Liu et al., 2016; Vandenberg & Lance, 2000). A measurement model is longitudinally invariant if the relations between the latent variable and the measured indicators (captured by indicator factor loadings, intercepts or thresholds, and error variances) are stable over time. If the measurement model were unstable, we would be unable to determine whether change in mean levels of the latent variable over time was due to true variation in depression severity (what we care about) or changing measurement properties (Liu et al., 2016). For example, if the strength of the association between the latent depression severity variable and a measured indicator (captured by a factor loading estimate) were to change over time, this would indicate that the quality of the measured indicator changes from one time point to another. Interpreting a latent variable whose factor loadings vary over time is similar to interpreting change in a composite score whose scoring procedure is altered across time points (e.g., weighting the same items differently at different time points). The conceptual meaning of the variable changes over time making comparisons across time points uninterpretable (Lai, 2021; Liu et al., 2016).

In this study, we evaluated the tenability of a latent variable model of depression severity captured by multiple observed indicators of depression-related impairment. This approach could lead to more precise measurements of depression severity and less biased parameter estimates, assuming our latent variable model is correct (Bollen, 1989). If measurements for depression are not valid or reliable, then they may not reflect the measured construct and lead to patients receiving improper treatment options, patients staying in therapy for longer periods of time than necessary, increased cost on institutions and patients, and inaccurate measures of progress (Stochl et al., 2020).

Current Study

This study advances the literature by using data from a prospective cohort study with frequent assessments to assess depression severity trajectories among first-time college students and incoming transfer students at a large public university. We focused on depression severity manifesting as depression-related functional impairments rather than symptom total scores. This study will also assess depression severity as a latent variable, which to our knowledge, has not been done in studies evaluating symptom trajectories during the transition to college.

We propose the following hypotheses:

1. Depression severity will follow a nonlinear trajectory with increasing severity in the early part of the semester when students are first adjusting to the university environment, followed by a plateauing of the trajectory in the second half of the semester as students adjust.
2. Transfer students will report higher incoming levels of depression severity relative to traditional first year students and this difference will persist throughout the semester.

Chapter 2

Method

Participants

This study used archival data from the College Transition Study--Replication (CTSR; Brunwasser, 2012), a prospective cohort study evaluating mental health predictors and outcomes among first-year and transfer students during their first semester at a large public university. Data collection took place during the fall semesters of 2010 and 2011. All incoming students aged 18 years old or older were able to participate, including first-time college students (first years) and transfer students in their first semester at the university (transfers). Recruitment emails were sent to all eligible students (approximately 1700 first years and 950 transfer students) in August prior to the start of the semester. Enrollment was intended to be capped at 350 students due to limited financial resources, though ultimately a total of 351 participated in the study. In total, the study included a convenience sample of 235 first years and 116 transfers.

Participants were invited to complete five web-based assessments over the course of the fall semester. Students completed a pre-semester assessment approximately two weeks prior to the start of the fall semester, then monthly follow-up assessments during each of the four months of the semester (September, October, November, and December). The participation rate among enrolled participants at each assessment was over 90%, and most participants (86%) completed all five assessments. Participants were compensated $7 for the first and longest assessment, $4 for completing assessments 2, 3, and 4, and $5 for completing the final assessment. Additionally, participants received bonus payments of $3 for completing three assessments, $5 for completing four assessments, and $7 for completing all five assessments. In total, participants could earn up to $31 for participating in the study.

Measures

The measures we will use in this study are a subset of those collected in the CTSR. All measures were web-based, self-report questionnaires completed using Qualtrics survey software (Qualtrics, Provo, UT).

Outcome Variable: Depression Severity

Of primary interest in this study was capturing the severity of student depressive symptoms as manifested in the degree to which symptoms caused impairment in daily functioning. Prior work using the CTSR data (Brunwasser, 2012) has evaluated depressive symptom trajectories using total scores (unit-weighted summed composites) from the 8-item version of the Patient Health Questionnaire Depression (PHQ-8; Kroenke et al., 2001). The PHQ-8 asks directly about eight of the nine signs/symptoms of depression included in Criterion A for Major Depressive Disorder in the fifth version of the Diagnostic and Statistical Manual of Mental Disorders (APA, 2013). The PHQ-8 also has a single-item in which respondents rate the degree to which depressive symptoms made it difficult to complete job-related, home-related, and social responsibilities on a four-point scale ranging from "Not difficult at all" to "Extremely difficult". The CTSR also included items from the Role-Emotional and Social Functioning subscales of the Short Form-36 (SF-36; Ware & Gandek, 1998), measuring the degree to which respondents perceived that depression impaired their daily activities and social functioning, respectively. Both the PHQ-8 and the SF-36 were completed at all five study assessments.

The initial plan was to measure depression severity as a latent factor at each of the five study assessments using three ordinal indicators:

- The impairment item from the PHQ-8 in which participants rated the degree to which depressive symptoms made it difficult to complete job-related, home-related, and social responsibilities on a four-point scale ranging from “Not difficult at all” to “Extremely difficult.” In order to avoid sparse cells in our analyses, this item was converted to a binary (0= no impairment, 1= any impairment) outcome.
- The second indicator was a three-level, unit-weighted and summed composite indicator from the three-item Role-Emotional subscale of the SF-36. This subscale contains three binary role impairment items asking whether (yes/no) respondents experienced any of the following due to feeling depressed in the past month: (1) cutting back on the amount of time working or in other activities; (2) accomplishing less than was desirable; and (3) being less careful when completing work and other activities.
- The final indicator was an item from the SF-36 in which participants indicated the degree to which feeling depressed interfered with their normal social functioning on the following five-point scale: 1=” Not at all”, 2= “Slightly”, 3= “Moderately”, 4= “Quite a bit”, and 5= “Extremely”. In order to avoid sparse cells, we aggregated across the top three highest levels of this item so that it was a three-level ordinal

variable: 1= “Not at all”, 2= “Slightly”, 3= “Moderately” or “Quite a bit” or “Extremely”.

As shown in Figure B1, we conceptualized these three impairment indicators as markers of an unobserved (latent) variable: depression severity. In our analyses, depression severity is operationalized as a continuous multiple-indicator latent variable (a latent factor) using structural equation modeling (Bollen, 1989).

As noted above, demonstrating that a multiple-indicator latent variable has a stable factor structure over time (longitudinal measurement invariance) is a prerequisite to modeling change over time (Lai, 2021). We first tested whether our initial depression severity measurement model was consistent with the data and stable over time. If our proposed depression severity model failed tests of longitudinal invariance or did not fit the data, we planned to evaluate a second multiple-indicator model of depression severity in which the three items from the SF-36 Role-Emotional subscale would serve as observed ordinal indicators of depression severity at each time point. The fact that the role impairment items were from the same subscale, used similar question structures, and asked about a narrower measurement domain (depression-related problems in carrying out daily responsibilities) might make it more likely for it to yield a stable factor structure. If both latent factor models failed tests of longitudinal invariance, we planned to measure the outcome using the single PHQ-8 depression severity item (which asks about impairment more broadly than the other impairment indictors) rather than using a multiple-indicator latent factor.

Predictor Variables

Transfer Status. Our primary exposure variable indicated whether participants were first-time postsecondary students (first-year students) or incoming transfer students in their first semester at the university (transfer students). Past research with this data set has shown that transfer students living on vs. off campus differed in their mental health trajectories during the transition to college (Brunwasser, 2012). Therefore, our models operationalized transfer status and living situation using a three-level categorical variable with first-year students being the reference level: 0=first-year, 1=transfer-on-campus, 2=transfer-off-campus. As nearly all first-year students (218/234, 93.2%) lived on campus, it was impractical to evaluate the effect of living on vs. off campus in this subgroup.

Plausible Confounding Factors. As a primary goal was to obtain a causal estimate of the effect of transfer status on depression severity, we constructed directed acyclic graphs (DAG; Figure B1) using DAGitty software (v3.0) to encode our causal assumptions and obtain a minimally sufficient set of variables that need to be adjusted (i.e., statistically controlled) in order to obtain the causal estimate of interest given our proposed causal model (Textor et al., 2017). Our DAG indicated that the following measured variables should be adjusted when estimating the effect of transfer status on depression severity:

- **Race/Ethnicity.** Participants indicated their self-identified race/ethnicity selecting from the following mutually exclusive options: Asian/Asian American, Black/African American, Hispanic/Latino, Middle Eastern, Multi-Racial, White/Caucasian, or Other (specify). As the vast majority of participants identified as Asian/Asian American (80, 22.8%) or White/Caucasian (231, 65.8%), a three-level race/ethnicity variable ("Asian/Asian American", "White/Caucasian", and "All Other Categories") was created for analytic purposes to avoid sparse cells. Major limitations of this variable include the conflating of race and ethnicity and that the potential responses were mutually exclusive rather than allowing participants to select all groups with which they identify.

- **Sex/Gender.** Gender was measured as a binary variable with participants indicating their self-identified gender as either male or female. This item was limited in several ways, including that respondents were not provided additional options (e.g., intersex) nor were they given the option to describe their identity in their own words. Finally, the item did not clearly distinguish between sex assigned at birth and gender identity.
- **Mental Health Treatment History.** Respondents reported whether they were currently receiving, and whether they had ever received, psychotherapy or pharmacotherapy for mental health problems at the first assessment. For analytic purposes, two binary variables (0=no, 1=yes) were derived indicating whether participants had ever received mental health treatment and whether they were actively receiving treatment at study onset.
- **Financial Comfort.** Respondents reported their current level of financial comfort as a three-level ordinal variable, indicating whether finances were 0= "not a problem", 1= "tight but fine", or 2= "a struggle".

- **Parental Education.** Respondents indicated the highest level of education completed by a parent/caregiver. To avoid sparse cells, a binary variable was created: 0= at least one parent with college degree, 1= no parents with a college degree.
- **Behavioral Inhibition.** The behavioral inhibition system (BIS) subscale of the BIS/BAS questionnaire was used to capture respondents' levels of behavioral inhibition (i.e., the extent to which participants are driven to avoid aversive experiences) as a continuous variable. The BIS/BAS is a widely used scale whose utility has been demonstrated in college samples (Carver & White, 1994).

Statistical Analyses

In this study, we proposed to analyze trends of depression severity over the course of the first semester using structural equation modeling (SEM), specifically ordinal latent growth curve modeling (T. K. Lee et al., 2018; Masyn et al., 2018). Analyses were conducted using the lavaan package (version 0.6-0) in the R statistical computing environment (Rosseel, 2012). As outcomes are ordinal, parameters were estimated using diagonally weighted least squares with robust standard errors (Muthen & Asparouhov, 2022). We used a mean- and variance-scaled chi-squared test statistic to determine whether there was evidence of a discrepancy between our model and observed data that exceeded chance expectation with alpha = .05. As recommended by Kline (2015), we reported robust versions of the following approximate fit indices: the root mean square error of approximation (RMSEA; (Steiger, 2016) with a 90% confidence interval, the Tucker-Lewis Index (TLI; Tuker & Lewis, 1973), and the square root mean residual

(SRMR). Smaller values of the RMSEA and SRMR are preferable and indicate smaller average model-data discrepancies. The TLI is an incremental fit index that compares the specified model to a null model to determine the extent to which the proposed model fits better than an alternative that makes few predictions (Tucker & Lewis, 1973). Higher values of the TLI (approaching 1) indicate that the proposed model is preferable compared to the null model.

Outcome Measurement

As described above, we planned to measure depression severity as a continuous latent factor with multiple ordinal indicators at each time point (Asparouhov & Muthén, 2019). We assume that each ordinal outcome measure (*Y*) is a crude approximation of an underlying continuous variable (*Y**) that could have been measured with greater precision. For example, we assume that depression severity in social functioning is a continuous construct (*Y**) that is measured crudely with the SF-36 as a five-level ordinal variable (*Y*). *Y** is approximated using *c*-1 thresholds, where *c* is the number of levels of the ordinal variable, estimated using probit regressions (Asparouhov & Muthén, 2019).

As noted above, our proposed model assumes that depression severity is a latent continuous construct that manifests in the degree to which respondents report impairment on the measured ordinal indicators. Variability in the measured indicators of depression severity (i.e., impairment variables) are assumed to be only partly due to depression severity ("true variance") and partly due to other causes that are not of interest ("unique variance"). Assuming the proposed model provides a close approximation of underlying causal processes, separating the true variance from the unique variance using SEM allows for more precise measurement of the construct of interest, free from extraneous sources of variability (e.g., measurement error) (Bollen, 1989). When there is imperfect measurement of an outcome variable in a longitudinal study, it can be unclear whether changes are due to actual changes in the construct of interest or fluctuations in extraneous processes (Y. Liu et al., 2017).

Longitudinal Invariance

It is important to demonstrate that measurement of the latent construct is stable over time – i.e., the meaning of the latent factor is constant so that we can readily interpret change (Vandenberg & Lance, 2000). Traditional approaches to modeling change over time assume that the observed outcome variable has the same meaning and measurement properties at each time point. This is difficult to test using traditional regression approaches but can be evaluated readily using latent variable models (Little et al., 2007). Prior to conducting our primary analyses, we evaluated whether there is evidence that measurement properties of the depression severity latent factor change over time (longitudinal measurement instability). We did this by comparing a series of hierarchically nested models (Liu et al., 2017): highly restricted models that impose measurement invariance (Stable measurement) to more general models that that allow the measurement process to change over time (unstable measurement). If the more general models, not imposing stability in measurement, fit better than the restricted models imposing stability then we have evidence against longitudinal invariance. The fit of the following four models allowing differing levels of measurement instability will be compared using scaled difference tests, with significant tests providing evidence of measurement instability:

1. **Configural invariance model.** This, the most general invariance model, requires that the same indicators load onto the same latent factors at each time point. Factor loadings as well as indicator thresholds and error variances are permitted to change over time.
2. **Loading invariance model.** The factor loadings freely estimated in the configural invariance model are constrained to be constant over time.
3. **Threshold invariance model.** Indicator thresholds permitted to vary in the more general models are constrained to be constant over time.
4. **Unique factor variances.** Indicator error variances permitted to vary in the more general models are constrained to be constant over time.

Modeling Change

We will use an ordinal latent growth curve modeling (LGCM) to capture change in depression severity over time (Bollen, 1989; Masyn et al., 2018).

LGCMs assume that there is an underlying population mean trajectory that individuals follow over time described by a latent intercept variable (typically representing starting levels of the outcome variable) and at least one latent slope (i.e., capturing rates of change in the outcome over time). Individuals are typically assumed to vary in their starting levels (random intercepts) and in their rates of change (random slopes), essentially giving all individuals their own trajectories that vary around the population mean trajectory (Bollen, 2006).

In our LGCMs, we coded time effects such that the latent intercept factor represented levels of depression severity at the start of the semester (September) and at least one latent slope factor capturing the rate of constant change in depressive severity over time. As noted in the hypotheses, we expected that change would be nonlinear, with notable increases in depression severity in the early part of the semester followed by a plateau. In our initial model, we modeled trajectories (i.e., time effects) using restricted cubic splines (F. E. Harrell, 2015) with three knots (k = 3) to allow change in depression severity to follow a highly flexible and nonlinear pattern. Restricted cubic splines require $k – 1$ degrees of freedom (df) to estimate, so the time effect was estimated with $df = 2$. In subsequent models, we simplified the model to evaluate whether there was evidence that the more complex restricted cubic spline growth model substantially improved model fit over a linear growth model. We regressed the latent intercept and slope(s) on our predictor variables representing participant characteristics (e.g., transfer status), capturing differences in starting levels of depression severity and rates of change over time. Effects of predictors on the latent slopes represented predictor by time interactions.

Modeling Approach. We used a top-down modeling approach, in which we started with a highly complex model and compared it to sequentially simpler models. The initial model included:

- All predictors, including the exposure variable and the covariates
- Restricted cubic spline effect ($df = 2$) allowing for nonlinear changes in depression severity over time
- Random intercepts allowing individual levels of depression severity to deviate randomly form the population mean during students' second week of the semester
- Random coefficients (slopes) for the time effects, allowing individuals to vary in their rates of change in depression severity over time

- A first-order autoregressive effect AR (1) allowing levels of depression severity at time *t* to be affected by levels at the prior time point (*t*-1)
- Time-varying latent factor (i.e., depression severity) error variances
- All possible covariate by time interactions

Subsequent models eliminated these modeling parameters systematically to determine whether their presence improved model fit, as determined by a scaled difference test (Satorra & Bentler, 2010). Significant tests indicate that the more complex model is preferred.

Sensitivity Analysis

As this is was an observational study, it is likely that there are confounding influences that were not measured or controlled in our analyses when estimating the effect of transfer status on depression severity (i.e., residual confounding). Consequently, in the event that there was a significant effect of transfer status on depression severity, we planned to calculate an E-Value using the Evalue package in R version 4.1.3 (Linden et al., 2020; VanderWeele & Ding, 2017). The E-Value computes how strong residual confounding would have to be to nullify an effect estimate or reduce it to an inconsequential value. The residual confounding would have to be very strong (i.e., a confounder that is a strong predictor of both the exposure variable and outcome) to nullify the estimated effect, this could increase confidence that the effect is causal. On the other hand, if only weak residual confounding would nullify the observed effect, this could lead to low confidence in causality (VanderWeele & Ding, 2017).

Chapter 3

Results

Descriptive Statistics

Participant characteristics are summarized in Table A1. The sample predominantly identified as White (66%) with a substantial number identifying as Asian or Asian American (23%). Most first-year students were of traditional college age (18-19), and transfer students tended to be older (19-21). Most students (82%) in the sample reported having at least one parent who completed college.

Table A2 shows the distributions of the depression severity variables that were used to measure depression severity as a latent factor in this study at each time point. A substantial minority of both first year and transfer students reported depression-related impairments on all three measures, with impairment generally appearing to become more common over the course of the semester.

Longitudinal Invariance

Prior to conducting our primary analysis, we evaluated whether there was evidence against longitudinal invariance in our proposed latent factor model with the SF-36 Role Impairment composite score, the SF-36 Social Functioning item, and the PHQ-8 impairment item as ordinal indicators. The configural invariance model yielded a better fit to the data than the simpler loading invariance model (χ^2 (df=8)=25.69, p=.001), indicating that the strength of the effect of the latent factor on the indicators changed over time. This meant that the latent factor was not stable, and we could not determine whether changes over time reflected changes in the true construct (depression severity) or changes in measurement properties. Our backup plan was to use the three indicators specifically about role impairment (Figure B2)

We did not find evidence against the assumption of longitudinal invariance when using the three Role-Emotional impairment items as indicators of the depression severity latent factor. Scaled difference tests did not provide evidence that the most complex model (assuming only configural invariance) was preferable to hierarchically nested models in which indicator factor loadings were held constant over time (loading invariance; $\chi^2(df = 8) = 5.81$, $p = .67$) and both indicator factor loadings and indicator errors were held constant over time (unique variances model; $\chi^2(df = 20) = 19.96$, $p = .46$). Consequently, we proceeded to evaluate changes in the mean level of the latent depression severity factor over time with a latent factor model defined by the three Role-Emotional indicators.

Ordinal Latent Growth Curve Models

Table A3 provides the full sequence of our ordinal latent growth curve modeling procedure, including model comparisons, and how our final model was selected. The final model was a linear growth curve model with random intercepts allowing individuals to vary in beginning of the semester depression severity scores and random slopes allowing individuals to vary in their linear rates of change in depression severity. Nonconstant latent factor error variances were retained as they improved model fit (comparison of models 1 and 4). The AR(1) effect and covariate by time interventions were removed from the model as there was no evidence that they improved model fit (comparison of models 1 and 5). Results from the final model are presented in Table A4.

Hypothesis 1

Contrary to hypothesis 1, which posited that changes in depression severity would follow a nonlinear trajectory, there was no evidence that a nonlinear trajectory model was preferable to a simpler linear trajectory model (Table A3, comparison between models 6 and 7). The scaled difference test was not significant. Overall, there was a tendency for depression severity to increase linearly over time (est = 1.41, 95% CI: [-0.15, 2.96]), though this increase was not significant at the conventional $\alpha = .05$ level.

Hypothesis 2

We compared our primary model (Model 7) to a simpler model that was identical except that it constrained the effects of being a transfer student on the intercept (beginning of the semester levels of depression severity) and linear slope (rate of change in depression severity) to 0. A scaled difference test between the fit of these two models provided an overall estimate of the effect of being a transfer student. Including transfer status as a predictor in Model 7 resulted in a marginally better fit compared to Model 8: $\chi 2(df = 4) = 9.47$, $p = .05$.

We next evaluated the individual contrasts comparing transfer and first-year students. Compared to first-year students, on-campus transfers scored an estimated 0.46 standard deviations (95% CI: [0.07, 0.85]) higher on depression severity at week 2 of the semester when adjusting for plausible confounders. Compared to first-year students, off-campus transfer students scored an estimated 0.30 standard deviations (95% CI: [-0.03, 0.64]) in depression severity at week 2 of the semester when adjusting for plausible confounders, with the confidence interval including the null. Compared to first-year students, transfer students living on campus tended to have a lower linear rate of increase in depression severity over the semester: est = -0.73, 95% CI [-1.43, -0.03]. There was no evidence that off-campus transfers differed from first-years in their average rate of linear change: est = -0.01, 95% CI [-0.50, 0.49].

Sensitivity to Residual Confounding

A missing confounder that increases risk for being an on-campus transfer student by 32% (RR = 1.32) and increases propensity for depression severity by 0.15 *SD*s (Cohen's $d = 0.15$) would be sufficient to nullify the effect.

Chapter 4

Discussion

Summary of Findings

Overall, the findings from this study provided some evidence that knowing incoming students' transfer status could be helpful in the deployment of depression prevention programs. Being a transfer student was predictive of higher depression severity in the early weeks of the semester, though this effect reached the conventional level of statistical significance only when comparing on-campus transfers to first-year students. We did not find compelling evidence for the hypothesized nonlinear trajectory of depressive symptoms. Students tended to show linear increases in levels of depression severity over the course of the semester, with on-campus transfers showing lesser increases relative to first-year students.

There remains a high degree of uncertainty about whether the process of transferring to a new academic institution contributes causally to depression severity during incoming students' first semester at a new institution, as it would take only modest residual confounding to nullify the observed effect. Furthermore, even if we assume that our estimated effects of transfer status on depression severity are unbiased, there is substantial uncertainty in the effect magnitude. We could not rule out either trivial or large effects of transfer status on depression severity in the early weeks of the semester.

Depression Severity Trajectory During the College Transition

The findings from this study did not provide compelling support for our first hypothesis that the beginning of the semester, when students have to make many adjustments to their lifestyles and acclimate to the campus environment, would be the time of greatest increase in depression severity. Rather, students tended to report linear increases in depression severity, though the increase did not meet the $\alpha = .05$ threshold for statistical significance. The confidence intervals for the rate of linear increase were wide, indicating that we need more data to make confident inferences about the extent to which depression severity increases during the first semester. It also plausible that we lacked sufficient power to detect nonlinear time effects.

In sum, we did not find evidence of notable accelerations in the rate of increase in depression severity (i.e., departure from linearity) over the course of the semester indicative of discrete periods of high or increasing risk. Given our findings and the relative dearth of information about the course of depression severity during the college transition, it seems prudent to deploy prevention programs early in the semester or perhaps before it even begins. It is common for higher education institutions to provide programs prior to the start of students' first semester (e.g., summer bridge programs) to help them more readily acclimate to college and campus life (Bradford et al., 2021; Martin et al., 2019). Future studies should evaluate the extent to which these existing programs might prevent depression during the first semester and potentially create new programs that explicitly target etiological factors believed to contribute to depression. It will be important for future studies to follow depression severity trajectories even further past the first semester to evaluate whether students continue to show increasing symptoms levels or recover later in their college careers. Overall, this study adds to evidence supporting that the transition is a time in a student's life where depression tends to increase, and affirms the prudency of intervening early to head off increasing depression during the transition to college.

Effect of Transfer Status

The findings provided only partial support for the second hypothesis that transfer students would report higher levels of depression severity early in the semester and that this effect would be maintained over time. Overall, including transfer status as a predictor in our latent growth curve models improved model fit marginally, suggesting that transfer status provides relevant information for predicting depression severity above the covariates included in the model.

There were notably different patterns of effects for on-campus vs. off-campus students. Both on- and off-campus transfers tended to have higher early semester level of depression severity than their first-year counterparts, though the effect was only statistically significant for first-year students. Consistent with a prior study using the same dataset (Brunwasser, 2012), it seemed that living on campus may be protective for transfer students in the long run as they reported lesser increases in depression severity over time relative to first-year students. Consequently, despite starting the semester with elevated depression severity levels relative to first-years, on-campus transfers had comparable levels of by the end of the semester. In contrast, off-campus transfers had very similar rates of increase in depression severity compared to first-years, maintaining their marginal elevation in depression severity throughout the semester. Future research is needed evaluating the potential protective effect of living on campus for incoming transfer students. It is possible that living on campus provides students better access to the academic institution's supportive resources and more opportunities to make strong social connections. It could also be that living on campus creates a better sense of community and belongingness within the university, which could affect depression severity.

Importantly, the confidence intervals for the effect estimates of transfer status on beginning-of-the-semester depression severity levels was wide. Our analyses could not rule out large differences between first years and on-campus transfers, as the upper bound of the 95% confidence interval indicated on-campus transfers might score as high as 0.81 standard deviations higher on average than first years at the beginning of the semester. Nor could we rule out an effect of trivial magnitude, as the lower bound of the 95% confidence interval indicated on-campus transfers might score as little as 0.03 standard deviations higher on average than first years at the beginning of the semester. The same could be said of the comparison between off-campus transfers and first-year students, with off-campus transfers scoring anywhere from about equal to first-year students on depression severity levels to 0.63 standard deviations higher at the outset of the semester. This indicates that more data are needed to increase the precision of our estimates and determine whether the observed difference is meaningful form a public health perspective.

Furthermore, it would take only moderate levels of residual confounding for the statistically significant effect of being an on-campus transfer vs. a first-year student to nullify the effect on early semester depression severity. Although we adjusted for a number of plausible confounders, there are likely unmeasured confounding factors (e.g., academic ability and preparation) that could have biased our effect estimates. We therefore conclude that there is a high level of uncertainty in the degree to which transfer status is causally related depression severity during the transition to college.

Overall, our study leaves us with a high degree of uncertainty regarding the role of transfer status in the trajectory of depression severity during the transition to college. At the very least, being a transfer student appeared to a marker – though not necessarily a strong marker – of risk for depression severity during the transition to college over and above race/ethnicity, sex/gender, parental college education status, behavioral inhibition, mental health treatment history, and financial comfort level. For on-campus transfers, the period of risk appeared to be limited to the early weeks of the semester, whereas off-campus transfers may have more stable risk relative to first-year students.

We believe these findings are compelling enough to warrant additional study of the effect of transfer status to allow for improved precision of estimates and greater confidence regarding the question of causality. At present, it may be useful for institutions and stakeholders to use transfer status as one of a number of factors used to determine priority for targeted prevention programs; however, we do not think there is sufficient evidence of causality to warrant the development of depression prevention programs specifically targeting aspects of the transfer experience. Knowing whether being a transfer student is a marker of risk or transferring is a causal factor is critical. If being a transfer student is a marker of risk, it is an easily identifiable way for stakeholders to distribute preventive interventions to an at-risk population. If transferring is causal, then it would have implications for the content of interventions rather than just informing who to deliver interventions to.

This study can also contribute to the educational literature and help inform reasons for drop out or persistence. Begdache et al. in 2019 and Lardier et al. in 2020 found depression in college was associated with academic performance and less college persistence, but other studies have found mixed results. This study can be used to add to the evidence that depression severity levels tend to start out higher for transfers and continue to be higher for off campus transfers, and future studies can use this to then analyze persistence in this subgroup. Knowing if depression severity is also related to persistence would be of high concern to academic institutions and help support funding resources for preventive interventions.

Measuring Depression Severity

Our initial latent factor model of depression severity, pulling measured indicators from different instruments and subscales, did not yield a stable factor structure. However, our second latent factor model using the three SF-36 measures of role impairment items resulted in a model that was consistent with the data with no evidence of violation of the assumptions of longitudinal invariance. Thus, this latent factor model may be a viable option for researchers modeling depression severity among college students. It should be noted, however, that the fact that the items are binary precludes testing of threshold invariance (Liu et al., 2016).

Limitations and Strengths

The proposed study has several notable limitations including a reliance on self-report measures and a limited representation of non-affluent students and students from traditionally underrepresented groups. Some additional limitations are that gender was measured as a binary variable without clear distinction from gender identity, measuring race with mutually exclusive categories, confounding of race and ethnicity, and a lack of a long-term follow-up. Meyer (2021) found a notable relationship with intersecting identities and stressors during the transition to college, but with low number of racially diverse participants and no demographic questions on many other identities, we could potentially be missing important confounders. Data collected this study were also from 2010 and 2011, which brings up questions if this data can still be representative of the current college climate given many aspects of college have changed in the last decade. Additionally, there is likely great variability the experience of transitioning to college across institutions, and we cannot assume that experiences of students at one institution provide a good representation of the transition experience more generally. Nevertheless, this study sets up a framework for future studies to replicate during different time frames and at different locations. It will be particularly noteworthy to evaluate mental health experiences during the transition to college in the context of the COVID-19 pandemic.

The study also has several notable strengths such as a longitudinal design during a critical transition period and a high retention rate with limited missing data. This study also explicitly measures depression severity rather than just the presence of symptoms. Lastly, structural equation modeling was used to model depression severity as a latent variable with unique variance in the measured impairment variables separated from the common variance to improve precision. Social connectedness was also measured in this data, so future analyses could evaluate this as a potential mechanism and explain why transfer students may have difficulty.

Future Directions

We are currently conducting a follow-up longitudinal study evaluating mental health trajectories among incoming students in their first semester at an academic institution. This study addresses a number of the limitations described above. We are using multiple scales to measure depression severity, have higher representation of students from diverse backgrounds, and better measurement of gender and sexual identity. Previously Meyer (2021) studied intersectionality and its effect on depression severity during the transition to college. Our follow-up study has a far more detailed demographic questionnaire asking about multiple markers of socioeconomic status and prior exposure to adverse experiences and impoverished environments. Students will rate their levels of belongingness throughout the semester, as well as experiences of discrimination. Thus, we will be better able to evaluate the role of intersecting identities in the development of depression during the transition to college.

Additionally, the follow-up study will also include access to academic administrative performance metrics, including GPA and dropout. These indicators of academic success will be collected throughout students' careers at the institution, serving as a long-term outcome measure. This study will be measuring student expectations for academic performance as well, so this combined with GPA can inform the educational literature and perhaps improve our understanding of the role of mental health in college persistence and drop out.

Conclusions

This study, combined with prior findings in the literature, suggests that incoming first-year and transfer students are likely to experience increases in depression severity during their first semester at a new higher education institution. Although it remains highly uncertain whether being a transfer student contributes to depression severity during the college transition, it appeared to at least be a risk marker for elevated levels in the early weeks of the semester. On-campus transfers reported lesser increases in depression severity over time relative to first-year students, whereas off-campus transfers maintained a marginal elevation in depression severity relative to first-year students throughout the semester. This raises the question of whether living on campus might be protective for transfer students. Findings from this study should spur future research aimed at improving precision in estimates of the effect of transfer status on depression severity and confidence regarding whether transferring is a causal contributor.

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Appendix A

Tables

Table A1

Participant Characteristics by Student Status

	First-Year (N=235)	On-Campus Transfer (N=44)	Off-Campus Transfer (N=70)	Total (N=351)
Sex				
Male	95 (40.4%)	23 (52.3%)	22 (31.4%)	141 (40.2%)
Female	140 (59.6%)	21 (47.7%)	48 (68.6%)	210 (59.8%)
Race				
White	165 (70.2%)	25 (56.8%)	40 (57.1%)	231 (65.8%)
Asian	44 (18.7%)	12 (27.3%)	23 (32.9%)	80 (22.8%)
Other	22 (9.4%)	6 (13.6%)	7 (10.0%)	35 (10.0%)
Missing	4 (1.7%)	1 (2.3%)	0 (0%)	5 (1.4%)
Parent Education				
No College Degree	40 (17.0%)	7 (15.9%)	16 (22.9%)	64 (18.2%)
College Degree	193 (82.1%)	36 (81.8%)	52 (74.3%)	282 (80.3%)
Missing	2 (0.9%)	1 (2.3%)	2 (2.9%)	5 (1.4%)
Financial Comfort				
Struggle	31 (13.2%)	6 (13.6%)	14 (20.0%)	51 (14.5%)
Tight but fine	122 (51.9%)	29 (65.9%)	44 (62.9%)	197 (56.1%)
Not a problem	82 (34.9%)	9 (20.5%)	11 (15.7%)	102 (29.1%)
Missing	0 (0%)	0 (0%)	1 (1.4%)	1 (0.3%)
Pre-Semester Mental Health Treatment				
No	219 (93.2%)	41 (93.2%)	66 (94.3%)	328 (93.4%)
Yes	16 (6.8%)	3 (6.8%)	4 (5.7%)	23 (6.6%)
Ever Used Mental Health Treatment				
No	176 (74.9%)	27 (61.4%)	46 (65.7%)	250 (71.2%)
Yes	59 (25.1%)	17 (38.6%)	24 (34.3%)	101 (28.8%)
Behavioral Inhibition Total Score				
Mean (SD)	21.0 (3.75)	21.3 (3.84)	21.5 (3.54)	21.2 (3.70)
Median [Min, Max]	22.0 [9.00, 28.0]	21.0 [13.0, 28.0]	22.0 [10.0, 28.0]	22.0 [9.00, 28.0]
Missing	1 (0.4%)	0 (0%)	0 (0%)	1 (0.3%)

Table A2

Frequencies for SF-36 Role-Emotional Impairment Items by Time Used in the Primary Outcome Analyses

	Aug (Pre-Semester) (N=351)	Sep (Week 2) (N=351)	Oct (Week 6) (N=351)	Nov (Week 11) (N=351)	Dec (Week 15) (N=351)
Cut Down on Time in Work or Activities					
No	313 (89.2%)	298 (84.9%)	270 (76.9%)	240 (68.4%)	233 (66.4%)
Yes	38 (10.8%)	35 (10.0%)	54 (15.4%)	79 (22.5%)	85 (24.2%)
Missing	0 (0%)	18 (5.1%)	27 (7.7%)	32 (9.1%)	33 (9.4%)
Accomplished Less than You Would LIke					
No	287 (81.8%)	268 (76.4%)	241 (68.7%)	219 (62.4%)	215 (61.3%)
Yes	64 (18.2%)	65 (18.5%)	83 (23.6%)	100 (28.5%)	103 (29.3%)
Missing	0 (0%)	18 (5.1%)	27 (7.7%)	32 (9.1%)	33 (9.4%)
Didn't Do Work or Activites as Carefully as Usual					
No	303 (86.3%)	295 (84.0%)	255 (72.6%)	238 (67.8%)	226 (64.4%)
Yes	48 (13.7%)	38 (10.8%)	69 (19.7%)	81 (23.1%)	92 (26.2%)
Missing	0 (0%)	18 (5.1%)	27 (7.7%)	32 (9.1%)	33 (9.4%)

Table A3

Ordinal Latent Growth Curve Modeling Sequence and Model Comparisons

Model	Description	Scaled Difference Model Comparison Test				
		Comparison Model	χ^2	*df*	*p**	Conclusion
1	Most complex model (Model *df* = 215)	-	-	-	-	-
2	Removed random time coefficients (Model *df* = 217)	Model 1	6.33	2	.042	Retain random time slope coefficients
3	Removed random intercept (Model *df* = 216)	Model 1	11.03	1	.001	Retain random intercept
4	Held latent factor error variances constant over time (Model *df* = 219)	Model 1	18.21	4	.001	Retain non-constant error variances
5	Removed first-order autoregressive	Model 1	0.42	1	.518	Eliminate AR1 effect

Model	Description	Comparison Model	χ^2	*df*	*p**	Conclusion
	(AR1) effect (Model *df* = 216)					
6	Removed covariate by time interactions (Model *df* = 236)	Model 5	19.97	20	.460	Eliminate covariate by time interactions
7	Removed nonlinear time effects (Model *df* = 242)	Model 6	10.19	6	.117	Eliminate nonlinear time effects
Model 8	Removes effects of transfer status on latent intercept and slope variables (Model *df* = 246)	Model 7	.47	4	.050	Transfer status is a borderline significant overall predictor of depression severity

Note: * Significant values indicate that the more complex model (with fewer model *df*) fits better than the hierarchically nested comparison model.

Table A4

Parameter Estimates from the Final Ordinal Latent Growth Curve Model

	Estimate	95% CI Lower	95% CI Upper
REGRESSIONS			
Latent Intercept Regressed ON			
Student Status (ref level = First-Years)			
On-Campus Transfers	1.367	0.105	2.630
Off-Campus Transfers	0.910	-0.158	1.978
Student Race (ref level: White/Caucasian)			
Asian/Asian American	1.610	0.483	2.737
Race—Other	0.881	-0.437	2.199
Parent Education (ref level: college degree)			
No college degree	-0.511	-1.577	0.555
Finances (ref level: Finances not a problem			
Finances are tight	0.570	-0.436	1.575
Finances are a struggle	1.895	0.403	3.387
Mental Health Treatment at Baseline (ref level: Not receiving treatment)			
Receiving Treatment	0.705	-0.639	2.048
Mental Health Treatment at any Time (ref level: Never received treatment)			
Ever Received Treatment	1.096	0.050	2.143
Behavioral Inhibition			
Linear Effect	0.824	0.131	1.518

		95%CI	
	Estimate	**Lower**	**Upper**
Nonlinear (restricted cubic spline) Effect	-0.520	-1.253	0.213
Latent Linear Slope Regressed ON			
Student Status (ref level = First-Years)			
On-Campus Transfers	-0.151	-0.301	-0.001
Off-Campus Transfers	-0.014	-0.114	0.086
INTERCEPTS			
Latent Intercept	=0	=0	=0
Latent Linear Slope	0.296	-0.01	0.602
VARIANCES/COVARIANCES			
Latent Intercept Variance	0.039	0.003	0.075
Latent Linear Slope Variance	6.599	1.020	12.177
Intercept—Linear Slope Covariance	-0.015	-0.184	0.153

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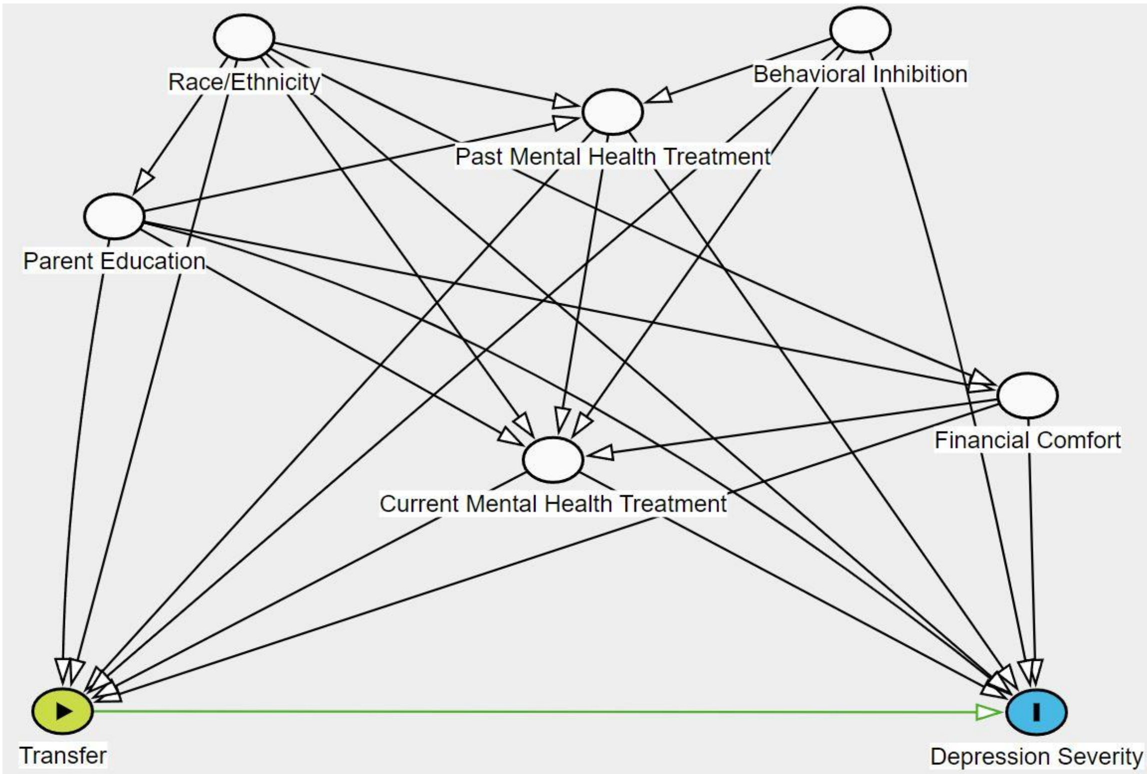
Appendix B

Figures

Figure B1

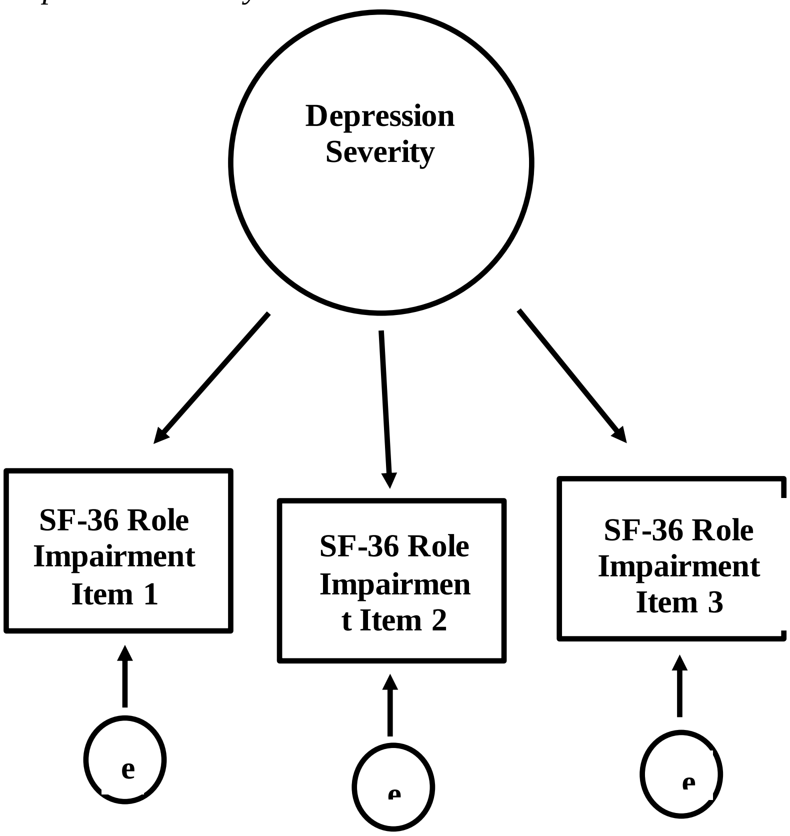
Directed Acyclic Graph (DAG)



Note. Directed Acyclic Graph (DAG) used to encode causal modeling assumptions and obtain a minimally sufficient set of variables that need to be adjusted to estimate the effect of transfer status on depression severity.

Figure B2

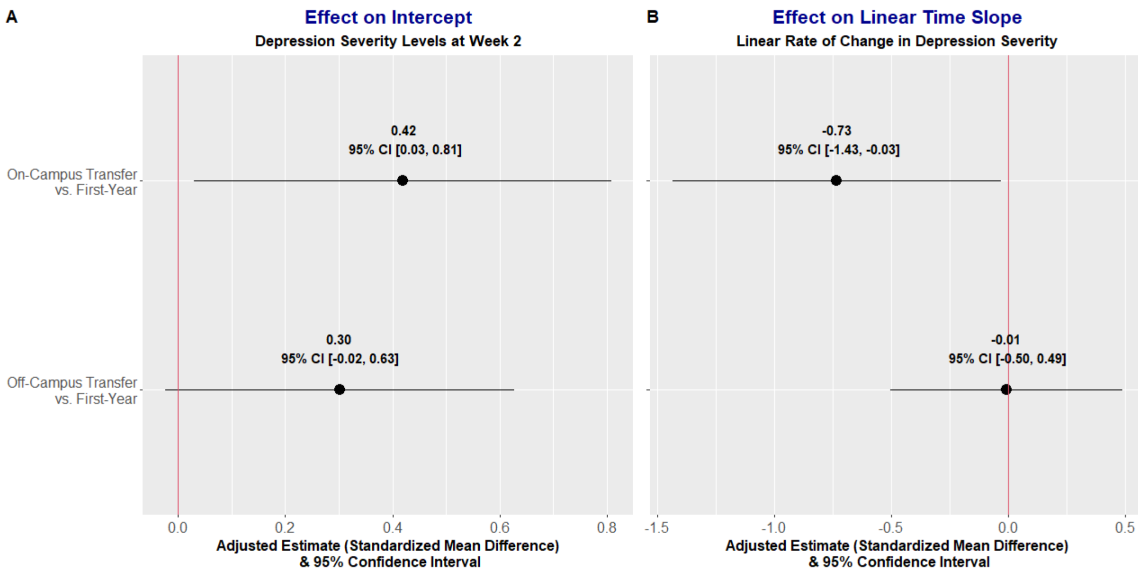
Depression Severity as a Latent Factor



Note. This figure represents the outcome variable, Depression Severity as a latent factor with three indicators.

Figure B3

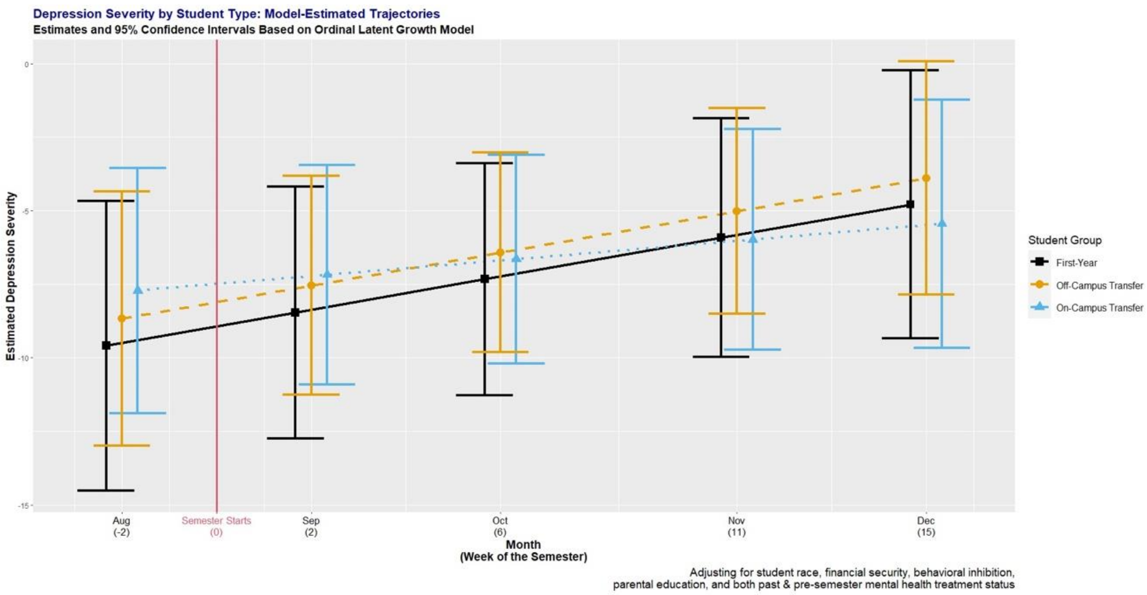
Ordinal Latent Growth Curve Model Estimated Effects



Note. Ordinal latent growth curve model estimated effect of being a transfer student on the latent intercept (week 2 levels of depression severity) and latent linear slope (rate of change in depression severity).

Figure B4

Depression Severity Trajectories



Note. Trajectory of depression severity by student type over the first semester.