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EXPLORING CAUSAL MECHANISMS BETWEEN BEHAVIOR AND COGNITION IN A THEORY-BASED ALCOHOL INTERVENTION

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EXPLORING CAUSAL MECHANISMS BETWEEN BEHAVIOR AND
COGNITION IN A THEORY-BASED ALCOHOL INTERVENTION

BY

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A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF

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IN

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2020

DOCTOR OF PHILOSOPHY DISSERTATION

OF

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2020

ABSTRACT

While the efficacy of Transtheoretical Model (TTM)-based interventions has been demonstrated time and time again, little has been done to understand the causal mechanisms responsible for the change resulting from exposure to a TTM-based intervention. The proposed study is to leverage sophisticated statistical techniques to examine the causal relationship among TTM constructs to better understand the direction of influence TTM-based interventions have. To accomplish this, a secondary data analysis using longitudinal data collected during a trial evaluating the efficacy of a TTM-based alcohol intervention targeting adults whose drinking exceeds national recommended guidelines was completed.

This study used a 2 x 5 factorial design to evaluate the efficacy of a computer-delivered alcohol intervention relative to assessment-only control. While the original study design involves participants randomly assigned to two conditions, the focus of these analyses will be on those who received the intervention (N=492), for whom data on TTM-related constructs was collected in addition to outcomes of interest. Participants in the intervention group were assessed on decisional balance and temptations at baseline, 3-, and 6-months. They were also assessed on stage of change to adhere to low-risk drinking guidelines and alcohol consumption outcomes (i.e., drinks per week, drinks per drinking day, and binge frequency) at five time points (baseline, 3-, 6-, 12-, and 18-months).

Preliminary analyses yielded no associations between decisional balance and drinking outcome variables, but there was a strong association between temptations and all measures of alcohol consumption. As such, the main outcome analyses focused

on understanding the relationship between temptations and alcohol use. Latent growth curve modeling (LGCM) was used to explore these relationships using the lavaan package in *R*. Parallel process models, simultaneously modeling temptations and each of the alcohol variables, were conducted with the inclusion of stage of change as a time-varying covariate. Models allowing for covariances to be freely estimated had significantly better fit than models that fixed these covariances at zero. These models were further extended with the inclusion of regression paths between the two slope factors in each model. Both potential directions of influence between these two factors were considered in separate models, but their addition negligibly changed model fit, and none of the six models examined yielded a significant regression path. While nonsignificant, the regression path regressing the slope of drinks per week on the slope of temptations approached significance, suggesting that change in drinks per week may precede change in temptations.

The relationships observed between cognitive constructs and drinking outcome behavior deviated from previous literature, in that there was no association between decisional balance and drinking, and there was some evidence that the direction of influence between temptations and drinking was not as expected. Future work is needed to replicate and elucidate these findings, especially given the many methodological issues inherent to these data.

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DEDICATION

This dissertation is dedicated to my dad, James Balestrieri, who instilled his perpetual curiosity and voracious appetite for knowledge in me.

TABLE OF CONTENTS

ABSTRACT	ii
ACKNOWLEDGEMENTS	iv
DEDICATION	vi
TABLE OF CONTENTS	vii
LIST OF TABLES	viii
LIST OF FIGURES	x
CHAPTER 1	1
CHAPTER 2	10
CHAPTER 3	22
CHAPTER 4	31
TABLES.....	44
FIGURES	64
APPENDICES	79
BIBLIOGRAPHY	101

LIST OF TABLES

TABLE	PAGE
Table 1. Baseline characteristics of treatment participants.....	44
Table 2. Descriptive information for alcohol consumption variables.....	45
Table 3. Descriptive information for cognitive variables.....	46
Table 4. Bivariate associations among pros, cons, temptations, and drinks per week.....	47
Table 5. Bivariate associations among pros, cons, temptations, and drinks per drinking day.....	48
Table 6. Bivariate associations among pros, cons, temptations, and binge frequency.....	49
Table 7. Bivariate associations among drinks per week, drinks per drinking day, and binge frequency.....	50
Table 8. Latent growth curve model of temptations including stage as a TVC.....	51
Table 9. Latent growth curve model of drinks per week including stage as a TVC....	52
Table 10. Latent growth curve model of drinks per drinking day including stage as a TVC.....	53
Table 11. Latent growth curve model of binge frequency including stage as a TVC.....	54
Table 12. Parallel process model, temptations x drinks per week including stage as a TVC, covariances freely estimated.....	55
Table 13. Parallel process model, temptations x drinks per drinking day including stage as a TVC, covariances freely estimated.....	56
Table 14. Parallel process model, temptations x binge frequency including stage as a TVC, covariances freely estimated.....	57
Table 15. Parallel process model, temptations x drinks per week including stage as a TVC with added regression path (Temptations → Drinks per week, β_{42}).....	58
Table 16. Parallel process model, temptations x drinks per week including stage as a TVC with added regression path (Drinks per week → Temptations, β_{24}).....	59
Table 17. Parallel process model, temptations x drinks per drinking day including stage as a TVC with added regression path (Temptations → Drinks per drinking day, β_{42}).....	60
Table 18. Parallel process model, temptations x drinks per drinking day including stage as a TVC with added regression path (Drinks per drinking day → Temptations, β_{24}).....	61

Table 19. Parallel process model, temptations x binge frequency including stage as a TVC with added regression path (Temptations → Binge frequency, β_{42}).....	62
Table 20. Parallel process model, temptations x binge frequency including stage as a TVC with added regression path (Binge frequency → Temptations, β_{24}).....	63

LIST OF FIGURES

FIGURE	PAGE
Figure 1. Consort chart.....	65
Figure 2. Profile of pros and cons sum scores across stage of change, baseline.....	66
Figure 3. Profile of pros and cons sum scores across stage of change, 3-months.....	67
Figure 4. Profile of pros and cons sum scores across stage of change, 6-months.....	68
Figure 5. Latent growth curve model of temptations including stage as a TVC.....	69
Figure 6. Latent growth curve model of drinks per week including stage as a TVC....	70
Figure 7. Latent growth curve model of drinks per drinking day including stage as a TVC.....	71
Figure 8. Latent growth curve model of binge frequency including stage as a TVC.....	72
Figure 9. Parallel process model, temptations x drinks per week including stage as a TVC.....	73
Figure 10. Parallel process model, temptations x drinks per drinking day including stage as a TVC.....	74
Figure 11. Parallel process model, temptations x binge frequency including stage as a TVC.....	75
Figure 12. Parallel process model, temptations x drinks per week including stage as a TVC with added regression paths.....	76
Figure 13. Parallel process model, temptations x drinks per week including stage as a TVC with added regression paths.....	77
Figure 14. Parallel process model, temptations x drinks per drinking day including stage as a TVC with added regression paths.....	78

CHAPTER 1

INTRODUCTION

Over the last fifteen years, there has been consensus in the medical community that modifiable behavioral risk factors are the leading cause of mortality in the United States (Mokdad et al., 2004). Accordingly, there has been a rise in the number of behavioral interventions available to create behavior change in those who engage in health risk behaviors. With the host of interventions now available to the public, it is important to gauge which are the most efficacious, and to learn in an iterative fashion so these interventions can be improved over time. Using behavior change theory is one way to improve the effectiveness of behavior change interventions (Davis et al., 2015; Glanz et al., 2008). Often intervention evaluation studies answer two of three key questions: do they work and how well do they work, but they often ignore the third question – *how* do they work (Michie & Abraham, 2004). In order to understand how an intervention works, studies must measure and report on the techniques or procedures responsible for behavior change. Improving intervention effectiveness, and having the ability to use intervention components across different behaviors, requires an understanding of the causal processes and mechanisms underlying the change. This review aimed at assessing the extent to which available evidence demonstrates the development of effective and theoretically-grounded behavior change techniques across different health behaviors (Michie & Abraham, 2004). The authors concluded that most descriptions of interventions are not specific about the techniques used, and

there is no clear link between theory and adoption of intervention components. When intervention development has been driven by empirically-supported theory, our ability to understand the mechanisms through which the intervention operates is greatly increased (Michie & Abraham, 2004).

A systematic review examined the application of theory in the health behavior literature, reviewing 193 articles that met inclusion criteria (Painter et al., 2008). Only one-third of these articles mentioned theory in any capacity. Of the third that make any mention of theory, the vast majority (nearly 70%) suggest that their research was informed by theory. Of this one-third of articles, only 18% actually engaged in theory-driven research (Painter et al., 2008). Another systematic review examined the role of theory in behavior change interventions specifically amongst interventions delivered via the Internet. This review found that across the 85 studies that met inclusion criteria, most had a small but statistically significant effect on health behavior. More importantly, those studies that involved a more extensive use of theory had increase in effect size. In addition, studies that incorporated more theory-driven behavior change techniques had larger effect sizes than those that incorporated fewer techniques (Webb et al., 2010).

The idea that theory-driven interventions are more effective was also supported by a meta-analysis that was more broadly focused on the efficacy of tailored health behavior interventions. Within this meta-analysis, one component of effective tailoring was identified to be the number of theoretical concepts an intervention is tailored on, such that there was a positive association between the number of theoretically-tailored intervention components and intervention efficacy (Noar et al., 2007). This article also

examined specific theoretically-driven concepts found in the literature and determined that the concepts associated with the largest effect sizes included attitudes, self-efficacy, stages of change, processes of change, and social support. The authors suggest that health behavior change theories that emphasize these concepts may lead to the most efficacious interventions (Noar et al., 2007). One such theory that is mentioned is the Transtheoretical Model of Behavior Change.

The Transtheoretical Model (TTM) is one of the most prominent in health behavior research (Clark & Janevic, 2018; J. O. Prochaska & Velicer, 1997). The TTM explains how individuals progress through a series of five stages of change: Precontemplation (not intending to take action within the next six months); Contemplation (intending to take action in the next six months); Preparation (intending to take action in the next 30 days); Action (made the behavior change less than six months ago); or Maintenance (made the behavior change more than six months ago) (Clark & Janevic, 2018; Glanz et al., 2008; J. O. Prochaska & Velicer, 1997).

In addition to the stages of change, the TTM is comprised of three additional core constructs: decisional balance (an individual's relative weighting of pros and cons for changing), processes of change (activities that people use to progress through the stages), and self-efficacy (an individual's situation-specific confidence in their ability to make and/or sustain a change) (Clark & Janevic, 2018; Glanz et al., 2008; J. O. Prochaska & Velicer, 1997). Oftentimes, studies examining the efficacy of TTM-based interventions measure self-efficacy using its converse measure, temptations, which assesses the intensity of urges to engage in a specific behavior when in difficult

situations (Glanz et al., 2008). These three constructs are systematically related to stages of change in predictable ways (DiClemente et al., 1991; Hall & Rossi, 2008). The predictable relationship between stages of change and other TTM constructs provides an evidence-based framework for developing tailored interventions that are more likely to change behavior (Johnson et al., 2006a; Kreuter et al., 1999; Noar et al., 2007). TTM-driven interventions have been found to be effective across many different behaviors, such as substance use (Evers et al., 2012; Hollis et al., 2005; Serafini et al., 2016), healthy eating/physical activity (Mauriello et al., 2010), medication adherence (Johnson et al., 2006a; Johnson et al., 2006b), stress (Evers et al., 2006), depression (Levesque et al., 2011)) as well as populations such as adolescents (Evers et al., 2012; Hollis et al., 2005; Levesque et al., 2017; Mauriello et al., 2010; Serafini et al., 2016), adults (Evers et al., 2006; Johnson et al., 2006a; Johnson et al., 2006b; D. Levesque et al., 2011), and veterans (Johnson et al., 2017). These lists exemplifying of the breadth and reach of the TTM are by no means comprehensive.

While the efficacy of TTM-based interventions has been demonstrated repeatedly, little has been done to understand the causal mechanisms responsible for the change resulting from exposure to a TTM-based intervention. Lack of evidence examining the causal mechanisms underlying behavior change theories is not unique to the TTM. In 2008, the National Institutes of Health (NIH) formed the Science of Behavior Change (SOBC) Common Fund Program, with the aim of identifying and measuring mechanisms that underlie behavior change. The second phase of SOBC began in 2015 to initiate a paradigm shift to reframe the key scientific question in

behavior change science from “Is the intervention efficacious?” to “How do our interventions work?” (Nielsen et al., 2018). The TTM has been criticized for describing the process of behavior change descriptively, rather than explaining the underlying causal mechanisms. Aware of this, the developers of the TTM have suggested that the TTM should be subject to causal modeling tests (J. O. Prochaska et al., 2008). What evidence exists examining the causal mechanisms of the TTM is largely dated and examines these mechanisms in the content of TTM-based tobacco cessation interventions (Pollak et al., 1998; Velicer et al., 1996).

One secondary analysis of prospective data of smokers examined the causal relationships between processes of change and decisional balance. Specifically, researchers were interested in determining if these causal relationships were stage-specific (i.e., differed based on what stages participants were in at baseline). Researchers only formed hypotheses regarding these causal relationships for participants in Contemplation and for those in Action. For those smokers in Contemplation (thinking about quitting in the next 6 months), researchers expected increases in experiential process use to causally influence changes in decisional balance, and that decisional balance would not causally influence experiential process use. Conversely, for those participants in Action (had quit smoking within the past 6 months), researchers expected changes in decisional balance to causally influence increases in behavioral process use, and behavioral process use would not causally influence decisional balance. Using cross-lagged panels analyzed using structural equation modeling (SEM), researchers were able to support their hypothesis regarding smokers in Contemplation, such that for these participants, experiential process use

had causal predominance over decisional balance. Their second hypothesis was not supported, with neither decisional balance nor behavioral process use having causal predominance for those participants in Action (Pollak et al., 1998). Although this secondary data analysis takes some important steps towards understanding the causal mechanisms underlying the TTM, it has some issues of note. First, researchers only hypothesized and tested models relating to two stages of change rather than all five, giving a limited view of the potential causal mechanisms underlying the TTM. Second, these analyses focus on the causal relationship between the processes of change and decision balance, but does not evaluate the relationship between either of these TTM constructs and the actual behavior of interest (i.e., the outcome an intervention is evaluating, such as smoking cessation in this case).

Another secondary data analysis, also analyzing prospective data collected during a study evaluating a smoking cessation intervention, takes an important step to overcome the second issue proposed above by examining the causal relationship between decisional balance and the outcome behavior. Velicer et al. (1996) examined the relationship between three constructs: outcome behavior (smoking cessation), pros (positive cognitive evaluations of smoking cessation), and cons (negative cognitive evaluations of smoking cessation). Researchers evaluated a series of structural equation models to determine the direction of influence between behavior and each of the cognitive dependent measures (pros and cons). Three alternative models were considered to explain the relationship between behavior and pros, as well as behavior and cons. Based on their prior work, the research team predicted different causal relationships for the pro-behavior model and the con-behavior model. For the pro-

behavior model, behavior was expected to precede cognition, as prior work had shown that behavior typically changes before or at the same time as cognition. The path of causation for the con-behavior model was more difficult to predict, as previous studies have demonstrated a curvilinear relationship between behavior and cons, such that for those in early stages of change, behavior precedes cognition, while those in later stages often demonstrate almost no relationship between behavior and cognition. As predicted, for the pro-behavior model, best fit was obtained by the model in which change in behavior predicted change in cognition. To test the con-behavior model, the sample was split in two subsamples to represent the two parts of the curve. The sample of participants in early stages of change was too small to complete analyses. The sample of those in later studies was examined, demonstrating the same causal relationship as the pro-behavior model (Velicer et al., 1996). As with the previous secondary data analysis, these analyses are also restricted to examining participants who were in Contemplation or Action at baseline. Another limitation highlighted by both teams of researchers is the inability of traditional SEM to model non-linear relationships. Unfortunately, traditional SEM assumes a linear relationship among the constructs being modeled, while the TTM assumes curvilinear relationships between constructs (J. O. Prochaska et al., 2008). While Velicer et al. (1996) dealt with this assumption by splitting the sample into subsamples to represent the two parts of the curve, more sophisticated SEM techniques that allow for curvilinear relationships have become more widely utilized in the last decade.

A much more recent study leveraged one such method, Latent Growth Curve Modeling (LGCM), to assess the direct and indirect effects of temptations on the

relationship between intervention group and stage of change (Brick et al., 2019). This study pooled data from three randomized controlled trials that aimed at assessing the efficacy of a TTM-based intervention for limiting dietary intake of high-fat foods. These analyses simultaneously modeled latent factors related to temptations and slope, and the researchers were interested in the influence of the intervention on these factors, and how the factors themselves covaried. The researchers hypothesized that the intervention would significantly affect the growth rate for both temptations and stage, and that the growth rate for temptations would be significantly related to the growth of stage. As expected, there was a significant relationship between intervention group and the growth rates for both the temptations and slope factors, however the growth of temptations was not significantly related to stage (Brick et al., 2019).

The aim of the current study is to examine the causal relationship between TTM constructs and outcome behavior to gain a better understanding of the mechanisms through which TTM-based interventions demonstrate efficacy. To accomplish this, I will be conducting a secondary data analysis using longitudinal data collected during a trial evaluating the efficacy of a TTM-based alcohol intervention targeting adults whose drinking exceeds national recommended guidelines. This study adopted a 2 x 5 factorial design to evaluate the efficacy of a computer-delivered alcohol intervention relative to assessment-only control. While the original study design involved participants randomly assigned to two conditions, my focus will be on those who received the intervention, for whom data was collected across five time points (baseline, and follow-ups at 3-, 6-, 12-, and 18-months post-baseline).

Whereas Brick et al. (2019) took an important step toward using more appropriate and sophisticated modeling procedures to investigate the relationships amount TTM constructs, the current analyses deviated in a few key ways. First, the primary aim of this prior work was to investigate the role that assignment to intervention (vs. control) had on the growth rate of temptations and stage of change over time. While the current study used an existing data set from a large clinical trial investigating the efficacy of a TTM-based intervention for alcohol use, the goal of these analyses was not to examine the impact of the intervention. Next, Brick et al. (2019) focused on the relationship between temptations and stage of change for diet, whereas the interest in this current study was to examine the relationship between TTM-related constructs and different measures of alcohol consumption. Additionally, although Brick et al. (2019) examined the relationship between the growth rate for temptations and the growth rate for stage of change, the direction of influence was assumed to flow from temptations to stage, a path that was not found to be significant. The analyses described here are more exploratory in nature and sought to examine the different possible patterns of association between temptations and alcohol consumption.

CHAPTER 2

METHODOLOGY

Participants and Procedures

Participants for the clinical trial were recruited over a seven-week period by a survey research company that sent email invitations to individuals on their panel. The invitation contained a link to a brief screener with three questions assessing the respondents' age, employment status, and whether they consumed alcohol during the past 30 days. Those who were under age 21, unemployed, and/or did not consume alcohol in the last 30 days were not eligible for study participation. Others continued to the study registration page, where they created a study login name and password and answered three security questions. Those who registered were taken to the study informed consent form and, after consenting, completed the baseline assessment. Individuals were excluded from the study if they: did not exceed the NIAAA low-risk drinking guidelines in the last 30 days (i.e., less than 14 drinks/week and less than 4 drinks/day for males; less than 7 drinks/week and less than 3 drinks/day for females); were alcohol-dependent, as determined by a score of 10 or more on the Alcohol Use Disorders Identification Test-Consumption (AUDIT-C; Bush et al., 1998); lived outside the U.S.; were a full-time college student; were pregnant; were ever involved in substance abuse treatment or interested in treatment now; were ever advised by a physician to avoid alcohol; or scored less than 7 on a 10-point scale assessing confidence to participate in this 18-month study. Details on the rationale of all

inclusion and exclusion criteria are detailed in Appendix A. Those who did not screen out were enrolled in the study and asked to provide a cell phone number for delivery of study text messages. At that point, they were asked to validate their cell phone number by responding “start” to a text message requesting permission for the delivery of text messages for this study. Individuals within a given stage (e.g., Precontemplation) were alternately assigned to treatment or control, to ensure similar stage distributions in the two study conditions.

The trial Consort chart is provided in Figure 1. A total of 3,502 individuals accessed the study link, met initial inclusion criteria, and registered for the study. Among those individuals, 350 did not consent to participate, 1,828 met one or more exclusion criteria, 12 did not complete the baseline survey, and 138 did not validate their phone number. Another seven withdrew from the study, and 194 were removed because they had registered two or more times for the study. Of the remaining 973 participants, 492 were assigned to treatment, and 481 to control. The analytic sample was restricted to those participants assigned to treatment due to the design of the study, which only assessed decisional balance and temptations among those who received the intervention. This sample was predominately female (57.1%), White (78.0%), and non-Hispanic (88.4%) with a mean age of 39.1. Participants had to be in a pre-action stage to be eligible for the study, with the highest number of participants endorsing being in Precontemplation (47.0%), followed by Contemplation (31.3%), and Preparation (21.7%). See Table 1 for details.

Intervention participants then continued immediately into their first computer-tailored intervention (CTI) session, and received follow-up sessions at 3- and 6-

months post-baseline session. They had access to their personalized activity center (PAC) and printed reports and received text messages throughout the 6-month intervention period. Both groups received online follow-up surveys at 6, 12, and 18 months. Participants received \$20 for completing the baseline assessment, \$20 for each of the 3- and 6-month time points, and \$30 for each of the 12- and 18-month follow-up assessments. The intervention group received a total of \$120 in incentives, and the control group received \$100 in incentives (\$20 less because they did not participate in the 3-month time point). Incentives were in the form of American Express or VISA gift cards. Participants who were due for a follow-up intervention session or assessment, or who had left a session incomplete, received up to seven weekly text messages and two email messages, and up to two telephone calls, encouraging the participant to come back. All email and text message reminders were automatically generated by the program.

Intervention

The CTI administers assessments and immediate on-screen feedback matched to stage of change and other dimensions of the TTM. At the end of each session, program users can review and print a report that contains all the feedback received during the session. The intervention also includes a PAC, a web portal that becomes available after the first CTI session. The PAC offers 40 stage-matched activities that reinforce key principles and processes of change matched to the user's stage of change. The PAC can be accessed as often as the user desires between CTI sessions. Additionally, two PAC activities are embedded within each of the three CTI sessions, as a way to increase session interactivity and engagement. The intervention

also included six months of tailored text messages. These text messages, matched to the individual's stage of change and other TTM dimensions, reinforce key intervention strategies addressed in the CTI sessions. The frequency of message delivery (one message every one to three days) was dependent on stage of change. While agreeing to receive text messages was a requirement for initial study enrollment, as described below, users could choose to stop text messages at any time.

Measures

Demographics Characteristics

During the baseline assessment and prior to randomization to condition, participants were asked to report their gender, race, ethnicity, employment status (full or part time), and age. Participants were also given the Gallup-Healthways Well-Being Index (Gallup, 2019), which categorizes people as “suffering,” “struggling,” or “thriving” based on their responses to the two-item Cantril Self-Anchoring Scale (Cantril, 1965).

Behavioral Measures

Alcohol Consumption. Prior to randomization, potential participants completed the Alcohol Use Disorders Identification Test-Consumption (AUDIT-C; Bush et al., 1998), a three-item scale used to assess drinking severity as an indicator of dependence. Those who were determined to be alcohol-dependent using this measure were excluded from participation. To measure the frequency and quantity of alcohol use, participants were asked “In a typical week, on how many days do you have at least one drink containing alcohol?” (drinks per week) and “How many drinks containing alcohol do you have on a typical day when you are drinking?” (drinks per

drinking day). To assess frequency of binge episodes (defined by NIAAA as the consumption of 4/5 drinks by female/males in a two-hour period (National Institute on Alcohol and Alcoholism [NIAAA], 2016)), participants were also asked “During the past 30 days, on how many days did you have 4/5 (for females/males) or more drinks containing alcohol in a row, that is, within a couple of hours?”. Alcohol consumption was measured at all five time points. Please see Appendix B1 for the full inventory of items related to alcohol consumption.

All continuous measures were assessed for test-retest reliability in SPSS (*IBM SPSS Statistics 25.0*, 2019) by calculating intraclass correlation coefficients (ICCs) and their 95% confidence intervals based on single measures, relative consistency, and 2-way mixed effects models (Koo & Li, 2016; Weir, 2005). When interpreting the acceptability standards of ICCs in the context of test-retest reliability, values between 0.40 and 0.59 are considered to be fair, values between 0.60 and 0.74 good, and values above 0.75 as excellent (Cicchetti, 1994). Using these thresholds, the test-retest reliability of measures related to alcohol consumption were considered good, including the AUDIT-C (ICC = 0.65, 95% CI [0.61, 0.69], $p < .001$), drinks per week (ICC = 0.67, 95% CI [0.63, 0.71], $p < .001$), drinks per drinking day (ICC = 0.62, 95% CI [0.58, 0.67], $p < .001$), and binge frequency (ICC = 0.60, 95% CI [0.56, 0.64], $p < .001$).

TTM Construct Measures.

Stages of Change for Limiting Drinking. One-item will assess readiness to limit drinking to the NIAAA gender-specific low-risk drinking guidelines (i.e., less than 14 drinks/week and less than 4 drinks/day for males; less than 7 drinks/week and

less than 3 drinks/day for females). Participants responded whether they were not intending to limit their drinking in the next six months (Precontemplation), intending to limit their drinking in the next six months (Contemplation), ready to limit their drinking in the next month (Preparation), limiting their drinking for less than six months (Action), or limiting their drinking for more than six months (Maintenance) (Migneault et al., 2005). Stage of change for limiting drinking was assessed at all five time points. Please see Appendix B2 for the stage of change items.

As this is an ordinal categorical measure, assessing for test-retest reliability using the ICC would not be appropriate. The kappa statistic was developed to test for inter-rater reliability between a fixed pair of raters when the method of assessment is measured on a categorical scale (Cohen, 1960). As these analyses are substituting trials for raters when assessing test-retest reliability, and stage of change was measured across five time points, Fleiss' kappa was calculated (Fleiss, 1971). Fleiss' kappa was calculated using the *irr* package in the program R (Gamer & Lemon, 2012; R Core Team, 2020). The strength of agreement standards for the kappa statistic are as follows: < 0.00 = poor, $0.00-0.20$ = slight, $0.21-0.40$ = fair, $0.41-0.60$ = moderate, $0.61-0.80$ = substantial, $0.81-1.00$ = almost perfect (Landis & Koch, 1977). The test-retest reliability for measuring stage of change over time in this sample resulted in only slight agreement ($\kappa = 0.14$, $p < .001$). It is important to note that stage of change is expected to be a dynamic construct, and, in fact, it will ideally change over time as an individual increases in their readiness to engage in the target health behavior.

Decisional Balance for Limiting Drinking. Participants were asked to indicate their level of agreement for a series of statements regarding the pros and cons of

limiting drinking. This scale consisted of eight items – four pros and four cons. All items were assessed on a 5-point scale (*1 = not important at all* to *5 = extremely important*), and the four items in each subscale (pros and cons) were summed together to create two sum scores. Decisional balance was assessed at baseline as well as 3- and 6-months post-baseline. The test-retest reliability for the pros sum score just met the threshold to be considered “good” (ICC = 0.60, 95% CI [0.49, 0.70], $p < .001$), while the cons sum score was fair (ICC = 0.49, 95% CI [0.36, 0.61], $p < .001$). Please see Appendix B3 for the full battery of items assessing decisional balance.

Temptations for Exceeding Low-Risk Drinking Guidelines. Temptations for exceeding low-risk drinking guidelines was measured using the Situational Temptation scale (DiClemente, 1986) adapted from Bandura’s self-efficacy theory (Bandura, 1977) as well as coping models of smoking relapse and maintenance (Shiffman et al., 1986). This measure is designed to determine how tempted an individual feels toward engaging in a non-desired behavior, or in this study, exceeding low-risk drinking guidelines. Each of the 10 items included in this scale was measured on a 5-point scale (*1 = not tempted at all* to *5 = extremely tempted*). This 10-item measure included two subscales, each consisting of five items, including a subscale measuring negative affect situations (e.g., drinking when you are feeling down) and positive social situations (e.g., drinking when it’s a special occasion). A total score for temptations was calculated by combining the sum scores for the two subscales. Temptations were assessed at baseline as well as 3- and 6-months post-baseline. The test-retest reliability for the total temptations score met the threshold for good

acceptability (ICC = 0.65, 95% CI [0.57, 0.71], $p < .001$). Please see Appendix B4 for the full battery of items assessing self-efficacy.

Analytic Approach

Examining Distributions of Key Variables

Before conducting any analyses, it is important to take a deeper look at the structure of the dataset and the nature of the variables that will be included in analyses. Because some of the key variables for subsequent analyses involved self-reported data on the frequency and quantity of alcohol use, the distribution of the variables was particularly important to examine (Atkins et al., 2013). First, measures of alcohol consumption will be examined for outliers, which will be identified as any observations that are 3 *SD* above the mean. Any observations determined to be outliers will be reduced to the highest non-outlying value plus 1 (Tabachnick & Fidell, 2013). Next, levels of skewness and kurtosis for all variables involved in modeling will be examined and any that were outside the acceptable range for these values (skewness acceptable range = -1.7 to 1.7, kurtosis ≤ 3.1 ; Tabachnick & Fidell, 2013) were considered for transformation. These analyses will be completed in IBM SPSS (*IBM SPSS Statistics 25.0*, 2019).

Examining Relationships among Key Variables

The primary set of analyses will explore the direction of the relationship between TTM-based cognitive constructs and the outcome behavior of interest (i.e., alcohol use). Before the direction of association can be examined, there needs to be evidence of an association among these variables to begin with. Bivariate associations among cognitive construct scores (pros, cons, temptations) and measures of alcohol

consumption (drinks per week, drinks per drinking day, number of binge episodes in the past 30 days) will be examined to determine whether the expected associations exist, and the strength of these associations.

The profile of sum scores for pros, cons, and temptations will also be examined in relation to stage of change at baseline as well as 3- and 6-months. To facilitate the ability to compare these profiles to previous TTM literature, the scores will be recoded into standardized *t* scores, which have a mean of 50 and a standard deviation of 10. This method will be used in lieu of *z* scores as it is the preferred method when the population variances are unknown (Tabachnick & Fidell, 2013). These analyses will also be conducted in IBM SPSS (*IBM SPSS Statistics 25.0*, 2019).

Consideration of Missing Data

One major concern when conducting longitudinal studies is loss of data over time. While many different techniques were used by the study team to retain participation over time, there will undoubtedly be missing data in this dataset. There are three types of missing data mechanisms, missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). Data are considered to be MCAR when the probability that responses are missing are unrelated to the missing values that should have been obtained and are unrelated to the set of observed responses. Data are considered MAR when the probability a response is missing is related to the set of observed variables, but is unrelated to the set of missing values that should have been obtained. Finally, data are considered MNAR when the probability that responses are missing is related to the values that should have been obtained (Fitzmaurice et al., 2011; Little, 1988). The distinction among these different

mechanisms is important as different forms of modeling assume that missing data meet different criteria for which mechanism they fall into. The main analyses of interest in this paper involve latent growth curve modeling, modeling which assumes the missing data mechanism to be MCAR or MAR (Preacher et al., 2008). These data are expected to be MAR because missingness in these data are by design, such that participants were administered measures based on their stage of change at each time point. This missingness is based on an observed variable (stage) and not on the missing values themselves, making the data MAR.

Latent Growth Curve Modeling

Latent Growth Curve Modeling (LGCM) is an application of SEM that permits the examination of both *intra* and *inter*-individual change over time. As an application of SEM, LGCM has a unique ability to determine model fit, account for measurement error, and deal with missing data. LGCM offers the same advantages as SEM, including the ability to account for measurement error by using latent repeated measures, and its ability to deal with missing data. In addition to allowing for the examination of intra- and inter-individual change, LGCM allows for the investigation of the antecedents and consequences of this change (Preacher et al., 2008). While LGCM involves the use of latent variables as in latent variable modeling (LVM), there is a key distinction between what these latent variables represent. In traditional LVM, the latent variables of interest often represent psychological constructs, whereas in LGCM, the latent factors of interest represent patterns of change in measured variables over time. There are two latent factors of interest, the intercept factor, which represents the level of an outcome measure when time equals zero, and the slope

factor, which represents the rate at which the outcome measure changes over time (Preacher et al., 2008). One extension of a basic LGCM, called a parallel process model, allows for the investigation of the relationships between aspects of change in two repeated-measures variables. These models contain two sets of intercepts and slopes and also estimate covariances among the intercepts and slopes. Parallel process models also allow for the investigation of causal relationships between the two repeated-measures variables of interest as these models allow for the inclusion of directional paths among growth factors (Preacher et al., 2008).

Overall model fit will be assessed by considering two fit indices: the comparative fit index (CFI; Bentler, 1990), and the root mean squared error of approximation (RMSEA; Steiger, 1998), along with the confidence interval associated with the RMSEA value. Models yielding a CFI value of at least .90 and ideally greater than .95, and an RMSEA value of .05 or less are considered to fit the data well. Although an RMSEA of .05 or less is ideal, RMSEA values of .08 or less are considered good, and values of .10 or less are seen as acceptable.

In addition to considering overall model fit, I will also examine parameters specific to LGCM, including the mean and variance for both the intercept and slope for each model component, and the covariances among intercept and slope for all model components (Preacher et al., 2008). Whereas the CFI and RMSEA will give insight into the fit of each overall model, examining the parameters related to the intercept and slope factors will offer more nuanced insight into the nature of change over time and the relationship between the factors being modeled. All LGCM will be conducted in *R* using the lavaan package for growth curve modeling (R Core Team,

2020; Rosseel, 2012). Final code used to conduct these models using the lavaan package is provided in Appendix C.

CHAPTER 3

RESULTS

Preliminary Analyses

Distributions of Key Variables

The three primary alcohol consumption-related variables of interest were examined for outliers, defined as any values greater than 3 *SD* above the mean. All three variables across all five time points included outlying observations ranging from two to 14 outlying observations. These observations were recoded to be the highest non-outlying value plus 1. After these outliers were recoded, the trimmed versions of all 15 alcohol consumption variables were examined for normality. Of the 15 variables, nine fell outside the range of acceptable skew and kurtosis values. These nine variables were transformed using the square root function, and their normality values re-examined. The square-root-transformed version of these nine variables all fell within the acceptable range. See Table 2 for detailed descriptive statistics for the alcohol consumption variables. This table includes the descriptive values for all 15 variables after outliers were removed, but before any linear transformation was applied. The second set of variables in Table 2 represents the transformed versions of the nine variables that did not have acceptable skew and/or kurtosis values. The cognitive scale scores of interest (pros, cons, and temptations) were also examined in terms of their skew and kurtosis values. All three scales fell within the acceptable

range for both skew and kurtosis at all three time points assessed (baseline, 3 months, 6 months) – see Table 3 for details.

Relationships among Key Variables

Bivariate associations among pros, cons, temptations and the three alcohol consumption variables were examined using Pearson's correlation coefficients. These correlation matrices yielded almost no significant association between pros or cons and alcohol consumption variables across time, with a few exceptions. There was a significant negative relationship between the pros sum score at baseline and drinks per week at both 6 ($r=-0.15, p=.01$) and 12 months ($r=-0.11, p=.047$), as well as a significant negative relationship between this same pros score and drinks per drinking day at 6 months ($r=-0.13, p=.02$) and a significant positive relationship with binge frequency at baseline ($r=0.15, p<.01$). The baseline cons sum score was also significantly and positively associated with binge frequency at baseline ($r=0.25, p<.01$), while the cons sum score at 6-months was positively associated with binge frequency at both 12 ($r=0.23, p<.01$) and 18-months ($r=0.22, p=.02$). There were no other significant associations between pros or cons sum scores and any drinking variable. All bivariate associations are included in Tables 4, 5, and 6 for drinks per week, drinks per drinking day, and binge frequency, respectively.

There was a consistent relationship among the three measurements of temptations total score and the five measurements of each alcohol consumption variable, such that all observations of temptations were significantly and positively associated with all three drinking variables across time ($ps<.05$). There was also a strong and positive relationship across the measurements of each drinking variable,

such that each observation of drinks per week was significantly associated with the other measurements of this variable, and so on ($ps<.01$). See Tables 4, 5, and 6 for all correlation coefficients. There were also strong positive relationships among the three drinking variables across time ($ps<.01$). See Table 7 for details.

The profile of pros and cons sum scores across stage of change was consistent across time points, but not consistent with prior work examining these relationships. At all three time points (baseline, 3-months, 6-months), participants in Contemplation had higher pros and cons scores than Precontemplation. Pros and cons were also assessed among participants in Preparation, but no participants were in this stage at baseline or 3-months, and only one participant was in this stage at 6-months. As such, Preparation was not included in Figures 3-5 for line graphs depicting these relationships. Mean scores are displayed as standardized t scores.

Consideration of Missing Data

For key variables of interest (i.e., pros, cons, temptations, and measures of alcohol consumption), patterns of response at follow-up were examined. At each time point, measures of pros and cons were assessed for any participants in Precontemplation or Contemplation for their readiness to drink according to low risk guidelines. Among participants in these stages at each time point, there were no missing data on either the pros or cons items. Temptations was also assessed according to current stage for readiness to adhere to low risk drinking guidelines, such that participants in Contemplation, Preparation, Action, or Maintenance received this measure. Among those in these stages at each follow-up, there were no missing data on the temptations scale. There were no missing data on measures of alcohol

consumption at any follow-up time point (3, 6, 12, and 18-month post-baseline) for any participants who initiated a survey at that time point.

Latent Growth Curve Models

The first set of LGCM's conducted examined the trajectories of temptations and each of the three drinking variables separately (drinks per week, drinks per typical drinking day, and binge frequency). In these models, all factor loadings for the intercept were fixed to 1.0. In addition, all four models used the same scaling of time to fix the slope factor loadings. Specifically, the scaling of time for these models, and all models moving forward, fixes baseline measurement to 0, then increases the fixed value by 1 for every three-month time increment. For temptations, which was only measured at baseline, 3- and 6-month follow-up, the loadings were fixed to 0, 1, and 2, respectively. For the models involving drinking variables, there were two additional measurement time points, at 12- and 18-months post-baseline, which were fixed to 4 and 6, respectively.

To account for the impact of stage of change on each measurement occasion of temptations and alcohol consumption, stage of change was added to each model as a time-varying covariate (TVC). In LGCM, TVCs can be added to a model as repeated exogenous predictors of an outcome (Preacher et al., 2008). Stage of change for each time point was added as an exogenous predictor of each corresponding measurement of temptations and each alcohol consumption variable. Including stage as a TVC for temptations is particularly important because each individual's stage of change at each time point determined whether temptations was assessed (i.e., temptations was only assessed for those who endorsed being in Contemplation, Preparation, Action, or

Maintenance). For the purposes of these analyses, stage of change was entered in the models as a quasi-continuous variable, rather than categorical, as stage is not completely categorical in nature because there is inherent order to the levels of this variable.

Full information maximum likelihood (FIML) estimation was used to account for missing data as it is frequently used in SEM (Dong & Peng, 2013). This method for handling missing data allows for case-wise deletion, rather than list-wise deletion, which allows the models to be analyzed with a larger sample. In an article examining the comparative efficacy of different methods for handling missing data in SEM, FIML was the best overall performer and highly recommended for use (compared to mean imputation, regression imputation, expectation maximization, and multiple imputation) (Olinsky et al., 2003). This method was also used to account for missing data in the analyses reported in Brick et al., (2009).

The growth model for temptations fit the data well ($N=395$, $\chi^2(7)=23.55$, $p<0.001$, CFI=0.960, RMSEA=0.077 [90% CI: 0.044, 0.113]) and the growth rate shown by the slope was nonsignificant ($M=-0.436$, $SE = 1.120$, $p=.70$) (see Table 8, Figure 5). The three separate growth models for the drinking variables of interest fit the data adequately, with CFI values exceeding the 0.90 threshold and approaching 0.95, and RMSEA values close to 0.08. Of the three models, only drinks per week ($N=354$, $\chi^2(30)=108.09$, $p<.001$, CFI=0.938, RMSEA=0.086 [90% CI: 0.069, 0.103]) (see Table 9, Figure 6) yielded a significant growth rate, evidenced by the mean slope parameter estimate for this model ($M=-0.351$, $SE=0.121$, $p=.004$), demonstrating a significant downward trend in drinks per week over time. The models for drinks per

drinking day ($N=354$, $\chi^2(30)=92.51$, $p<.001$, CFI=0.946, RMSEA=0.077 [90% CI: 0.059, 0.095]) (see Table 10, Figure 7) and binge frequency ($N=354$, $\chi^2(30)=92.698$, $p<.001$, CFI=0.941, RMSEA=0.077 [90% CI: 0.059, 0.095]) (see Table 11, Figure 8) did not yield significant mean slope values, demonstrating that in these models, when including stage of change as a TVC, there is not a significant change in these drinking metrics over time. The models for drinks per week and drinks per drinking day demonstrated significant negative covariances between the intercept and slope factors in each model, indicated an inverse relationship between initial status and change over time (i.e., individuals who reported higher levels of alcohol use at baseline reported steeper decreases in use over time).

The next set of models involved a series of parallel process models simultaneously estimating temptations and each of the three drinking variables, with one drinking variable in each model. These models employed the same structure of fixing both intercepts and slopes as described in the first set of models, and also included stage of change as a TVC. For each drinking outcome variable of interest, two parallel process models were examined. First, an intermediate model that included no relations among the growth factors (i.e., the covariances were fixed to be zero). These intermediate models were included as a comparison to the parallel process models that freely estimated the covariances among the growth factors. The lavaan package also includes a function (lavTestLRT) that allows for the comparison of nested lavaan models by conducting a chi-square difference. This function will be used to compare each set of models, with a significant chi-square difference value

indicating that the null hypothesis of no difference in fit between the models should be rejected.

The parallel process model for drinks per week x temptations including freely estimated covariances among the growth factors ($N=354$, $\chi^2(54)=149.72$, $p<.001$, CFI=0.943, RMSEA=0.071 [90% CI: 0.057, 0.084]) had significantly better fit than the intermediate model with no covariances ($N=354$, $\chi^2(58)=201.95$, $p<.001$, CFI=0.915, RMSEA=0.084 [90% CI: 0.071, 0.096]; $\chi^2_{\text{difference}}(4)=52.23$, $p<.001$) (see Table 12, Figure 9). This was also found for the two models for drinks per drinking day, with the freely estimated model ($N=354$, $\chi^2(54)=155.21$, $p<.001$, CFI=0.936, RMSEA=0.073 [90% CI: 0.060, 0.086]) outperforming the intermediate model ($N=354$, $\chi^2(58)=190.47$, $p<.001$, CFI=0.916, RMSEA=0.080 [90% CI: 0.068, 0.093]; $\chi^2_{\text{difference}}(4)=35.27$, $p<.001$) (see Table 13, Figure 10). The final pair of models including binge frequency followed this same pattern, with the freely estimated model ($N=354$, $\chi^2(54)=142.73$, $p<.001$, CFI=0.940, RMSEA=0.068 [90% CI: 0.055, 0.082]) having significantly better fit than the intermediate model ($N=354$, $\chi^2(58)=180.07$, $p<.001$, CFI=0.917, RMSEA=0.077 [90% CI: 0.064, 0.090]; $\chi^2_{\text{difference}}(4)=37.34$, $p<.001$) (see Table 14, Figure 11).

The intercept covariance for all three models was significant and positive, indicating that those with higher levels of temptations at baseline also had greater alcohol use across all three measures of use (i.e., drinks per week, drinks per drinking day, binge frequency). The slope covariance for the drinks per week and binge frequency models was nonsignificant, but for drinks per drinking day there was a significant and positive slope covariance. This indicated that those characterized by a

steeper incline in temptations also experienced a steeper incline in drinks per drinking day over time. The intercept-slope covariance between factors for all three parallel process models was nonsignificant. There was significant intercept-slope covariance within factors for drinks per week and drinks per drinking day, but not for binge frequency or temptations (see Tables 12-14).

The final set of models extended the freely estimated parallel process models described above by adding regression paths between the two slope factors, exploring the strength and direction of the relationship between these two factors. Two sets of models for each drinking variable were conducted, one model including a regression path where the slope of temptations predicted the slope of the drinking variable, and another where this path was reversed and the slope of the drinking variable predicted the slope of temptations. Conducting two separate models reversing the direction of association between the two slope factors sought to elucidate the direction of influence between the factors. Unfortunately, including FIML estimation for the missing data in this final set of models prevented the models from converging. As such, maximum likelihood (ML) was used to account for missingness, which is considered the default within the lavaan package. While FIML uses case-wise deletion to account for missing data while retaining the majority of the sample size, ML uses list-wise deletion, causing this set of models to have a decreased sample size.

As with the previous set of models, these models fit the data well, including for drinks per week x temptations (temptations $\rightarrow$ drinks per week: $N=155$, $\chi^2(56)=91.68$, $p=.002$, CFI=0.955, RMSEA=0.064 [90% CI: 0.039, 0.087]; drinks per week $\rightarrow$ temptations: $N=155$, $\chi^2(56)=91.21$, $p=.002$, CFI=0.955, RMSEA=0.064 [90% CI:

0.039, 0.087]) (see Tables 15-16, Figure 12), drinks per drinking day x temptations (temptations → drinks per drinking day: $N=155$, $\chi^2(56)=102.29$, $p<.001$, CFI=0.941, RMSEA=0.073 [90% CI: 0.050, 0.095]; drinks per drinking day → temptations: $N=155$, $\chi^2(56)=103.02$, $p<.001$, CFI=0.940, RMSEA=0.074 [90% CI: 0.051, 0.096]) (see Table 17-18, Figure 13), and binge frequency x temptations (temptations → binge frequency: $N=155$, $\chi^2(56)=95.72$, $p=.001$, CFI=0.947, RMSEA=0.068 [90% CI: 0.044, 0.090]; binge frequency → temptations: $N=155$, $\chi^2(56)=96.65$, $p=.001$, CFI=0.946, RMSEA=0.068 [90% CI: 0.045, 0.091]) (see Table 19-20, Figure 14). While these models fit the data well, of the six regression paths examined, none were significant, although the path for the slope of drinks per week predicting the slope of temptations was nearly significant ($p=.079$). The lack of significance of the added regression paths across these models may be due to low statistical power from the loss of participants retained in these models, resulting in a total sample size of 155 participants.

CHAPTER 4

DISCUSSION

The current study examined the relationships between cognitive constructs from the Transtheoretical Model and the outcome behavior of interest, alcohol consumption. The dataset used was from a large clinical trial investigating the efficacy of a TTM-based alcohol intervention for changing the drinking behavior among a sample of employed adult drinkers in the United States, all who reported drinking above national low-risk drinking guidelines at baseline. The goal of this intervention was to move participants along the stages of change for readiness to limit their drinking to these guidelines, which would also result in reductions in actual alcohol consumption. The intervention group was compared to a control condition who received assessment only.

The results of these analyses diverge from previous work assessing the comprehensiveness of the TTM. A seminal article, authored by some of the founders of the TTM, demonstrated the systematically predictable relationship between standardized *t* scores on decisional balance (separate scores for pros and cons) and stage of change. The relationship profile generalized across all 12 health behaviors examined, such that participants in Precontemplation had the lowest pros score while having the highest con score. These two scores acted in a linear fashion across the stages, such that pros experienced a positive trend between Precontemplation and Maintenance while cons experienced a negative trend between these same stages, (J.

O. Prochaska et al., 1994). This work was extended in the context of a meta-analysis, which calculated effect sizes for both pros and cons scores across 48 health behaviors. The results of this meta-analysis were consistent with the results report in Prochaska, et al.'s (1994) previous work, reiterating the strength of association between decisional balance and stage of change and suggesting the importance of targeting these constructs to move individuals along the continuum of change (Hall & Rossi, 2008).

In the current study, the expected difference in mean values for the pros sum score for those in Precontemplation for their readiness to limit their drinking compared to those in Contemplation was as expected based on prior literature, such that those in Contemplation had higher mean values than Precontemplation at all three time points. Counter to predictions, while a negative trend in cons values was expected between Precontemplation and Contemplation at all time points, the same positive trend as pros was observed. In addition to this unexpected profile of decisional balance scores, bivariate correlation coefficients demonstrated almost no significant associations between pros or cons sum scores and measures of alcohol consumption (drinks per week, drinks per typical drinking day, and binge frequency).

Because there was no significant relationship between pros or cons and drinking behavior, the cognitive factor of interest for these analyses was temptations. The aim was to determine the causal relationship between temptations and three measures of alcohol consumption (drinks per week, drinks per drinking day, and binge frequency). Preliminary analyses found a strong relationship between the temptations total score and all three drinking variables, such that higher scores on situational temptations (i.e., more likely to be tempted to drink under certain circumstances) were

strongly associated with higher levels of drinking. The strength and direction of this relationship was expected. To better understand the relationship between change in temptations score over time and change in drinking, latent growth curve modeling was used, leveraging the lavaan package that supports this modeling in *R*.

The first set of models examined growth curve models for each outcome of interest, separately (i.e., the intercepts and slopes for temptations, drinks per week, drinking per drinking day, and binge frequency). Next, a series of parallel process models simultaneously modeling growth of temptations and each of the three drinking variables were examined. Intermediate versions of each model, where the covariances among the growth factors was fixed at zero, were conducted and compared to the same models allowing for these covariances to be freely estimated. Using chi-square difference tests, the set of models allowing for the free estimation of the covariances among growth factors had significantly better fit than the intermediate models. In all three models (i.e., drinks per week, drinks per drinking day, binge frequency), the covariance between the intercept factors was significant and positive, suggesting that there is a strong relationship between participants' initial temptations score and their initial drinking levels. The covariance between the slope factors was significant in the model including drinks per drinking day, which demonstrates a relationship between the rate of change in temptations scores and the rate of change in this measure of alcohol consumption, although a covariance does not provide an indication of the direction of causation, even while revealing a significant relationship.

The final set of models sought to extend the previous set of freely estimated parallel process models by adding regression paths between the growth factors,

exploring the strength and direction of the relationships between them. Because these analyses were exploratory, which path would achieve significance, or if both paths would be significant, was not hypothesized a priori, but a significant relationship was expected. This was not found to be the case. Across the six models, none of the regression paths added between the two slope factors were found to be significant, but the model including a path where drinks per week predicted temptations approached significance ($p=.079$). Unfortunately, this last set of models did not converge when using FIML to account for missing data. Instead, ML was used, resulting in a large decrease in sample size from the previous set of parallel process models due to list-wise deletion. This led to a decrease from 354 to 155 observations included in the models, which would have reduced the statistical power to find significant effects.

There are many potential explanations for this departure from previous literature, including limitations to consider based on the design of the larger clinical trial. It is important to start off by highlighting that while the design of this study did not facilitate the analyses reported here, it was also not intended to. The clinical trial was designed and powered to address the key aim of the project, which was to evaluate the efficacy of an online alcohol intervention vs. assessment only control on readiness to limit drinking to low-risk guidelines. The research team did not design or power the study to explore the causal mechanisms discussed here. That being said, in order to plan for these types of analyses during the study design process, it is also necessary to consider what could be altered in future designs to facilitate these models. First, decisional balance and temptations were not included in the battery of assessments given to participants in both treatment and control, and they were also

only administered to participants in particular stages. These assessments were built into the CTI itself, to allow for treatment participants to answer these scales and immediately receive on-screen feedback related to their responses. While this contributes to the level of tailoring within the intervention, these data are not collected for participants in the control group. Therefore, there can be no comparison of changes in decisional balance or temptations between the two groups. In addition, skip logic included in the CTI only administered decisional balance to participants in Pre-Action stages (Precontemplation, Contemplation, and Preparation), and temptations were only assessed for those not in Precontemplation. At both baseline and 3-month follow-up, participants in the intervention group reported only being in either Precontemplation or Contemplation, meaning a large portion of the sample (those in Precontemplation at either time point) did not receive the temptations scale.

Because the overall study was not designed to power these analyses, while the trial sample was large ($N= 973$) and retention high (80% retention at 6 months, 75% at 18 months), the sample size available for these analyses was much smaller. In the future, it would be interesting to replicate these models with a larger sample that assessed temptations and decisional balance for all participants, regardless of stage. Hopefully, this change in design would mitigate many of the key issues seen in these data and allow for more definitive insight into direction of influence between TTM-based cognitive constructs and outcome behavior. I would also be interested in re-conceptualizing these analyses to implement parallel process modeling as an SEM-based mediational framework. I would be interested to re-run these models simultaneously modeling stage of change and the drinking outcome variables, while

including temptations as an exogenous variable predicting stage of change. Finally, it would be interesting to run both sets of these analyses, then compare how the different types of models fit the data and to determine if one conceptualization or another had significantly better fit.

Future study designs should consider being less restrictive in who is assessed on decisional balance and temptations (i.e., don't just limit to the treatment group and certain stages in this study), and also could consider assessing at additional follow-up time points rather than just during the "active" treatment period. Decisional balance and temptations were only assessed at baseline as well as 3- and 6-month follow-up, while outcome behaviors of interest were also measured at 12 and 18-months post-baseline. When considering latent factors for each of these scales in the latent growth curve models assessed, there were only three longitudinal observations included, while the latent factors representing the different alcohol consumption variables were represented by all five observations.

I had also wanted to examine the internal consistency of the decisional balance and temptations scales, but the data set only included the derived sum scores and not the raw item-level information. While outside the scope of the current work, in the future, I would like to be afforded access to the raw data to go back and examine the levels of reliability for these scales measured at the item level. Specifically, I would be interested in examining pros and cons, as neither behaved as expected in this sample. Using these item-level data, I could also conduct a Confirmatory Factor Analysis (CFA) to determine if the two-factor structure of having separate pros and cons subscales holds up in this sample, or if a one-factor solution for the entire decisional

balance scale would fit these data better. While these data did not permit the examination of internal consistency, I was able to assess the test-retest reliability of each continuous variable of interest by calculating ICCs, using trials in lieu of raters. All but one ICC were found to exceed the threshold for good agreement, with one only meeting the threshold for fair agreement. None met the threshold to be considered excellent ($ICC > 0.75$). While the test-retest reliability was acceptable, none of the ICC values meeting the threshold for excellent may suggest some of the change between measurements over time may be due to measurement error (Matheson, 2019). Another possibility is that these variables were measured in the context of studying behavior change across time, and thus were expected to be dynamic and less stable than an inherent trait or characteristic.

An additional limitation to consider is how stage of change was included in the models as a time-varying covariate. In some cases, stage of change is conceptualized as a categorical variable. Categorical variables can be included as TVCs in growth models, but this requires dummy coding this variable, resulting in four variables representing stage at each time point. If this had been applied to the parallel process models described here, there would have been 32 TVCs included in the model just to account for stage. With the sample size issues described above, the addition of this many variables was not feasible. Stage of change can also be conceptualized as an ordinal, rather than categorical, variable because there is some inherent ordering to the levels of this variable. A strong case has been made for treating ordinal variables as continuous, even when the spacing is not known to be equal across levels (Pasta,

2009). While the case for this has been made, it would be difficult to verify that stage is completely continuous.

While there are many potential explanations described above for why these results deviated from prior literature in this area, it is also possible that the expected generalizability of TTM constructs across different behaviors does not entirely hold up when looking at alcohol use. In the 2008 meta-analysis previously cited, of the 48 behaviors examined, there was only one study that looked at the relationship between decisional balance, stage of change, and alcohol use (Hall & Rossi, 2008). Looking into this prior study, the researchers found that the systematic relationship between decisional balance and stage of change held up in a study examining binge drinking among adolescents (Migneault et al., 1997). The aim of this prior study was to develop an instrument to assess decisional balance for alcohol use, assess the factor structure of the measure using confirmatory factor analysis (CFA), and evaluate the relationship between this measure of decisional balance and stage of change. There are several key differences between this study and the current work. First, the focus of the prior study was measure development and analyses conducted with cross-sectional data, splitting this sample to conduct a principal components analysis (PCA) on one-half, and confirmatory analyses on the other (Migneault et al., 1997). This is in contrast to the current study, which was interested in the longitudinal associations between decisional balance and stage of change. Second, the sample of interest in the prior study consisted entirely of adolescents between the ages of 15 and 18 versus the sample used in the current analyses focusing on adults of legal drinking age (over the age of 21), with a mean age of 39. Next, the behavior of interest on which participants were

staged differed between the two studies. In Migneault et al. (1997), researchers were interested in binge frequency, but defined this by asking participants if they usually had three or more drinks on days that they drank, what their intention was to cut down to less than three drinks (Pre-Action), or how long ago they had cut back to the defined levels (Action/Maintenance) (Migneault et al., 1997). Perhaps the most critical difference between the current work and this previous study was the way in which pros and cons were assessed. In the prior study, participants were assessed on decisional balance using an inventory of 37 items, which was reduced to 16-item measurement model after the research team subsequently examined the scale using PCA followed by a CFA. The final scale recommended by the researchers for use with this population of adolescent drinkers suggested assessing eight pros items and eight cons (Migneault et al., 1997). In the current study, pros and cons were assessed using only four-items each. It is possible that using only four-item scales to yield pros and cons sum scores led to truncated variability in these scores, or as explained above, the items selected may not reliably and cohesively measure the pros and cons.

Another potentially contributing factor is the sample itself. First, this trial included a long list of inclusion and exclusion criteria, which limits the generalizability of the sample. To be eligible for participation, participants had to endorse exceeding both the daily AND weekly low-risk drinking guidelines as defined by NIAAA (less than 14 drinks/week and less than 4 drinks/day for males, less than 7 drinks/week and less than 3 drinks/day for females). Not meeting both the daily and weekly criteria was the most common reason that potential participants screened ineligible for study participation, with 823 of the 1,828 participants (45%) excluded at

baseline for not exceeding these low-risk drinking guidelines. Using both guidelines, potential participants who endorsed binge drinking (exceeding the daily limit) but not the weekly total would have screened out, but are a population that could have benefitted from the intervention. According to the Center for Disease Control and Prevention (CDC), an individual meets the criteria for excessive alcohol use if they endorse binge drinking (consuming 4/5 drinks for females/males on one occasion) OR if they endorse heavy drinking (consuming 8 or more/15 or more drinks for females/males per week) (Centers for Disease Control and Prevention [CDC], 2020). These definitions parallel NIAAA's daily and weekly low-risk drinking guidelines, but individuals are considered excessive drinkers if they meet either criteria, rather than necessitating both (CDC, 2020). I also believe that the exclusion criterion related to substance use treatment was too stringent, in that it screened out potential participants who reported having ever received substance use treatment, not just those who were currently or recently in treatment. Shortly after the completion of this study, the same research team changed this criterion to assess potential participants for any substance use treatment in the past 30 days for ensuing studies evaluating TTM-based interventions for substance use.

Another exclusion criterion included in this study that may limit the generalizability of these analyses, as well as the larger clinical trial these data are taken from, was full-time college student status. The research team's rationale for the inclusion of this criterion was that patterns of drinking among college students are unique and they would be better served by alcohol interventions targeted toward college students, specifically (see Appendix A). While there is a great deal of evidence

in the literature supporting the efficacy of alcohol interventions tailored for college students, the vast majority of this work only focuses on “traditional” college students attending four-year colleges/universities (Carey et al., 2012, 2016). Although this rationale may hold up for this specific group of college students, it does not take into account the myriad of experiences that “full-time college student” can represent, including those who attend two-year colleges, those who are older and decide to go to/go back to college, and those who are in graduate school. In my own personal experience as a graduate student who has been considered a full-time student while also working full-time, my drinking patterns are not at all captured by those of undergraduate college students, and I would expect interventions targeted at this specific group to be less efficacious for me. Rather than abandoning the criterion completely, perhaps the question could have asked more specifically if potential participants were currently enrolled at a four-year institution.

In addition, the final report documenting the results of the main outcome analyses related to this study described the use of logistic regression analyses to examine predictors of nonresponse at follow-up. These analyses found lower rates ($p < .05$) of response at 6, 12, and/or 18 months among participants who were Nonwhite, in the youngest age group (≤ 29) as opposed to the oldest group (≥ 50), in the Preparation stage as opposed to Precontemplation, and among those in thriving as opposed to suffering or struggling at baseline (Levesque, 2016). What is particularly concerning about these non-response factors is that participants who were Nonwhite were more likely to be lost to follow-up than those reporting being White. At baseline, while the sample was predominately White (78.0%) and Hispanic (11.6%), these

proportions are similar in magnitude to the racial/ethnic breakdown of the United States in 2019, which estimated the population of the U.S. to be 76.3% White and 18.5% Hispanic. With the lower rates of retention of Nonwhite participants over the course of the study, the sample became even more homogeneous and less diverse than at baseline. The high representation of White participants at baseline may be, in part, due to the strict eligibility criteria used to screen potential participants into the study. Less is known about why there was higher rates of attrition for Nonwhites in this study. This is important because the Transtheoretical Model is put forth as a comprehensive model that can be applied across all people and behaviors of interest. Not only has this work demonstrated that the systematic relationships among TTM constructs and behavior diverges from previous literature, but it may be suggestive that the model is not appropriate for all groups of people, at least for one or more behaviors. It is possible that these Nonwhite participants dropped out of study participation for a host of reasons, but included among them could be that they did not feel that the intervention was representative of their experience.

Future work assessing the efficacy of TTM-based interventions for health behavior change should aim to recruit more diverse samples of participants, or even specifically recruit certain minoritized groups to assess the applicability of the model. Not only would this allow for a more definitive determination of whether the TTM is as broadly applicable as thought by its proponents, but it could contribute a new level of tailoring to TTM interventions, taking the experience of different populations of individuals into account. While I am a proponent of the TTM and interventions that are tailored using its proposed constructs, I also believe that more can be done to make

these interventions more culturally sensitive and applicable to different populations.

This would only help to increase the efficacy these interventions have already demonstrated, as well as enhance the comprehensiveness of the model.

TABLES

Table 1. Baseline characteristics of treatment participants (n = 492)

	<i>N</i>	<i>%</i>
Gender		
Female	281	57.1
Male	211	42.9
Ethnicity		
Non-Hispanic	435	88.4
Hispanic	57	11.6
Race		
American Indian/Alaska Native	3	0.6
Asian	28	5.7
Black or African American	61	12.4
Native Hawaiian/Other Pacific Islander	2	0.4
White	384	78.0
More Than One Race	6	1.2
Unknown	8	1.6
Stage of Change for Limiting Drinking		
Precontemplation	231	47.0
Contemplation	154	31.3
Preparation	107	21.7
	<i>M</i>	<i>SD</i>
Age	39.1	11.8

Table 2. Descriptive information for alcohol consumption variables

	<i>N</i>	<i>M</i>	<i>SD</i>	skew	kurtosis
dpw.bl.trim	492	9.78	6.67	1.18	1.16
dpw.3m.trim	407	7.52	7.09	1.68	2.95
dpw.6m.trim	402	5.93	6.56	2.03	4.35
dpw.12m.trim	386	6.19	6.70	1.80	3.50
dpw.18m.trim	367	5.78	6.62	1.99	4.45
ddd.bl.trim	492	3.20	1.53	1.19	1.98
ddd.3m.trim	407	2.73	1.64	1.34	2.16
ddd.6m.trim	402	2.43	1.59	1.74	4.19
ddd.12m.trim	386	2.53	1.69	1.49	3.04
ddd.18m.trim	367	2.42	1.65	1.40	2.84
binge.bl.trim	492	4.68	5.27	1.97	3.43
binge.3m.trim	407	2.82	4.18	2.25	5.18
binge.6m.trim	402	2.12	3.62	2.65	7.27
binge.12m.trim	386	2.31	4.32	2.54	6.04
binge.18m.trim	367	2.18	4.27	2.80	7.69
dpw.6m.trim.sq	402	2.09	1.26	0.57	0.39
dpw.12m.trim.sq	386	2.08	1.36	0.31	-0.18
dpw.18m.trim.sq	367	1.97	1.37	0.38	-0.11
ddd.6m.trim.sq	402	1.47	0.51	-0.04	2.003
binge.bl.trim.sq	492	1.89	1.05	0.997	0.63
binge.3m.trim.sq	407	1.21	1.17	0.77	-0.05
binge.6m.trim.sq	402	0.97	1.09	1.03	0.51
binge.12m.trim.sq	386	0.94	1.2	1.24	0.77
binge.18m.trim.sq	367	0.89	1.18	1.34	1.16

dpw = drinks per week; ddd = drinks per drinking day; binge = # of binge episodes in the past 30 days; bl = observed at baseline; 3m = observed at 3 months; 6m = observed at 6 months; 12m = observed at 12 months; 18m = observed at 18 months; trim = outliers removed; sq = square-root transformed

Table 3. Descriptive information for cognitive variables

	<i>N</i>	<i>M</i>	<i>SD</i>	skew	kurtosis
prosum.bl	385	11.49	5.10	0.00	-1.23
prosum.3m	173	11.33	4.75	0.06	-1.07
prosum.6m	137	11.07	4.84	0.13	-1.11
consum.bl	385	10.25	4.06	0.36	-0.47
consum.3m	173	10.98	4.29	0.18	-0.76
consum.6m	137	10.32	4.10	0.21	-0.59
tmpttotal.bl	261	25.49	9.40	0.35	-0.65
tmpttotal.3m	364	24.44	9.20	0.43	-0.62
tmpttotal.6m	368	22.19	9.06	0.74	0.01

prosum = pros sum score; consum = con sum score; tmpttotal = temptations total score; bl = observed at baseline; 3m = observed at 3 months; 6m = observed at 6 months; 12m = observed at 12 months; 18m = observed at 18 months;

Table 4. Bivariate associations among pros, cons, temptations, and drinks per week

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 prosum.bl	1													
2 prosum.3m	0.68**	1												
3 prosum.6m	0.59**	0.60**	1											
4 consum.bl	0.66**	0.47**	0.40**	1										
5 consum.3m	0.46**	0.68**	0.39**	0.55**	1									
6 consum.6m	0.34**	0.39**	0.67**	0.47**	0.52**	1								
7 tmpttotal.bl	0.39**	0.38**	0.59**	0.46**	0.37**	0.57**	1							
8 tmpttotal.3m	0.15*	0.25**	0.38**	0.29**	0.35**	0.57**	0.60**	1						
9 tmpttotal.6m	0.17**	0.24**	0.37**	0.28**	0.27**	0.55**	0.62**	0.69**	1					
10 dpw.bl.trim	-0.004	-0.06	-0.02	0.07	-0.04	-0.01	0.29**	0.24**	0.21**	1				
11 dpw.3m.trim	-0.06	-0.11	-0.06	<0.001	-0.03	-0.02	0.27**	0.42**	0.41**	0.64**	1			
12 dpw.6m.trim.sq	-0.15*	-0.16*	-0.04	-0.06	-0.02	0.04	0.24**	0.39**	0.42**	0.53**	0.68**	1		
13 dpw.12m.trim.sq	-0.11*	-0.16*	0.03	-0.01	-0.03	0.15	0.12*	0.35**	0.41**	0.44**	0.60**	0.70**	1	
14 dpw.18m.trim.sq	-0.10	-0.12	0.06	0.02	0.07	0.12	0.19*	0.36**	0.40**	0.48**	0.58**	0.69**	0.77**	1

prosum = pros sum score; consum = cons sum score; tmpttotal = temptations total score; dpw = drinks per week; bl = baseline; 3m = 3 month timepoint; 6m = 6 month timepoint; 12m = 12 month timepoint; 18m = 18 month timepoint; trim = outliers reduced to highest non-outlying value plus 1; sq = square-root transformed

**p<.01

*p<.05

Table 5. Bivariate associations among pros, cons, temptations, and drinks per drinking day

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 prosum.bl	1													
2 prosum.3m	0.68**	1												
3 prosum.6m	0.59**	0.60**	1											
4 consum.bl	0.66**	0.47**	0.40**	1										
5 consum.3m	0.46**	0.68**	0.39**	0.55**	1									
6 consum.6m	0.34**	0.39**	0.67**	0.47**	0.52**	1								
7 tmpttotal.bl	0.39**	0.38**	0.59**	0.46**	0.37**	0.57**	1							
8 tmpttotal.3m	0.15*	0.25**	0.38**	0.29**	0.35**	0.57**	0.60**	1						
9 tmpttotal.6m	0.17**	0.24**	0.37**	0.28**	0.27**	0.55**	0.62**	0.69**	1					
10 ddd.bl.trim	-0.02	-0.01	0.05	0.05	-0.02	0.004	0.28**	0.20**	0.16**	1				
11 ddd.3m.trim	-0.06	-0.10	0.001	-0.02	-0.09	0.02	0.20**	0.35**	0.32**	0.66**	1			
12 ddd.6m.trim.sq	-0.13*	-0.15	-0.02	-0.08	-0.06	0.06	0.17**	0.30**	0.33**	0.53**	0.67**	1		
13 ddd.12m.trim	-0.08	-0.11	0.05	-0.01	-0.09	0.16	0.18*	0.24**	0.34**	0.51**	0.60**	0.56**	1	
14 ddd.18m.trim	-0.07	-0.08	0.08	0.05	0.05	0.16	0.26**	0.31**	0.37**	0.52**	0.62**	0.59**	0.68**	1

prosum = pros sum score; consum = cons sum score; tmpttotal = temptations total score; ddd = drinks per drinking day; bl = baseline; 3m = 3 month timepoint; 6m = 6 month timepoint; 12m = 12 month timepoint; 18m = 18 month timepoint; trim = outliers reduced to highest non-outlying value plus 1; sq = square-root transformed

**p<.01

*p<.05

Table 6. Bivariate associations among pros, cons, temptations, and binge frequency

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 prosum.bl	1													
2 prosum.3m	0.68**	1												
3 prosum.6m	0.59**	0.60**	1											
4 consum.bl	0.66**	0.47**	0.40**	1										
5 consum.3m	0.46**	0.68**	0.39**	0.55**	1									
6 consum.6m	0.34**	0.39**	0.67**	0.47**	0.52**	1								
7 tmpttotal.bl	0.39**	0.38**	0.59**	0.46**	0.37**	0.57**	1							
8 tmpttotal.3m	0.15*	0.25**	0.38**	0.29**	0.35**	0.57**	0.60**	1						
9 tmpttotal.6m	0.17**	0.24**	0.37**	0.28**	0.27**	0.55**	0.62**	0.69**	1					
10 binge.bl.trim.sq	0.15**	-0.06	-0.01	0.25**	0.04	0.04	0.27**	0.20**	0.19**	1				
11 binge.3m.trim.sq	-0.04	-0.05	0.04	0.10	0.08	0.11	0.30**	0.44**	0.42**	0.51**	1			
12 binge.6m.trim.sq	-0.04	-0.05	-0.01	0.08	-0.02	0.08	0.30**	0.38**	0.51**	0.42**	0.62**	1		
13 binge.12m.trim.sq	-0.05	-0.11	0.04	0.10	-0.01	0.23**	0.25**	0.33**	0.43**	0.33**	0.52**	0.63**	1	
14 binge.18m.trim.sq	-0.07	-0.01	0.09	0.08	0.12	0.22*	0.25**	0.34**	0.39**	0.42**	0.55**	0.65**	0.68**	1

prosum = pros sum score; consum = cons sum score; tmpttotal = temptations total score; binge = binge frequency; bl = baseline; 3m = 3 month timepoint; 6m = 6 month timepoint; 12m = 12 month timepoint; 18m = 18 month timepoint; trim = outliers reduced to highest non-outlying value plus 1; sq = square-root transformed

**p<.01

*p<.05

Table 7. Bivariate associations among drinks per week, drinks per drinking day, and binge frequency

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 dpw.bl.trim	1														
2 dpw.3m.trim	0.64**	1													
3 dpw.6m.trim.sq	0.53**	0.68**	1												
4 dpw.12m.trim.sq	0.44**	0.60**	0.70**	1											
5 dpw.18m.trim.sq	0.48**	0.58**	0.69**	0.77**	1										
6 ddd.bl.trim	0.56**	0.34**	0.29**	0.25**	0.21**	1									
7 ddd.3m.trim	0.44**	0.66**	0.45**	0.43**	0.37**	0.66**	1								
8 ddd.6m.trim.sq	0.38**	0.48**	0.67**	0.53**	0.43**	0.53**	0.67**	1							
9 ddd.12m.trim	0.30**	0.38**	0.38**	0.62**	0.42**	0.51**	0.60**	0.56**	1						
10 ddd.18m.trim	0.39**	0.43**	0.44**	0.57**	0.67**	0.52**	0.62**	0.59**	0.68**	1					
11 binge.bl.trim.sq	0.59**	0.43**	0.32**	0.23**	0.32**	0.39**	0.32**	0.23**	0.23**	0.31**	1				
12 binge.3m.trim.sq	0.41**	0.66**	0.52**	0.44**	0.46**	0.32**	0.56**	0.45**	0.41**	0.49**	0.51**	1			
13 binge.6m.trim.sq	0.41**	0.55**	0.67**	0.54**	0.55**	0.34**	0.44**	0.52**	0.45**	0.49**	0.42**	0.62**	1		
14 binge.12m.trim.sq	0.37**	0.49**	0.49**	0.70**	0.60**	0.39**	0.48**	0.51**	0.63**	0.59**	0.33**	0.52**	0.63**	1	
15 binge.18m.trim.sq	0.48**	0.48**	0.57**	0.63**	0.71**	0.39**	0.43**	0.51**	0.53**	0.66**	0.42**	0.55**	0.64**	0.68**	1

bl = baseline; 3m = 3 month timepoint; 6m = 6 month timepoint; 12m = 12 month timepoint; 18m = 18 month timepoint; trim = outliers reduced to highest non-outlying value plus 1; sq = square-root transformed

**p<.01

*p<.05

Table 8. Latent growth curve model of temptations including stage as a TVC

N=395, $\chi^2(7)=23.55$, $p<0.001$, CFI=0.960, RMSEA=0.077 [90% CI: 0.044, 0.113]		
Parameter	Intercept	Growth Rate
Intercept/Slope Factor Loading: Baseline	1	0
Intercept/Slope Factor Loading: 3 Months	1	1
Intercept/Slope Factor Loading: 6 Months	1	2
	Parameter Estimate	Standard Error
Mean Intercept (α_1)	32.524*	1.855
Mean Slope (α_2)	-0.436	1.120
Intercept Variance (ψ_{11})	42.670*	9.089
Slope Variance (ψ_{22})	-0.948	4.041
Regression Path: Stage of Change, Baseline (β_0)	-3.039*	0.754
Regression Path: Stage of Change, 3 Months (β_1)	-2.594*	0.346
Regression Path: Stage of Change, 6 Months (β_2)	-2.832*	0.346
Intercept/Slope Covariance (ψ_{21})	1.726	4.857
Residual Variance: Baseline	39.969*	9.295
Residual Variance: 3 Months	28.216*	3.739
Residual Variance: 6 Months	23.747*	6.679

* = significant

Table 9. Latent growth curve model of drinks per week including stage as a TVC

N=354, $\chi^2(30)=108.09$, $p<.001$, CFI=0.938, RMSEA=0.086 [90% CI: 0.069, 0.103]		
Parameter	Intercept	Growth Rate
Intercept/Slope Factor Loading: Baseline	1	0
Intercept/Slope Factor Loading: 3 Months	1	1
Intercept/Slope Factor Loading: 6 Months	1	2
Intercept/Slope Factor Loading: 12 Months	1	4
Intercept/Slope Factor Loading: 18 Months	1	6
	Parameter Estimate	Standard Error
Mean Intercept (α_1)	11.428*	0.533
Mean Slope (α_2)	-0.351*	0.121
Intercept Variance (ψ_{11})	25.713*	2.580
Slope Variance (ψ_{22})	0.466*	0.080
Regression Path: Stage of Change, Baseline (β_0)	-0.916*	0.272
Regression Path: Stage of Change, 3 Months (β_1)	-1.292*	0.146
Regression Path: Stage of Change, 6 Months (β_2)	-1.464*	0.117
Regression Path: Stage of Change, 12 Months (β_4)	-1.206*	0.108
Regression Path: Stage of Change, 18 Months (β_6)	-1.073*	0.136
Intercept/Slope Covariance (ψ_{21})	-1.116*	0.335
Residual Variance: Baseline	19.013*	1.971
Residual Variance: 3 Months	14.230*	1.441
Residual Variance: 6 Months	14.546*	1.320
Residual Variance: 12 Months	11.262*	1.092
Residual Variance: 18 Months	3.677*	1.290

* = significant

Table 10. Latent growth curve model of drinks per drinking day including stage as a TVC

N=354, $\chi^2(30)=92.51$, $p<.001$, CFI=0.946, RMSEA=0.077 [90% CI: 0.059, 0.095]		
Parameter	Intercept	Growth Rate
Intercept/Slope Factor Loading: Baseline	1	0
Intercept/Slope Factor Loading: 3 Months	1	1
Intercept/Slope Factor Loading: 6 Months	1	2
Intercept/Slope Factor Loading: 12 Months	1	4
Intercept/Slope Factor Loading: 18 Months	1	6
	Parameter Estimate	Standard Error
Mean Intercept (α_1)	3.632*	0.129
Mean Slope (α_2)	-0.019	0.031
Intercept Variance (ψ_{11})	1.604*	0.156
Slope Variance (ψ_{22})	0.020*	0.005
Regression Path: Stage of Change, Baseline (β_0)	-0.222*	0.065
Regression Path: Stage of Change, 3 Months (β_1)	-0.313*	0.035
Regression Path: Stage of Change, 6 Months (β_2)	-0.351*	0.029
Regression Path: Stage of Change, 12 Months (β_4)	-0.300*	0.030
Regression Path: Stage of Change, 18 Months (β_6)	-0.321*	0.038
Intercept/Slope Covariance (ψ_{21})	-0.065*	0.021
Residual Variance: Baseline	1.008*	0.104
Residual Variance: 3 Months	0.732*	0.076
Residual Variance: 6 Months	0.859*	0.080
Residual Variance: 12 Months	1.093*	0.097
Residual Variance: 18 Months	0.599*	0.107

* = significant

Table 11. Latent growth curve model of binge frequency including stage as a TVC

N=354, $\chi^2(30)=92.698$, $p<.001$, CFI=0.941, RMSEA=0.077 [90% CI: 0.059, 0.095]		
Parameter	Intercept	Growth Rate
Intercept/Slope Factor Loading: Baseline	1	0
Intercept/Slope Factor Loading: 3 Months	1	1
Intercept/Slope Factor Loading: 6 Months	1	2
Intercept/Slope Factor Loading: 12 Months	1	4
Intercept/Slope Factor Loading: 18 Months	1	6
	Parameter Estimate	Standard Error
Mean Intercept (α_1)	5.742*	0.354
Mean Slope (α_2)	-0.119	0.085
Intercept Variance (ψ_{11})	7.681*	0.889
Slope Variance (ψ_{22})	0.090*	0.035
Regression Path: Stage of Change, Baseline (β_0)	-0.753*	0.203
Regression Path: Stage of Change, 3 Months (β_1)	-1.077*	0.099
Regression Path: Stage of Change, 6 Months (β_2)	-1.097*	0.075
Regression Path: Stage of Change, 12 Months (β_4)	-0.953*	0.075
Regression Path: Stage of Change, 18 Months (β_6)	-0.854*	0.095
Intercept/Slope Covariance (ψ_{21})	-0.197	0.133
Residual Variance: Baseline	16.971*	1.455
Residual Variance: 3 Months	5.306*	0.560
Residual Variance: 6 Months	3.594*	0.385
Residual Variance: 12 Months	5.812*	0.537
Residual Variance: 18 Months	4.733*	0.689

* = significant

Table 12. Parallel process model, temptations x drinks per week including stage as a TVC, covariances freely estimated¹

N=354, $\chi^2(54)=149.72$, $p<.001$, CFI=0.943, RMSEA=0.071 [90% CI: 0.057, 0.084]				
Parameter	Intercept	Growth Rate		
Intercept/Slope Factor Loading: Baseline	1	0		
Intercept/Slope Factor Loading: 3 Months	1	1		
Intercept/Slope Factor Loading: 6 Months	1	2		
Intercept/Slope Factor Loading: 12 Months	1	4		
Intercept/Slope Factor Loading: 18 Months	1	6		
	<i>Temptations</i>		<i>Drinks per week</i>	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Mean Intercept (α_1, α_3)	31.520*	1.960	11.400*	0.531
Mean Slope (α_2, α_4)	-0.362	1.170	-0.369*	0.120
Intercept Variance (ψ_{11}, ψ_{33})	51.732*	10.001	25.773*	2.582
Slope Variance (ψ_{22}, ψ_{44})	1.387	4.060	0.464*	0.079
Regression Path: Stage of Change, Baseline (β_0)	-2.628*	0.798	-0.905*	0.271
Regression Path: Stage of Change, 3 Months (β_1)	-2.241*	0.358	-1.275*	0.145
Regression Path: Stage of Change, 6 Months (β_2)	-2.532*	0.348	-1.442*	0.116
Regression Path: Stage of Change, 12 Months (β_4)	N/A	N/A	-1.177*	0.108
Regression Path: Stage of Change, 18 Months (β_6)	N/A	N/A	-1.034*	0.136
Intercept/Slope Covariance, within factors (ψ_{21}, ψ_{43})	-3.310	5.177	-1.106*	0.335
Intercept/Slope Covariance, between factors (ψ_{41}, ψ_{32})	-0.647	0.538	-0.499	1.700
Intercept/Intercept Covariance (ψ_{13})	N/A	N/A	15.534*	3.556
Slope/Slope Covariance (ψ_{24})	N/A	N/A	0.428	0.262
Residual Variance: Baseline	31.817*	9.350	18.863*	1.951
Residual Variance: 3 Months	27.325*	3.706	14.119*	1.427
Residual Variance: 6 Months	20.911*	6.293	14.616*	1.320
Residual Variance: 12 Months	N/A	N/A	11.234*	1.082
Residual Variance: 18 Months	N/A	N/A	3.790*	1.282

* = significant

¹ Detailed parameter estimates are reported for the freely estimated versions of the parallel process models, not the intermediate models.

Table 13. Parallel process model, temptations x drinks per drinking day including stage as a TVC, covariances freely estimated¹

N=354, $\chi^2(54)=155.21$, $p<.001$, CFI=0.936, RMSEA=0.073 [90% CI: 0.060, 0.086]				
Parameter	Intercept	Growth Rate		
Intercept/Slope Factor Loading: Baseline	1	0		
Intercept/Slope Factor Loading: 3 Months	1	1		
Intercept/Slope Factor Loading: 6 Months	1	2		
Intercept/Slope Factor Loading: 12 Months	1	4		
Intercept/Slope Factor Loading: 18 Months	1	6		
	<i>Temptations</i>		<i>Drinks per drinking day</i>	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Mean Intercept (α_1, α_3)	31.724*	1.968	3.621*	0.128
Mean Slope (α_2, α_4)	-0.263	1.167	-0.026	0.031
Intercept Variance (ψ_{11}, ψ_{33})	52.594*	9.923	1.605*	0.156
Slope Variance (ψ_{22}, ψ_{44})	2.076	4.055	0.020*	0.005
Regression Path: Stage of Change, Baseline (β_0)	-2.697*	0.800	-0.216*	0.064
Regression Path: Stage of Change, 3 Months (β_1)	-2.332*	0.361	-0.306*	0.035
Regression Path: Stage of Change, 6 Months (β_2)	-2.648*	0.346	-0.342*	0.029
Regression Path: Stage of Change, 12 Months (β_4)	N/A	N/A	-0.288*	0.030
Regression Path: Stage of Change, 18 Months (β_6)	N/A	N/A	-0.305*	0.038
Intercept/Slope Covariance, within factors (ψ_{21}, ψ_{43})	-3.978	5.106	-0.063*	0.021
Intercept/Slope Covariance, between factors (ψ_{41}, ψ_{32})	-0.105	0.133	-0.132	0.412
Intercept/Intercept Covariance (ψ_{13})	N/A	N/A	2.890*	0.872
Slope/Slope Covariance (ψ_{24})	N/A	N/A	0.125*	0.064
Residual Variance: Baseline	30.577*	9.293	0.980*	0.103
Residual Variance: 3 Months	27.883*	3.811	0.741*	0.077
Residual Variance: 6 Months	19.334*	6.378	0.864*	0.080
Residual Variance: 12 Months	N/A	N/A	1.088*	0.097
Residual Variance: 18 Months	N/A	N/A	0.614*	0.106

* = significant

¹ Detailed parameter estimates are reported for the freely estimated versions of the parallel process models, not the intermediate models.

Table 14. Parallel process model, temptations x binge frequency including stage as a TVC, covariances freely estimated¹

N=354, $\chi^2(54)=142.73$, $p<.001$, CFI=0.940, RMSEA=0.068 [90% CI: 0.055, 0.082]				
Parameter	Intercept	Growth Rate		
Intercept/Slope Factor Loading: Baseline	1	0		
Intercept/Slope Factor Loading: 3 Months	1	1		
Intercept/Slope Factor Loading: 6 Months	1	2		
Intercept/Slope Factor Loading: 12 Months	1	4		
Intercept/Slope Factor Loading: 18 Months	1	6		
	<i>Temptations</i>		<i>Binge frequency</i>	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Mean Intercept (α_1, α_3)	31.938*	1.966	5.690*	0.354
Mean Slope (α_2, α_4)	-0.452	1.164	-0.127	0.085
Intercept Variance (ψ_{11}, ψ_{33})	52.344*	9.975	7.688*	0.889
Slope Variance (ψ_{22}, ψ_{44})	2.735	4.023	0.089*	0.035
Regression Path: Stage of Change, Baseline (β_0)	-2.805*	0.798	-0.728*	0.203
Regression Path: Stage of Change, 3 Months (β_1)	-2.361*	0.362	-1.056*	0.099
Regression Path: Stage of Change, 6 Months (β_2)	-2.611*	0.346	-1.075*	0.075
Regression Path: Stage of Change, 12 Months (β_4)	N/A	N/A	-0.928*	0.075
Regression Path: Stage of Change, 18 Months (β_6)	N/A	N/A	-0.827*	0.095
Intercept/Slope Covariance, within factors (ψ_{21}, ψ_{43})	-4.181	5.102	-0.191	0.133
Intercept/Slope Covariance, between factors (ψ_{41}, ψ_{32})	0.043	0.329	0.871	0.921
Intercept/Intercept Covariance (ψ_{13})	N/A	N/A	6.193*	1.942
Slope/Slope Covariance (ψ_{24})	N/A	N/A	-0.045	0.155
Residual Variance: Baseline	29.365*	9.252	17.095*	1.464
Residual Variance: 3 Months	28.451*	3.818	5.314*	0.557
Residual Variance: 6 Months	17.998*	6.330	3.557*	0.379
Residual Variance: 12 Months	N/A	N/A	5.780*	0.533
Residual Variance: 18 Months	N/A	N/A	4.751*	0.691

* = significant

¹ Detailed parameter estimates are reported for the freely estimated versions of the parallel process models, not the intermediate models.

Table 15. Parallel process model, temptations x drinks per week including stage as a TVC with added regression path (Temptations → Drinks per week, β_{42})

N=155, $\chi^2(56)=91.68, p=.002, CFI=0.955, RMSEA=0.064$ [90% CI: 0.039, 0.087]				
Parameter	Intercept	Growth Rate		
Intercept/Slope Factor Loading: Baseline	1	0		
Intercept/Slope Factor Loading: 3 Months	1	1		
Intercept/Slope Factor Loading: 6 Months	1	2		
Intercept/Slope Factor Loading: 12 Months	1	4		
Intercept/Slope Factor Loading: 18 Months	1	6		
	<i>Temptations</i>		<i>Drinks per week</i>	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Mean Intercept (α_1, α_3)	31.254*	2.203	12.190*	1.074
Mean Slope (α_2, α_4)	-0.862	1.332	-0.004	1.657
Intercept Variance (ψ_{11}, ψ_{33})	45.963*	6.387	18.537*	2.980
Slope Variance (ψ_{22}, ψ_{44})	0.603	1.552	0.148	0.608
Regression Path Slope/Slope (β_{42})	0.687	1.593	N/A	N/A
Regression Path: Stage of Change, Baseline (β_0)	-2.536*	0.872	-1.376*	0.429
Regression Path: Stage of Change, 3 Months (β_1)	-1.991*	0.417	-1.615*	0.280
Regression Path: Stage of Change, 6 Months (β_2)	-2.108*	0.429	-1.711*	0.210
Regression Path: Stage of Change, 12 Months (β_4)	N/A	N/A	-1.188*	0.158
Regression Path: Stage of Change, 18 Months (β_6)	N/A	N/A	-0.995*	0.190
Intercept/Slope Covariance, within factors (ψ_{21})	-0.492	1.504	N/A	N/A
Intercept/Slope Covariance, between factors (ψ_{32})	N/A	N/A	-0.544	1.262
Intercept/Intercept Covariance (ψ_{13})	N/A	N/A	14.321*	3.563
Residual Variance: Baseline	34.573*	5.341	17.876*	2.706
Residual Variance: 3 Months	20.718*	3.579	16.162*	2.249
Residual Variance: 6 Months	17.204*	4.381	14.641*	1.917
Residual Variance: 12 Months	N/A	N/A	11.494*	1.586
Residual Variance: 18 Months	N/A	N/A	0.543	1.663

* = significant

Table 16. Parallel process model, temptations x drinks per week including stage as a TVC with added regression path (Drinks per week → Temptations, β_{24})

N=155, $\chi^2(56)=91.21$, $p=.002$, CFI=0.955, RMSEA=0.064 [90% CI: 0.039, 0.087]				
Parameter	Intercept	Growth Rate		
Intercept/Slope Factor Loading: Baseline	1	0		
Intercept/Slope Factor Loading: 3 Months	1	1		
Intercept/Slope Factor Loading: 6 Months	1	2		
Intercept/Slope Factor Loading: 12 Months	1	4		
Intercept/Slope Factor Loading: 18 Months	1	6		
	<i>Temptations</i>		<i>Drinks per week</i>	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Mean Intercept (α_1, α_3)	31.166*	2.193	12.169*	1.074
Mean Slope (α_2, α_4)	-0.306	1.369	-0.590*	0.224
Intercept Variance (ψ_{11}, ψ_{33})	44.472*	6.387	18.635*	2.984
Slope Variance (ψ_{22}, ψ_{44})	1.386	1.996	0.436*	0.109
Regression Path Slope/Slope (β_{24})	N/A	N/A	0.953**	0.542
Regression Path: Stage of Change, Baseline (β_0)	-2.501*	0.869	-1.368*	0.429
Regression Path: Stage of Change, 3 Months (β_1)	-1.961*	0.419	-1.610*	0.280
Regression Path: Stage of Change, 6 Months (β_2)	-2.080*	0.431	-1.708*	0.210
Regression Path: Stage of Change, 12 Months (β_4)	N/A	N/A	-1.188*	0.158
Regression Path: Stage of Change, 18 Months (β_6)	N/A	N/A	-0.999*	0.190
Intercept/Slope Covariance, within factors (ψ_{34})	N/A	N/A	-0.397	0.385
Intercept/Slope Covariance, between factors (ψ_{41})	N/A	N/A	-0.388	0.540
Intercept/Intercept Covariance (ψ_{13})	N/A	N/A	14.308*	3.250
Residual Variance: Baseline	33.282*	5.318	17.855*	2.704
Residual Variance: 3 Months	21.601*	3.801	16.150*	2.247
Residual Variance: 6 Months	14.375*	5.659	14.640*	1.917
Residual Variance: 12 Months	N/A	N/A	11.530*	1.589
Residual Variance: 18 Months	N/A	N/A	0.487	1.664

* = significant

** $p = .079$

Table 17. Parallel process model, temptations x drinks per drinking day including stage as a TVC with added regression path (Temptations → Drinks per drinking day, β_{42})

N=155, $\chi^2(56)=102.29$, $p<.001$, CFI=0.941, RMSEA=0.073 [90% CI: 0.050, 0.095]				
Parameter	Intercept	Growth Rate		
Intercept/Slope Factor Loading: Baseline	1	0		
Intercept/Slope Factor Loading: 3 Months	1	1		
Intercept/Slope Factor Loading: 6 Months	1	2		
Intercept/Slope Factor Loading: 12 Months	1	4		
Intercept/Slope Factor Loading: 18 Months	1	6		

	<i>Temptations</i>		<i>Drinks per week</i>	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Mean Intercept (α_1 , α_3)	31.394*	2.225	3.810*	0.261
Mean Slope (α_2 , α_4)	-0.855	1.332	-0.181	0.230
Intercept Variance (ψ_{11} , ψ_{33})	46.617*	6.880	1.413*	0.204
Slope Variance (ψ_{22} , ψ_{44})	-0.583	0.805	0.027	0.020
Regression Path Slope/Slope (β_{24})	-0.124	0.172	N/A	N/A
Regression Path: Stage of Change, Baseline (β_0)	-2.593*	0.881	-0.315*	0.103
Regression Path: Stage of Change, 3 Months (β_1)	-2.037*	0.417	-0.377*	0.065
Regression Path: Stage of Change, 6 Months (β_2)	-2.152*	0.421	-0.389*	0.051
Regression Path: Stage of Change, 12 Months (β_4)	N/A	N/A	-0.264*	0.047
Regression Path: Stage of Change, 18 Months (β_6)	N/A	N/A	-0.287*	0.060
Intercept/Slope Covariance, within factors (ψ_{21})	-0.234	1.145	N/A	N/A
Intercept/Slope Covariance, between factors (ψ_{32})	N/A	N/A	0.238	0.304
Intercept/Intercept Covariance (ψ_{13})	N/A	N/A	2.732*	0.874
Residual Variance: Baseline	37.181*	5.293	1.198*	0.168
Residual Variance: 3 Months	19.836*	3.554	0.481*	0.085
Residual Variance: 6 Months	19.127*	4.041	0.725*	0.102
Residual Variance: 12 Months	N/A	N/A	1.162*	0.152
Residual Variance: 18 Months	N/A	N/A	0.581*	0.160

* = significant

Table 18. Parallel process model, temptations x drinks per drinking day including stage as a TVC with added regression path (Drinks per drinking day $\rightarrow$ Temptations, β_{24})

N=155, $\chi^2(56)=103.02$, $p<.001$, CFI=0.940, RMSEA=0.074 [90% CI: 0.051, 0.096]				
Parameter	Intercept	Growth Rate		
Intercept/Slope Factor Loading: Baseline	1	0		
Intercept/Slope Factor Loading: 3 Months	1	1		
Intercept/Slope Factor Loading: 6 Months	1	2		
Intercept/Slope Factor Loading: 12 Months	1	4		
Intercept/Slope Factor Loading: 18 Months	1	6		
	<i>Temptations</i>		<i>Drinks per week</i>	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Mean Intercept (α_1, α_3)	31.168*	2.211	3.824*	0.259
Mean Slope (α_2, α_4)	-0.200	1.427	-0.088	0.060
Intercept Variance (ψ_{11}, ψ_{33})	43.617*	6.363	1.309*	0.191
Slope Variance (ψ_{22}, ψ_{44})	-0.104	2.076	0.015*	0.007
Regression Path Slope/Slope (β_{24})	N/A	N/A	6.783	4.679
Regression Path: Stage of Change, Baseline (β_0)	-2.500*	0.877	-0.321*	0.103
Regression Path: Stage of Change, 3 Months (β_1)	-1.985*	0.420	-0.378*	0.065
Regression Path: Stage of Change, 6 Months (β_2)	-2.124*	0.426	-0.386*	0.051
Regression Path: Stage of Change, 12 Months (β_4)	N/A	N/A	-0.255*	0.047
Regression Path: Stage of Change, 18 Months (β_6)	N/A	N/A	-0.272*	0.060
Intercept/Slope Covariance, within factors (ψ_{34})	N/A	N/A	-0.002	0.024
Intercept/Slope Covariance, between factors (ψ_{41})	N/A	N/A	0.084	0.144
Intercept/Intercept Covariance (ψ_{13})	N/A	N/A	2.937*	0.812
Residual Variance: Baseline	36.500*	5.618	1.182*	0.164
Residual Variance: 3 Months	21.024*	3.823	0.515*	0.086
Residual Variance: 6 Months	15.706*	5.652	0.733*	0.103
Residual Variance: 12 Months	N/A	N/A	1.154*	0.152
Residual Variance: 18 Months	N/A	N/A	0.620*	0.161

* = significant

Table 19. Parallel process model, temptations x binge frequency including stage as a TVC with added regression path (Temptations → Binge frequency, β_{42})

N=155, $\chi^2(56)=95.72$, $p=.001$, CFI=0.947, RMSEA=0.068 [90% CI: 0.044, 0.090]				
Parameter	Intercept	Growth Rate		
Intercept/Slope Factor Loading: Baseline	1	0		
Intercept/Slope Factor Loading: 3 Months	1	1		
Intercept/Slope Factor Loading: 6 Months	1	2		
Intercept/Slope Factor Loading: 12 Months	1	4		
Intercept/Slope Factor Loading: 18 Months	1	6		
	<i>Temptations</i>		<i>Drinks per week</i>	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Mean Intercept (α_1, α_3)	31.525*	2.221	6.740*	0.713
Mean Slope (α_2, α_4)	-0.792	1.335	-0.558	0.535
Intercept Variance (ψ_{11}, ψ_{33})	45.430*	6.543	7.621*	1.252
Slope Variance (ψ_{22}, ψ_{44})	0.206	0.637	0.208*	0.072
Regression Path Slope/Slope (β_{24})	-0.332	0.325	N/A	N/A
Regression Path: Stage of Change, Baseline (β_0)	-2.647*	0.880	-1.165*	0.294
Regression Path: Stage of Change, 3 Months (β_1)	-2.102*	0.421	-1.309*	0.184
Regression Path: Stage of Change, 6 Months (β_2)	-2.229*	0.429	-1.288*	0.134
Regression Path: Stage of Change, 12 Months (β_4)	N/A	N/A	-1.049*	0.109
Regression Path: Stage of Change, 18 Months (β_6)	N/A	N/A	-0.863*	0.143
Intercept/Slope Covariance, within factors (ψ_{21})	-0.163	1.232	N/A	N/A
Intercept/Slope Covariance, between factors (ψ_{32})	N/A	N/A	1.078	0.925
Intercept/Intercept Covariance (ψ_{13})	N/A	N/A	5.545*	2.224
Residual Variance: Baseline	35.762*	5.203	12.617*	1.694
Residual Variance: 3 Months	20.797*	3.538	6.016*	0.885
Residual Variance: 6 Months	17.359*	3.390	3.746*	0.570
Residual Variance: 12 Months	N/A	N/A	4.827*	0.682
Residual Variance: 18 Months	N/A	N/A	1.599	0.860

* = significant

Table 20. Parallel process model, temptations x binge frequency including stage as a TVC with added regression path (Binge frequency $\rightarrow$ Temptations, β_{24})

N=155, $\chi^2(56)=96.65$, $p=.001$, CFI=0.946, RMSEA=0.068 [90% CI: 0.045, 0.091]				
Parameter	Intercept	Growth Rate		
Intercept/Slope Factor Loading: Baseline	1	0		
Intercept/Slope Factor Loading: 3 Months	1	1		
Intercept/Slope Factor Loading: 6 Months	1	2		
Intercept/Slope Factor Loading: 12 Months	1	4		
Intercept/Slope Factor Loading: 18 Months	1	6		
	<i>Temptations</i>		<i>Drinks per week</i>	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Mean Intercept (α_1 , α_3)	31.361*	2.207	6.747*	0.713
Mean Slope (α_2 , α_4)	-0.697	1.351	-0.299	0.162
Intercept Variance (ψ_{11} , ψ_{33})	43.862*	6.344	7.596*	1.251
Slope Variance (ψ_{22} , ψ_{44})	1.266	2.069	0.230*	0.058
Regression Path Slope/Slope (β_{24})	N/A	N/A	-0.027	0.761
Regression Path: Stage of Change, Baseline (β_0)	-2.581*	0.875	-1.167*	0.293
Regression Path: Stage of Change, 3 Months (β_1)	-2.083*	0.423	-1.310*	0.184
Regression Path: Stage of Change, 6 Months (β_2)	-2.243*	0.435	-1.287*	0.134
Regression Path: Stage of Change, 12 Months (β_4)	N/A	N/A	-1.046*	0.110
Regression Path: Stage of Change, 18 Months (β_6)	N/A	N/A	-0.857*	0.143
Intercept/Slope Covariance, within factors (ψ_{34})	N/A	N/A	-0.348	0.197
Intercept/Slope Covariance, between factors (ψ_{41})	N/A	N/A	0.092	0.416
Intercept/Intercept Covariance (ψ_{13})	N/A	N/A	6.656*	2.010
Residual Variance: Baseline	34.453*	5.423	12.424*	1.674
Residual Variance: 3 Months	21.988*	3.916	6.009*	0.886
Residual Variance: 6 Months	14.577*	5.810	3.781*	0.574
Residual Variance: 12 Months	N/A	N/A	4.833*	0.683
Residual Variance: 18 Months	N/A	N/A	1.625	0.862

* = significant

FIGURES

Figure 1. Consort chart

Figure 2. Profile of pros and cons sum scores across stage of change, baseline

Figure 3. Profile of pros and cons sum scores across stage of change, 3-months

Figure 4. Profile of pros and cons sum scores across stage of change, 6-months

Figure 5. Latent growth curve model of temptations including stage as a TVC

Figure 6. Latent growth curve model of drinks per week including stage as a TVC

Figure 7. Latent growth curve model of drinks per drinking day including stage as a TVC

Figure 8. Latent growth curve model of binge frequency including stage as a TVC

Figure 9. Parallel process model, temptations x drinks per week including stage as a TVC

Figure 10. Parallel process model, temptations x drinks per drinking day including stage as a TVC, covariances freely estimated

Figure 11. Parallel process model, temptations x binge frequency including stage as a TVC, covariances freely estimated

Figure 12. Parallel process model, temptations x drinks per week including stage as a TVC with added regression paths

Figure 13. Parallel process model, temptations x drinks per drinking day including stage as a TVC with added regression paths

Figure 14. Parallel process model, temptations x binge frequency including stage as a TVC with added regression paths

APPENDICES

APPENDX A: RATIONALE FOR STUDY INCLUSION/EXCLUSION CRITERIA

As outlined in Chapter 2, there were many inclusion and exclusion criteria related to participating in this study. While some criteria may be obvious, the rationale for others may not be as evident. To participate in this study, participants had to:

1. *Be over the age of 21* – The focus of the intervention program was harm reduction and asked participants to limit their drinking rather than encourage abstinence only. Because it is illegal for adults between the ages of 18 and 20 to consume alcohol, interventions targeting this group typically focus on abstinence as there is no recommended level of consumption for this age range.
2. *Be employed* – A secondary aim of the clinical trial was to examine the impact of alcohol use on work productivity. As such, the original grant proposal limited the population to be included in this trial to employed adults. Both part- and full-time employment satisfied this criteria.
3. *Have exceeded low-risk drinking guidelines in the past 30 days* – The focus of this trial was to examine the efficacy of an alcohol intervention in changing the target behavior, which was following low-risk drinking guidelines. As such, those who participated were required to be drinking above these guidelines in the 30 days prior to study participation.
4. *Not be alcohol-dependent* – For those who are alcohol-dependent, focusing on risk reduction rather than abstinence may not be an appropriate intervention target. In addition, these individuals most likely need a higher level of care than the intervention provides and were referred to treatment resources when screening out of the program.

5. *Not be a full-time college student* – Patterns of drinking behavior among college students differ from other adult populations and are better served by alcohol interventions targeted to a college student population.
6. *Not be pregnant* – The rationale for this criterion is similar to being over the age of 21. There is no safe amount of alcohol consumption for women who are pregnant, so an intervention aimed at harm reduction is not appropriate for this group.
7. *Never have been involved in substance abuse treatment* – Similar to the alcohol dependence criterion, those who have previously been involved in substance use treatment may require a higher level of treatment than what is provided by this intervention.
8. *Not have been advised by a physician to avoid alcohol* – The messaging of the intervention focused on risk reduction rather than abstinence, which would conflict with a physician's recommendations in this case.
9. *Live in the United States*- This criterion was a requirement set by the funding agency, stipulating that participants involved in this study must reside in the United States.
10. *Score at least 7 out of 10 on confidence to participate in an 18-month study* – This criterion was used to help with trial retention and avoid dropout over the long study period.

APPENDIX B1: MEASURES OF ALCOHOL CONSUMPTION

AUDIT-C (Bush et al., 1998)

A standard drink is any drink that contains about 14 grams of pure alcohol (about 0.6 ounces or 1.2 tablespoons). Below are standard drink equivalents for a few alcoholic beverages. These are approximate, as different brands and types of beverages vary in their actual alcohol content. When responding to the following questions, please refer to this definition when thinking about drink sizes.

(One drink = one alcoholic beverage = one standard drink)

1. How often do you have a drink containing alcohol?
 - Never
 - Monthly or less
 - 2-4 times a month
 - 2-3 times a week
 - 4 or more times a week
2. How many drinks containing alcohol did you have on a typical day when you were drinking in the past year?
 - 1 or 2 drinks
 - 3 or 4
 - 5 or 6
 - 7 to 9
 - 10 or more
3. How often did you have six or more drinks on one occasion in the past year?

- Never
- Less than monthly
- Monthly
- Weekly
- Daily or almost daily

Quantity & Frequency

1. In a typical week, on how many days do you have at least one drink containing alcohol? (0 to 7 days)
2. How many drinks containing alcohol do you have on a typical day when you are drinking?
3. During the past 30 days, on how many days did you have 4/5 (for females/males) or more drinks containing alcohol in a row, that is, within a couple of hours? (0 to 30 days)

APPENDIX B2: STAGE OF CHANGE FOR LIMITING DRINKING

(for males)

Are you planning to limit your drinking to 14 or less drinks per week **and** no more than 4 drinks in one day?

(for females)

Are you planning to limit your drinking to 7 or less drinks per week **and** no more than 3 drinks in one day?

Response Options

No, I am not planning to limit

Yes, I am planning to limit my drinking in the next 6 months

Yes, I am planning to limit my drinking in the next 30 days

I have been limiting my drinking for less than 6 months

I have been limiting my drinking for more than 6 months

APPENDIX B3: DECISIONAL BALANCE

On the next screen are opinions people have about limiting their drinking. We're not asking whether you agree or disagree with each statement. Instead, please rate how important each opinion is in your decision whether or not to limit your drinking to the low-risk guidelines.

Your answer choices are:

Not Important At All

A Little Important

Moderately Important

Very Important

Extremely Important

If the statement does not apply to you, you should respond "Not Important At All."

How important are the following in your decision whether or not to limit your drinking?

Pros

1. I would be less likely to say things I regret.
2. I would feel more in control of myself.
3. I would be more productive.
4. I would feel more responsible.

Cons

1. I would miss letting go of my problems and responsibilities for a while.
2. I would feel less comfortable in social situations.

3. I would miss the feeling I get from drinking more than a couple of drinks.
4. I would have to pay more attention to how much I drink.

APPENDIX B4: TEMPTATIONS

Just as it can be hard to avoid the temptation to have dessert, it can be hard to limit your drinking in some situations. Please tell us how tempted you would be to drink more than the recommended limit in each of the following situations.

Your answer choices are:

Not Tempted At All

A Little Tempted

Tempted

Very Tempted

Extremely Tempted

How tempted would you be to drink more than the recommended limit in each of the following situations?

1. You have had a bad day.
2. You are having trouble at work.
3. You're feeling angry.
4. You are feeling overwhelmed by responsibilities.
5. You're feeling down.
6. It's a special occasion.
7. Everyone around you is drinking.
8. The person you're with is drinking a lot.
9. You are enjoying a good conversation.
10. You are enjoying the effect of the alcohol.

APPENDIX C. R LAVAAN CODE

```
library(lavaan)
```

```
#Model 1: temptations, TVC=stage, missing=FIML
```

```
tmpt <- '
```

```
i =~ 1*tmpttotal.bl + 1*tmpttotal.3m + 1*tmpttotal.6m
```

```
s =~ 0*tmpttotal.bl + 1*tmpttotal.3m + 2*tmpttotal.6m
```

```
#time-varying covariates
```

```
tmpttotal.bl ~ blstagenum
```

```
tmpttotal.3m ~ m3stagenum
```

```
tmpttotal.6m ~ m6stagenum
```

```
,
```

```
fit_tmpt <- growth(tmpt, data=alcoholdata, missing="FIML")
```

```
summary(fit_tmpt, fit.measures=TRUE)
```

```
#Model 2: drinks per week, TVC=stage, missing=FIML
```

```
dpw <- '
```

```
i =~ 1*dpw.bl.trim + 1*dpw.3m.trim + 1*dpw.6m.trim + 1*dpw.12m.trim +  
1*dpw.18m.trim
```

```
s =~ 0*dpw.bl.trim + 1*dpw.3m.trim + 2*dpw.6m.trim + 4*dpw.12m.trim +  
6*dpw.18m.trim
```

```
#time-varying covariates
```

```
dpw.bl.trim ~ blstagenum
```

```
dpw.3m.trim ~ m3stagenum
```

```
dpw.6m.trim ~ m6stagenum
```

```
dpw.12m.trim ~ m12stagenum
```

```
dpw.18m.trim ~ m18stagenum
```

```
,
```

```

fit_dpw <- growth(dpw, data=alcoholdata, missing="FIML")
summary(fit_dpw, fit.measures=TRUE)

#Model 3: drinks per drinking day, TVC=stage, missing=FIML
ddd <- '

i=~ 1*ddd.bl.trim + 1*ddd.3m.trim + 1*ddd.6m.trim + 1*ddd.12m.trim +
1*ddd.18m.trim

s=~ 0*ddd.bl.trim + 1*ddd.3m.trim + 2*ddd.6m.trim + 4*ddd.12m.trim +
6*ddd.18m.trim

#time-varying covariates
ddd.bl.trim ~ blstagenum
ddd.3m.trim ~ m3stagenum
ddd.6m.trim ~ m6stagenum
ddd.12m.trim ~ m12stagenum
ddd.18m.trim ~ m18stagenum
'

fit_ddd <- growth(ddd, data=alcoholdata, missing="FIML")
summary(fit_ddd, fit.measures=TRUE)

#Model 4: binge frequency, TVC=stage, missing=FIML
binge <- '

i=~ 1*binge.bl.trim + 1*binge.3m.trim + 1*binge.6m.trim + 1*binge.12m.trim +
1*binge.18m.trim

s=~ 0*binge.bl.trim + 1*binge.3m.trim + 2*binge.6m.trim + 4*binge.12m.trim +
6*binge.18m.trim

#time-varying covariates
binge.bl.trim ~ blstagenum
binge.3m.trim ~ m3stagenum

```

```

binge.6m.trim ~ m6stagenum
binge.12m.trim ~ m12stagenum
binge.18m.trim ~ m18stagenum
'

fit_binge <- growth(binge, data=alcoholdata, missing="FIML")
summary(fit_binge, fit.measures=TRUE)


#Model 5: parallel process, temptations & drinks per week, TVC=stage,
missing=FIML, covar=0

tmpt_dpw0 <- '
i1 =~ 1*tmpttotal.bl + 1*tmpttotal.3m + 1*tmpttotal.6m
s1 =~ 0*tmpttotal.bl + 1*tmpttotal.3m + 2*tmpttotal.6m
i2 =~ 1*dpw.bl.trim + 1*dpw.3m.trim + 1*dpw.6m.trim + 1*dpw.12m.trim +
1*dpw.18m.trim
s2 =~ 0*dpw.bl.trim + 1*dpw.3m.trim + 2*dpw.6m.trim + 4*dpw.12m.trim +
6*dpw.18m.trim

#covariances
i1 ~~ 0*i2
s1 ~~ 0*s2
i1 ~~ 0*s2
s1 ~~ 0*i2

#time-varying covariates
tmpttotal.bl ~ blstagenum
tmpttotal.3m ~ m3stagenum
tmpttotal.6m ~ m6stagenum
dpw.bl.trim ~ blstagenum
dpw.3m.trim ~ m3stagenum
dpw.6m.trim ~ m6stagenum

```

```

dpw.12m.trim ~ m12stagenum
dpw.18m.trim ~ m18stagenum
'

fit_tmpt_dpw0 <- growth(tmpt_dpw0, data=alcoholdata, missing="FIML")
summary(fit_tmpt_dpw0, fit.measures=TRUE)


#Model 6: parallel process, temptations & drinks per week, TVC=stage,
missing=FIML
tmpt_dpw1 <- '
i1=~ 1*tmpttotal.bl + 1*tmpttotal.3m + 1*tmpttotal.6m
s1=~ 0*tmpttotal.bl + 1*tmpttotal.3m + 2*tmpttotal.6m
i2=~ 1*dpw.bl.trim + 1*dpw.3m.trim + 1*dpw.6m.trim + 1*dpw.12m.trim +
1*dpw.18m.trim
s2=~ 0*dpw.bl.trim + 1*dpw.3m.trim + 2*dpw.6m.trim + 4*dpw.12m.trim +
6*dpw.18m.trim
#time-varying covariates
tmpttotal.bl ~ blstagenum
tmpttotal.3m ~ m3stagenum
tmpttotal.6m ~ m6stagenum
dpw.bl.trim ~ blstagenum
dpw.3m.trim ~ m3stagenum
dpw.6m.trim ~ m6stagenum
dpw.12m.trim ~ m12stagenum
dpw.18m.trim ~ m18stagenum
'

fit_tmpt_dpw1 <- growth(tmpt_dpw1, data=alcoholdata, missing="FIML")
summary(fit_tmpt_dpw1, fit.measures=TRUE)

```



```
lavTestLRT(fit_tmpt_dpw0, fit_tmpt_dpw1)
```

```
#Model 7: parallel process, temptations & drinks per drinking day, TVC=stage,  
missing=FIML, covar=0
```

```
tmpt_ddd0 <- '
```

```
i1 =~ 1*tmpttotal.bl + 1*tmpttotal.3m + 1*tmpttotal.6m
```

```
s1 =~ 0*tmpttotal.bl + 1*tmpttotal.3m + 2*tmpttotal.6m
```

```
i2 =~ 1*ddd.bl.trim + 1*ddd.3m.trim + 1*ddd.6m.trim + 1*ddd.12m.trim +  
1*ddd.18m.trim
```

```
s2 =~ 0*ddd.bl.trim + 1*ddd.3m.trim + 2*ddd.6m.trim + 4*ddd.12m.trim +  
6*ddd.18m.trim
```

```
#covariances
```

```
i1 ~~ 0*i2
```

```
s1 ~~ 0*s2
```

```
i1 ~~ 0*s2
```

```
s1 ~~ 0*i2
```

```
#time-varying covariates
```

```
tmpttotal.bl ~ blstagenum
```

```
tmpttotal.3m ~ m3stagenum
```

```
tmpttotal.6m ~ m6stagenum
```

```
ddd.bl.trim ~ blstagenum
```

```
ddd.3m.trim ~ m3stagenum
```

```
ddd.6m.trim ~ m6stagenum
```

```
ddd.12m.trim ~ m12stagenum
```

```
ddd.18m.trim ~ m18stagenum
```

```
,
```

```
fit_tmpt_ddd0 <- growth(tmpt_ddd0, data=alcoholdata, missing="FIML")
```

```
summary(fit_tmpt_ddd0, fit.measures=TRUE)
```

```
#Model 8: parallel process, temptations & drinks per drinking day, TVC=stage,
missing=FIML
```

```
tmpt_ddd1 <- '
```

```
i1=~ 1*tmpttotal.bl + 1*tmpttotal.3m + 1*tmpttotal.6m
```

```
s1=~ 0*tmpttotal.bl + 1*tmpttotal.3m + 2*tmpttotal.6m
```

```
i2=~ 1*ddd.bl.trim + 1*ddd.3m.trim + 1*ddd.6m.trim + 1*ddd.12m.trim +
1*ddd.18m.trim
```

```
s2=~ 0*ddd.bl.trim + 1*ddd.3m.trim + 2*ddd.6m.trim + 4*ddd.12m.trim +
6*ddd.18m.trim
```

```
#time-varying covariates
```

```
tmpttotal.bl ~ blstagenum
```

```
tmpttotal.3m ~ m3stagenum
```

```
tmpttotal.6m ~ m6stagenum
```

```
ddd.bl.trim ~ blstagenum
```

```
ddd.3m.trim ~ m3stagenum
```

```
ddd.6m.trim ~ m6stagenum
```

```
ddd.12m.trim ~ m12stagenum
```

```
ddd.18m.trim ~ m18stagenum
```

```
,
```

```
fit_tmpt_ddd1 <- growth(tmpt_ddd1, data=alcoholdata, missing="FIML")
```

```
summary(fit_tmpt_ddd1, fit.measures=TRUE)
```

```
lavTestLRT(fit_tmpt_ddd0, fit_tmpt_ddd1)
```

```
#Model 9: parallel process, temptations & binge frequency, TVC=stage,
missing=FIML, covar=0
```

```
tmpt_binge0 <- '
```

```

i1 =~ 1*tmpttotal.bl + 1*tmpttotal.3m + 1*tmpttotal.6m
s1 =~ 0*tmpttotal.bl + 1*tmpttotal.3m + 2*tmpttotal.6m

i2 =~ 1*binge.bl.trim + 1*binge.3m.trim + 1*binge.6m.trim + 1*binge.12m.trim +
1*binge.18m.trim
s2 =~ 0*binge.bl.trim + 1*binge.3m.trim + 2*binge.6m.trim + 4*binge.12m.trim +
6*binge.18m.trim

#covariances
i1 ~~ 0*i2
s1 ~~ 0*s2
i1 ~~ 0*s2
s1 ~~ 0*i2

#time-varying covariates
tmpttotal.bl ~ blstagenum
tmpttotal.3m ~ m3stagenum
tmpttotal.6m ~ m6stagenum
binge.bl.trim ~ blstagenum
binge.3m.trim ~ m3stagenum
binge.6m.trim ~ m6stagenum
binge.12m.trim ~ m12stagenum
binge.18m.trim ~ m18stagenum
'

fit_tmpt_binge0 <- growth(tmpt_binge0, data=alcoholdata, missing="FIML")
summary(fit_tmpt_binge0, fit.measures=TRUE)


#Model 10: parallel process, temptations & binge frequency, TVC=stage,
missing=FIML
tmpt_binge1 <- '
i1 =~ 1*tmpttotal.bl + 1*tmpttotal.3m + 1*tmpttotal.6m

```

```

s1=~ 0*tmpttotal.bl + 1*tmpttotal.3m + 2*tmpttotal.6m

i2=~ 1*binge.bl.trim + 1*binge.3m.trim + 1*binge.6m.trim + 1*binge.12m.trim +
1*binge.18m.trim

s2=~ 0*binge.bl.trim + 1*binge.3m.trim + 2*binge.6m.trim + 4*binge.12m.trim +
6*binge.18m.trim

#time-varying covariates
tmpttotal.bl ~ blstagenum
tmpttotal.3m ~ m3stagenum
tmpttotal.6m ~ m6stagenum
binge.bl.trim ~ blstagenum
binge.3m.trim ~ m3stagenum
binge.6m.trim ~ m6stagenum
binge.12m.trim ~ m12stagenum
binge.18m.trim ~ m18stagenum
'

fit_tmpt_binge1 <- growth(tmpt_binge1, data=alcoholdata, missing="FIML")
summary(fit_tmpt_binge1, fit.measures=TRUE)

lavTestLRT(fit_tmpt_binge0, fit_tmpt_binge1)


#Model 11: parallel process, temptations & drinks per week, TVC=stage
#temptations predicting drinks per week
tmpt_dpw2 <- '
i1=~ 1*tmpttotal.bl + 1*tmpttotal.3m + 1*tmpttotal.6m
s1=~ 0*tmpttotal.bl + 1*tmpttotal.3m + 2*tmpttotal.6m
i2=~ 1*dpw.bl.trim + 1*dpw.3m.trim + 1*dpw.6m.trim + 1*dpw.12m.trim +
1*dpw.18m.trim
s2=~ 0*dpw.bl.trim + 1*dpw.3m.trim + 2*dpw.6m.trim + 4*dpw.12m.trim +
6*dpw.18m.trim

```

```

#regressions
s2 ~ s1

#time-varying covariates
tmpttotal.bl ~ blstagenum
tmpttotal.3m ~ m3stagenum
tmpttotal.6m ~ m6stagenum
dpw.bl.trim ~ blstagenum
dpw.3m.trim ~ m3stagenum
dpw.6m.trim ~ m6stagenum
dpw.12m.trim ~ m12stagenum
dpw.18m.trim ~ m18stagenum
'

fit_tmpt_dpw2 <- growth(tmpt_dpw2, data=alcoholdata)
summary(fit_tmpt_dpw2, fit.measures=TRUE)


#Model 12: parallel process, temptations & drinks per week, TVC=stage
#drinks per week predicting temptations
tmpt_dpw3 <- '
i1=~ 1*tmpttotal.bl + 1*tmpttotal.3m + 1*tmpttotal.6m
s1=~ 0*tmpttotal.bl + 1*tmpttotal.3m + 2*tmpttotal.6m
i2=~ 1*dpw.bl.trim + 1*dpw.3m.trim + 1*dpw.6m.trim + 1*dpw.12m.trim +
1*dpw.18m.trim
s2=~ 0*dpw.bl.trim + 1*dpw.3m.trim + 2*dpw.6m.trim + 4*dpw.12m.trim +
6*dpw.18m.trim

#regressions
s1 ~ s2

#time-varying covariates
tmpttotal.bl ~ blstagenum

```

```

tmpttotal.3m ~ m3stagenum
tmpttotal.6m ~ m6stagenum
dpw.bl.trim ~ blstagenum
dpw.3m.trim ~ m3stagenum
dpw.6m.trim ~ m6stagenum
dpw.12m.trim ~ m12stagenum
dpw.18m.trim ~ m18stagenum
'

fit_tmpt_dpw3 <- growth(tmpt_dpw3, data=alcoholdata)
summary(fit_tmpt_dpw3, fit.measures=TRUE)

#Model 13: parallel process, temptations & drinks per week, TVC=stage
#temptations predicting drinks per week
tmpt_ddd2 <- '
i1=~ 1*tmpttotal.bl + 1*tmpttotal.3m + 1*tmpttotal.6m
s1=~ 0*tmpttotal.bl + 1*tmpttotal.3m + 2*tmpttotal.6m

i2=~ 1*ddd.bl.trim + 1*ddd.3m.trim + 1*ddd.6m.trim + 1*ddd.12m.trim +
1*ddd.18m.trim

s2=~ 0*ddd.bl.trim + 1*ddd.3m.trim + 2*ddd.6m.trim + 4*ddd.12m.trim +
6*ddd.18m.trim

#regressions
s2 ~ s1

#time-varying covariates
tmpttotal.bl ~ blstagenum
tmpttotal.3m ~ m3stagenum
tmpttotal.6m ~ m6stagenum
ddd.bl.trim ~ blstagenum
ddd.3m.trim ~ m3stagenum

```

```

ddd.6m.trim ~ m6stagenum
ddd.12m.trim ~ m12stagenum
ddd.18m.trim ~ m18stagenum
'

fit_tmpt_ddd2 <- growth(tmpt_ddd2, data=alcoholdata)
summary(fit_tmpt_ddd2, fit.measures=TRUE)

#Model 14: parallel process, temptations & drinks per week, TVC=stage
#drinks per drinking day predicting temptations
tmpt_ddd3 <- '
i1=~ 1*tmpttotal.bl + 1*tmpttotal.3m + 1*tmpttotal.6m
s1=~ 0*tmpttotal.bl + 1*tmpttotal.3m + 2*tmpttotal.6m

i2=~ 1*ddd.bl.trim + 1*ddd.3m.trim + 1*ddd.6m.trim + 1*ddd.12m.trim +
1*ddd.18m.trim

s2=~ 0*ddd.bl.trim + 1*ddd.3m.trim + 2*ddd.6m.trim + 4*ddd.12m.trim +
6*ddd.18m.trim

#regressions
s1 ~ s2

#time-varying covariates
tmpttotal.bl ~ blstagenum
tmpttotal.3m ~ m3stagenum
tmpttotal.6m ~ m6stagenum
ddd.bl.trim ~ blstagenum
ddd.3m.trim ~ m3stagenum
ddd.6m.trim ~ m6stagenum
ddd.12m.trim ~ m12stagenum
ddd.18m.trim ~ m18stagenum
'

```

```

fit_tmpt_ddd3 <- growth(tmpt_ddd3, data=alcoholdata)
summary(fit_tmpt_ddd3, fit.measures=TRUE)

#Model 15: parallel process, temptations & binge frequency, TVC=stage
#temptations predicting binge frequency
tmpt_binge2 <- '
i1=~ 1*tmpttotal.bl + 1*tmpttotal.3m + 1*tmpttotal.6m
s1=~ 0*tmpttotal.bl + 1*tmpttotal.3m + 2*tmpttotal.6m

i2=~ 1*binge.bl.trim + 1*binge.3m.trim + 1*binge.6m.trim + 1*binge.12m.trim +
1*binge.18m.trim
s2=~ 0*binge.bl.trim + 1*binge.3m.trim + 2*binge.6m.trim + 4*binge.12m.trim +
6*binge.18m.trim

#regressions
s2 ~ s1

#time-varying covariates
tmpttotal.bl ~ blstagenum
tmpttotal.3m ~ m3stagenum
tmpttotal.6m ~ m6stagenum
binge.bl.trim ~ blstagenum
binge.3m.trim ~ m3stagenum
binge.6m.trim ~ m6stagenum
binge.12m.trim ~ m12stagenum
binge.18m.trim ~ m18stagenum
'

fit_tmpt_binge2 <- growth(tmpt_binge2, data=alcoholdata)
summary(fit_tmpt_binge2, fit.measures=TRUE)

```



```

#Model 16: parallel process, temptations & binge frequency, TVC=stage
#binge frequency predicting temptations
tmpt_binge3 <- '
i1=~ 1*tmpttotal.bl + 1*tmpttotal.3m + 1*tmpttotal.6m
s1=~ 0*tmpttotal.bl + 1*tmpttotal.3m + 2*tmpttotal.6m
i2=~ 1*binge.bl.trim + 1*binge.3m.trim + 1*binge.6m.trim + 1*binge.12m.trim +
1*binge.18m.trim
s2=~ 0*binge.bl.trim + 1*binge.3m.trim + 2*binge.6m.trim + 4*binge.12m.trim +
6*binge.18m.trim

#regressions
s1 ~ s2

#time-varying covariates
tmpttotal.bl ~ blstagenum
tmpttotal.3m ~ m3stagenum
tmpttotal.6m ~ m6stagenum
binge.bl.trim ~ blstagenum
binge.3m.trim ~ m3stagenum
binge.6m.trim ~ m6stagenum
binge.12m.trim ~ m12stagenum
binge.18m.trim ~ m18stagenum
'

fit_tmpt_binge3 <- growth(tmpt_binge3, data=alcoholdata)
summary(fit_tmpt_binge3, fit.measures=TRUE)

```

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