WOOD, CLAIRE A., Ph.D. Person-Centered Approaches to Modeling Trajectories of Concurrent Substance Use across Adolescence and Adulthood: Individual and Family Background Predictors (2017)
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Informed by theoretical approaches that emphasize variation in the developmental pathways of substance use (e.g., Moffit, 1993; Muthén & Muthén, 2000), the current study examined two person-centered approaches to assessing concurrent substance use across adolescence and adulthood (ages 16 to 28). Person-centered approaches have the advantage of capturing heterogeneity within a sample thus allowing for the explicit assessment of different developmental pathways of substance use for subsections of a larger population. Furthermore, trajectories of *concurrent* substance use have seldom been modeled in the extant literature, partially due to the complexity of data and models required to do so. Instead, studies have primarily relied on one indicator or one specific substance over time, which limits the extent to which those models accurately reflect individuals' lived experiences. The analytical sample for the current study was drawn from the Center for Education and Drug Abuse Research (CEDAR, 2015) dataset and included 722 predominantly White male participants, approximately half of whom had fathers with diagnosed substance use disorders (SUD). Substance use was assessed across five waves of data from age 16 to age 28. Two approaches to modeling concurrent substance use trajectories were assessed: the multiple-indicator multilevel (MIML) growth mixture model (GMM) and the parallel processes latent class growth analysis (LCGA) model. Each model identified heterogeneity in substance use over time. Furthermore, family background and individual predictors differentially predicted

membership into the profiles providing some evidence of at-risk versus normative patterns of substance use over time. Results indicated both the MIML GMM and parallel processes mixture model were appropriate methods for modeling concurrent substance use over time. Whereas results from the multiple-indicator multilevel growth mixture model indicated approximately 75% of the sample being classified as increasing low users, results from the parallel process mixture model indicated only 56% of the sample was classified as predominantly increasing low alcohol-only users. The typologies identified via these two different approaches are an important first step in assessing concurrent substance use trajectories from adolescence into adulthood and advance research that has been limited to a focus on modeling only one substance at a time. Furthermore, the ability of this study to identify at-risk versus normative patterns of use while simultaneously accounting for concurrent substance use is especially helpful for clinicians working with individuals who use or abuse substances.

PERSON-CENTERED APPROACHES TO MODELING TRAJECTORIES OF

CONCURRENT SUBSTANCE USE ACROSS ADOLESCENCE

AND ADULTHOOD: INDIVIUDAL AND FAMILY

BACKGROUND PREDICTORS

by

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TABLE OF CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Rates of substance use are highest during adolescence and emerging adulthood, which is highly problematic given the lasting negative consequences substance abuse can prompt in terms of intrapersonal (e.g., abuse and dependence), interpersonal (e.g., divorce, relationship conflict), and social consequences (e.g., crime, health care expenses). Substance use in adolescence may contribute to life-long interpersonal, behavioral, and addiction-related problems, and it is imperative that we understand not only the trajectories and patterns of substance use during the developmental periods from adolescence to adulthood, but also how family background and personal characteristics may play a role in the pattern of substance use over time.

Previous research has demonstrated normative changes in rates of substance use from adolescence to adulthood (i.e., increasing use in adolescence, peaking in emerging adulthood, and declining thereafter) for a number of substances (e.g., Chen & Jacobsen, 2012; Chen & Kandel, 1995; Hicks & Zucker, 2014; Johnston et al., 2016; Miech et al., 2016; Muthen & Muthen, 2000b; Schulenberg & Maggs, 2002). However, additional work has demonstrated the benefits of person-centered approaches to examining patterns of substance use over time, identifying several, rather than one, distinct patterns of use trajectories across a variety of substances (e.g., Tucker et al. 2005, Nelson et al., 2015; White et al., 2015). Using person-centered approaches to examine patterns of substance use trajectories is imperative as previous research has highlighted the deleterious consequences of belonging to more problematic (e.g., chronic and polysubstance) patterns of use, including increased risk of substance abuse or dependence diagnosis (e.g., Chassin, Flora, & King, 2004). However, studies assessing *trajectories* of substance use have often relied on only one substance classification (e.g., alcohol or marijuana use). These studies often fail to account for the highly interrelated nature of substance use. For example, Jackson, Sher, and Schulenberg (2008) demonstrated that classification in chronic patterns of alcohol use trajectories was linked with increased odds of being classified in chronic patterns of marijuana and tobacco use trajectories. Missing from this body of literature is a consideration of patternings of concurrent tobacco, alcohol, marijuana, and other hard drug use over an extended period of time (e.g., from adolescence through adulthood) and a consideration of concurrent patterns of substance use that differentiates between marijuana use and the use of other hard drugs. Furthermore, the identification of patterns of substance use that account for concurrent substance use over time, particularly once we determine the outcomes of different patterns of use, can help shape clinical practice and policy decisions related to substance use and abuse.

It is not only important to be able to describe and understand different patterns of use over time, but it is also imperative to understand what predicts variation in those patterns. Including individual and family background predictors of patterns of substance use trajectories will help clarify which patterns of use may be considered high-risk and may be particularly helpful in clarifying specific factors that are maladaptive—or make membership into higher risk patterns more likely—or adaptive, and are linked with lower odds of being in high risk patterns of use over time.

For these reasons, it is imperative to (a) study substance use trajectories, particularly with models that can account for concurrent use of multiple substances, using person-centered approaches than can explicitly model different developmental pathways of use and (b) examine family background (i.e., household SES and paternal SUD) and individual predictors (i.e., gender and race) that have been shown to be influential in predicting differential patterns of substance use and may be differentially related to these unique patterns of concurrent use over time.

CHAPTER II

THEORETICAL FRAMEWORK

Although there is a substantial amount of variation in the extent to which research on substance use incorporated theoretical or conceptual frameworks, the literature that has incorporated theoretical underpinnings on substance use has integrated an array of perspectives. The research question of interest—to examine patterns of concurrent substance use trajectories and assess differential probabilities of membership using family background and individual predictors—is guided by conceptual frameworks emphasizing multiple developmental pathways. As a guiding framework, these perspectives underscore the importance of applying longitudinal and person-centered approaches to studying substance use and examining factors that predict differential membership into different patterns of use. Additional theoretical perspectives that provide support for the examination of family background and individual predictors of substance abuse pathways are also discussed.

Multiple Developmental Pathways: The Need for Person-Centered Approaches

The first empirically driven framework: multiple developmental pathways (e.g., Muthén & Muthén, 2000a), underscored by previous person-centered research on substance use and abuse, emphasizes the heterogeneity in populations of substance users. This is not a unique proposition as other conceptual frameworks have suggested variation in patterns of behaviors including life-course pervasive (i.e., chronic) and adolescent-limited trajectories of antisocial behavior (e.g.,Moffitt, 1993).

Supporting these conceptual frameworks, previous research has empirically demonstrated that rather than one pattern that explains substance use over time, several patterns of substance use trajectories across substance categories (e.g., alcohol and marijuana) exist including low/non-use, adolescent limited, adolescent onset, decreasing, increasing, adult onset, and chronic high use (e.g., Nelson, Ryzin, & Dishion, 2015). However, there is some variation in the extent to which each pattern of substance across time is identified, particularly for studies that assess trajectories of hard drug use (e.g., Borders & Booth, 2012; Guo et al., 2002) or concurrent substance use (e.g., Jackson, Sher, & Schulenberg, 2005). Conceptual perspectives emphasizing diverging patterns of engagement in risk behaviors (e.g., substance use) and associated empirical support highlights the need for person-centered approaches to assessing patterns substance use over time.

Gender: Differential Probabilities of Engagement in Risk Behaviors

There are several perspectives that postulate differential engagement in risk behaviors based on gender including Arnett's (1992) developmental perspective on adolescent risk taking, risk as value (Kelling, Zirkes, & Myerowitz, 1976), and psychobiology of personality (Zuckerman, 1991). Although there are differences in the extent to which these theoretical perspectives account for different contexts (e.g., cultural norms, parenting practices), specific behaviors (e.g., substance use, unprotected sexual encounters), and personal characteristics (e.g., sensation-seeking), these theories and associated empirical work (e.g., Byrnes, Miller, & Schaefer, 1999) generally support the notion that men are prone to engage in risk behaviors to a greater extent than women. Extrapolating these perspectives to gender differences in substance use over time, we might expect that men would be more likely to be classified in patterns of substance use that are high risk relative to women or that the slope of substance use (i.e., rate of increase over time) is less steep for women relative to men. In other words, increases in substance use over time will be smaller for women.

Racial Differences in Substance Use

Relatively few studies that examined racial differences in the initiation, trajectories, antecedents, and consequences of substance use incorporated theoretical perspectives attempting to understand or hypothesize why these differences are found. This body of literature is primarily atheoretical or includes theoretical perspectives justifying different substantive questions. In one of the few articles that explicitly discussed theoretical perspectives for racial differences in substance use, Caetano, Clark, & Tam (1998) focused only on racial differences in alcohol use. Drawing from the theory of mental illness and social integration (Leighton, 1968) and the theory of anomie (Durkheim, 1933), these authors suggested that drinking patterns among racial and ethnic minority individuals may be driven by stress related to “social adjustment to the dominant U.S. culture” (Caetano et al., 1998, p. 234). Caetano et al. (1998) noted stress may arise from both socioeconomic conditions (i.e., socioeconomic stress) as well as a result of membership in a racial/ethnic minority group (i.e., minority stress) both arising from living in a racialized society. Caetano et al. (1998) also discussed historical perspectives on alcohol use among different racial and ethnic groups highlighting the deficit-based perspectives from which these approaches originated including that heavy drinking patterns were a result of social disorganization, family breakdown, or were characteristic of the “Black lifestyle.” Deficit based theoretical perspectives are generally not supported in the empirical literature, which evidences mixed and sometimes contradictory findings regarding racial difference in substance use patterns. For example, some work related to smoking and marijuana use shows lower baseline levels but higher rates of use in adulthood among African Americans (e.g., Chen & Jacobs), whereas other studies have suggested lower rates of alcohol use and higher rates of abstaining from alcohol among African Americans (e.g., Caetano et al., 1998). Importantly, these mixed findings on racial difference underscore the importance of an approach that attends to variation and heterogeneity in patterns of concurrent substance use and the likelihood that racial differences do not uniformly predict membership into high or low-risk patterns of use. Regardless of these empirical findings, theoretical perspectives that accurately account for racial variation in the differential trajectories of use across both individual and multiple substances are lacking.

Parental SUD: Intergenerational Transmission of Risk Behavior

Several perspectives across a variety of disciplines including biological (e.g., genetic), behavioral (e.g., modeling), and cognitive (e.g., parental acceptance) have been used to explain intergenerational transmission of risk behaviors. Although empirical and theoretical work has highlighted links between parental acceptance and attitudes surrounding substance with adolescent substance use, we cannot assume parental SUD necessarily translates to more permissive attitudes surrounding their child's use. Therefore, the focus of the theoretical literature in this section will underscore primarily biological and behavioral perspectives linking paternal SUD with adolescent substance use.

Theoretical and empirical work from a biological perspective (e.g., probabilistic-epigenetic framework, transactional models) emphasize the influence of genetic transmission of risk, which can occur through a variety of mechanisms including through interactions with both internal and external environmental factors (e.g., Gottlieb, 1998, 2007; Samaroff, 2009). These perspectives and associated empirical work (e.g., Agrawal & Lynskey, 2008; Li & Burmeister, 2009) suggest that genetic factors associated with addiction, which are shared between parents and offspring, increase offspring's vulnerability to developing substance use or addiction-related problems.

Behavioral theories, such as social learning and modeling theories, emphasize the transmission of substance use behavior to adolescents through parents' engagement in those behaviors. Numerous studies have supported these theoretical assertions demonstrating that parental modeling of substance use is linked with their children's expectation to use and actual use of substances (see Hawkins, Catalano, & Miller, 1992). Although parents may not be the only models of substance use to which children and adolescents are exposed (e.g., peers and siblings), because the effects of parental SUD on their child(ren)'s substance use may also operate biologically (e.g., genetically) and cognitively (e.g., more permissive attitudes about substance use) as well, it is a pertinent risk factor for subsequent substance use by their child(ren). Although the current study is incapable of distinguishing between environmental or behavioral and biological influences on children's substance use, there is substantial theoretical and empirical support suggesting paternal SUD remains a risk factor for increased use and for problematic use specifically regardless of the mechanism(s) through which it may be operating.

Household Socioeconomic Status (SES): Stress and Coping

Theories of stress and coping (e.g., social stress theory, Pearlin et al., 1981; strain theory, Merton, 1968) have been used as a framework for understanding the links between SES and substance use. In general, these perspectives propose that substance use may be a coping strategy. Pearlin et al.'s (1981) perspective suggests that substance use may be a coping mechanism arising from "exposure to stress including chronic economic deprivation" (Barrett & Turner, 2005, p. 101), whereas Merton suggests that substance use may be a coping mechanism due to economic disadvantage, which limits access to legitimate avenues of success. However, empirical support of the links between household SES and substance use are more mixed. Therefore, although theoretically we might expect SES to be linked with membership in high-risk patterns of substance use, the mixed findings in the empirical literature suggests we may or may not find these associations.

CHAPTER III

LITERATURE REVIEW

Conceptual and Operational Clarification

Substance use is conceptually distinct from diagnosed substance use disorders, encompassing abuse and dependence, and is assessed differently empirically as well. Substance use is the actual use of substances (e.g., tobacco, alcohol, marijuana, and hard drugs). It has been operationalized several different ways. Many studies use measures of the frequency of substance use, although there is still variation in the operationalization of substance use frequency. For example, Orlando et al., (2005), assessed substance (i.e., tobacco and alcohol) use in the past year, Harrington, Velicer, and Ramsey (2014) assessed daily alcohol use, and Passarotti, Crane, Hedecker, & Mermelstein (2015) assessed past-month marijuana use. Some studies of tobacco use have also created composite measures that assess both the frequency and quantity of cigarettes used (e.g., Tucker et al., 2005). Particularly with alcohol use, studies have diverged along two operationalization options. Some studies have used the frequency of alcohol use, similar to how the other substances are measured. However, several other studies have incorporated aspects of binge drinking or heavy alcohol use, which include measures of quantity (i.e., 5 drinks in one sitting for men, and 4 drinks in one setting for women) in addition to frequency of use. In contrast to alcohol use, illicit drug use has no standard operationalization for quantity because the route of administration and concentration levels of the substances are highly variable. Furthermore, it is important to clarify differences between concurrent versus simultaneous substance use. Concurrent use refers to using multiple substances during the same period (e.g., during the past month), whereas simultaneous use refers to using multiple substances at the same time (e.g., Collins, Ellickson, & Bell, 1999; Kokkevi et al., 2014; Smit, Monshouwer, & Verdurmen, 2002).

Alternatively, abuse and dependence, commonly called addiction, are features of diagnosed substance use disorders. Substance dependence, which is a higher order classification encompassing both substance abuse and dependence is a "cluster of cognitive, behavioral and physiological symptoms indicating that the individual continues use of the substance despite significant substance-related problems" (Kranzler & Li, 2008). In many instances, studies using diagnostic criteria lump together individuals diagnosed with either substance abuse or substance dependence. Historically, individuals could not be diagnosed with both substance abuse and substance dependence. Substance abuse, characterized by risky use or social impairment, was diagnosed only when an individual did not meet the additional criteria for substance dependence. As substance dependence was the higher order classification, individuals who met diagnostic criteria for both substance abuse and substance dependence were classified or diagnosed as dependent. However, there was some debate about whether these two classifications were distinct rather than indicative of addiction more broadly. For example, Saha, Chou, and Grant (2006) highlighted that rather than describing discrete categories, problems related to alcohol use are better represented as a continuum. Recent updates to the DSM resulted in addiction being treated as a single classification of SUD rather than distinguishing between abuse and dependence. Furthermore, it is important to differentiate physical dependence on a substance from dependence as a diagnostic classification (O'Brien, Volkow, & Li, 2006). Whereas physical dependence refers to "changes in the body and brain that cause signs of withdrawal but which are not necessarily associated with addiction," dependence as a diagnostic classification refers to "chronic, relapsing, and compulsive substance use associated with addiction" (National Institute on Alcohol Abuse and Alcoholism, 2008).

In the current study, substance use will include four categories of use (i.e., tobacco, alcohol, marijuana, and hard drugs) and will be assessed using a measure of average frequency of past-month use. This method for assessing substance use is not particularly novel; however, the current study is one of the few studies to assess concurrent substance use trajectories and the only study to date that assessed marijuana and other illicit drugs separately using a parallel processes model and general substance use trajectories by incorporating a measurement model and latent variables. These approaches allow for (a) distinguishing specific patterns of different substances over time and (b) general patterns of substance use over time while also accounting for measurement error.

Patterns of Substance Use Trajectories

There is a substantial body of literature on substance use. Studies have utilized cross-sectional and longitudinal data and variable- and person-centered frameworks, encompassing a wide variety of statistical methods. An exhaustive review of this entire body of literature is outside the scope of this section, which will primarily focus on person-centered approaches to substance use trajectories and, to a lesser extent, normative trends in substance use. Although there is a growing body of literature examining typologies of substance users based on daily patterns of use (i.e., short-term longitudinal studies) (e.g., Bobashev, Liao, Hampton, & Helzer, 2014; Harrington, Velicer, & Ramsey, 2014), identified patterns of users are conceptually distinct from those identified by studies that examine substance use across developmental periods (i.e., long-term longitudinal studies). Therefore, daily use patterns will not be included in the review of person-centered approaches applied to substance use over time. The subsequent sections will discuss identified patterns of trajectories of smoking or tobacco use, alcohol use or binge drinking, marijuana use, and other illicit drug use. Following these sections will be a description of person-centered approaches to concurrent or polysubstance use. However, as only four studies assessed *trajectories* of concurrent/polysubstance use, this section will also include studies that incorporated cross-sectional approaches (i.e., latent class analyses) and short-term longitudinal approaches (i.e., latent transition analyses) to assessing polysubstance use. Then I will discuss two studies that compared overlap, or comborditiy, among classifications of substance users to highlight the importance of examining multiple substances concurrently. Finally, I will conclude with limitations of the extant literature and summarize how the current research study will contribute to the understanding of substance use over time.

In general, studies have demonstrated normative trends in substance use, particularly tobacco use, alcohol use or binge drinking, and marijuana use evidencing increases through adolescence with peak usage during emerging adulthood (e.g., 18-25) followed by declines in use in adulthood (Chen & Jacobsen, 2012; Chen & Kandel, 1995; Hicks & Zucker, 2014; Muthen & Muthen, 2000b; Schulenberg & Maggs, 2002). However, there is variation in the normative pattern of use and initiation by specific substance. For example, peak initiation for cigarette use is around 16 years old, for alcohol and marijuana use peak initiation is around 18 years old, and peak initiation of cocaine use ranges from 21 to 24 years old (Chen & Kandel, 1995). Several scholars have further highlighted that after age 29, use of virtually no substances is initiated (e.g., Chen & Kandel, 1995; Bachmann et al., 1997). There is some debate, however, about normative patterns of use for particular substances. For example, Tucker et al. (2005) suggested that normative patterns of use for smoking, binge drinking, and marijuana use involved light or moderate persistent use (e.g., Colder et al., 2001, 2002; Schulenberg et al., 1996), whereas other studies of smoking trends suggested that the dominant pattern of smoking, rather than involving increases and decreases in use, involved escalation or increases to higher levels of use (e.g., Chassin, Presson, Pitts, & Sherman, 2000; Soldz & Cui, 2002). Although in general, there is agreement about the normative patterns of substance use over time, assessing substance use trajectories via pattern-analytic approaches can be helpful in clarify normative patterns of use for various substances as normative patterns often characterize a large portion of the sample.

Patterns of Tobacco Use and Cigarette Smoking Trajectories

Several studies have assessed patterns of tobacco use or cigarette smoking over time and have identified relatively consistent patterns of use. For example, a study using mixture models of growth trajectories for past-month tobacco used frequency among college students (6 years of assessment starting from freshman year) identified 5 unique patterns of tobacco use over time: non-use (*n*=809, 72.3%), low-stable use (*n*=193, 12.5%) increasing use (*n*=89, 6.2%), decreasing use (*n*=87, 4.8%), and chronic high use (*n*=75, 4.2%) (Caldeira, O'Grady, Vincent, & Arria, 2012). Another study using the nationally representative Monitoring the Future Study, identified five distinct patterns of past-month smoking among emerging adults (age 18-26): Low Smokers (69%), Moderate Smoking (8%), Developmentally Limited Smokers (6%), Late Onset Smokers (6%), and Chronic Smokers (12%; Jackson, Sher, & Schulenberg, 2008). Tucker et al., (2005) identified five tobacco use trajectories among adolescents and emerging adults (aged 13-23) using a composite measure of tobacco use that included both past-month use and quantity including Stable Highs (*n*=33), Decreasers (*n*=371), Triers (*n*=2347), Early Increasers (*n*=593), and Steady Increasers (*n*=601). Results from this body of literature suggest that infrequent/low use or non-use may be indicative of a normative pattern, rather than developmentally limited use as is evident with other patterns of substance use (e.g., alcohol use).

Patterns of Alcohol Use and Binge Drinking Trajectories

Several studies have assessed trajectories of alcohol use or binge drinking, finding relatively consistent patterns of use over time, albeit somewhat different patterns in studies focused specifically on alcohol use. Studies that assess alcohol use using only frequency measures tend to identify high baseline increasing (32 – 35% of the sample) and low baseline increase use (65 – 68% of the sample) patterns (e.g., Li et al., 2001; Li et al., 2002). However, binge-drinking studies tend to identify patterns consistent with those found for tobacco use and marijuana use. For example, using the nationally representative Monitoring the Future Study, Jackson, et al. (2008) identified four distinct patterns of past-two week *heavy drinking* among emerging adults (age 18-26), named: Low Heavy Drinkers (63%), Developmentally Limited Heavy Drinkers (16%), Late Onset Heavy Drinkers (8%), and Chronic Heavy Drinkers (12%). Tucker et al (2005) identified four binge drinking trajectories among adolescents and adults (aged 13-23) using past-month frequency of binge drinking: Early Highs (*n*=342), Moderate Stables (*n*=2103), Steady Increasers (*n*=927), and Adolescent Bingers (*n*=517). In studies of drinking among college student samples, the identified profiles are slightly different and evidence more dispersion across classes. For example, a study using mixture models of growth trajectories for past-year alcohol use frequency among college students (6 years of assessment starting from freshman year) identified 7 unique patterns of alcohol use over time: Non-use (*n*=126, 15.3%), weekly-stable use (*n*=219, 16.3%) frequent-stable use (*n*=261, 15.1%), infrequent, slight-increase use (*n*=180, 19.0%), infrequent, moderate-increase use (*n*=235, 20.5%), weekly, great-increase use (*n*=123, 8.0%), and near-daily, decreasing use (*n*=109, 5.7%) (Caldeira, O'Grady, Vincent, & Arria, 2012). Unlike patterns for other substances, this body of literature, overall, indicates that there is variability in the most prevalent profile; however, developmentally limited profiles, which would be consistent with normative trends, are seldom found as the most prevalent pattern.

Patterns of Marijuana Use Trajectories

Marijuana use trajectories are relatively similar across studies. Using growth mixture modeling and allowing for non-linear quadratic effects (i.e., the upturn or downturn of a trajectory) of marijuana use for adolescents and emerging adults (aged 14-20), Passarotti, et al. (2015) found four patterns of use, (i.e., High Users (17.36%) including those who used marijuana almost daily, Escalating Users (8.31%), Low Users (29.07%) including those who use marijuana less than weekly but more than monthly, and Medium Users (23.42%) including those who used marijuana multiple times a week) after specifying two groups a priori: Never Users (10.71%) and Non-Users (11.13%). Another study examined past-year marijuana use trajectories of at-risk adolescents and emerging adults (aged 15-26) using latent class growth analysis (LCGA). The authors found 4 profiles of users (i.e., Low/Non Users accounting for 51.0% of the sample, Chronic High Users accounting for 19.7% of the sample, Adolescent Limited Users accounting for 8.9% of the sample, and Late Increasing Users accounting for 20.3% of the sample) (White, Bechtold, Loeber, & Pardini, 2015). A study using mixture models of growth trajectories for past-month marijuana use frequency among college students (6 years of assessment starting from freshman year) identified 6 unique patterns of marijuana use over time: Non Use (*n*=766, 71.5%), Low-Stable Use (*n*=154, 10.0%) Late-Increasing Use (*n*=75, 4.7%), Early Decline (*n*=81, 4.3%), College Peak (*n*=100, 5.2%), and Chronic High Use (*n*=78, 4.2%) (Caldeira, O'Grady, Vincent, & Arria, 2012; Aria et al., 2016). After identifying a group of abstainers (45% of the sample) a priori, Tucker et al. (2005) identified four marijuana use trajectories among adolescents and adults (aged 13-23) using past-year frequency of use: Early Highs (*n*=147), Stable Light Users (*n*=555), Steady Increasers (*n*=809), and Occasional Light Users (*n*=1674).

Using longitudinal multi-group mixture modeling of retrospective accounts of marijuana use from childhood to adulthood (i.e., age 7 to age 32) among African Americans, Juon et al. (2011) identified 5 patterns of trajectories of marijuana use for men and 4 patterns of trajectories of marijuana use among women. The 5 patterns of identified among men were as follows: Abstainers (49.4%), Adolescent-Only Users (7.2%), Persistent Users (23.2%), Early Adult Decliners (11.5%), and Late Starters (8.6%). Among women, the following 4 patterns emerged: Abstainers (65.2%), Adolescent-Only Users (10.7%), Persistent Users (19.1%), and Early Adult Decliners (5.0%). Using the nationally representative Monitoring the Future Study, Jackson, et al. (2008) identified four distinct patterns of past-month marijuana use among emerging adults (age 18-26): Low Marijuana Users (80%), Developmentally Limited Marijuana Users (9%), Late Onset Marijuana Users (4%), and Chronic Marijuana Users (7%). Across this literature on marijuana use, a large majority of people are consistently classified as abstainers or non-users, with some studies that use reports over longer-time periods demonstrating occasional/infrequent patterns as most common. It appears that for marijuana use, and particularly use that is measure via past-month rather than past-year use, abstaining seems to be the normative pattern. However, abstaining from marijuana use over the past month does not provide information on lifetime use.

Patterns of Hard Drug Use Trajectories

Few studies have modeled trajectories of hard drug use using person-centered approaches. More variation in identified patterns of use characterize the few identified studies of hard drug use relative to studies that evaluated patterns of other substance use. One study assessed hard drug use using a composite measure (Guo et al., 2002), another assessed patterns of use trajectories for specific substances (i.e., cocaine and ketamine; Lankenau et al., 2011), and a third study estimated distinct patterns of cocaine use trajectories for "three groups of antisocial/rebellious respondents and a group of non-offenders" (Hamil-Luker, Land, & Blau, 2004, p. 300). Two of the studies that assessed specific substances sampled individuals who reported current use of the substance under investigation (i.e., Borders & Booth, 2000; Lankenau, Jackson Bloom, & Shin, 2011). As one might expect, these studies identified somewhat different profiles of users. Using average past-year use of seven hard drugs among adolescents (aged 13-16), Guo et al. (2002) identified three patterns of hard drug use trajectories: "'Early Onsetters' (6.9%), 'Late Onsetters' (4.3%), and 'Nonusers' (88.8%)" (p. 357). Non-use characterizes a larger proportion of the sample when examining hard drug use relative to the use of more normative substances (e.g., alcohol). Lankenau et al. (2011) sampled relatively young injection drug users (aged 16-29) who reported having injected ketamine. Using reports of ketamine injection at two time-points, Lankenau et al. (2011) identified three patterns of ketamine injection use over time: "'Moderates,' who injected ketamine several times per year (*n*=5); 'Occasionals,' who injected ketamine approximately once per year (*n*=21); and 'Abstainers,' who did not inject any ketamine during follow-up (*n*=40)" (p. 306).

In their longitudinal three-year study of adult stimulant users (average age at baseline 33.05, *SD* = 10.35), Borders and Booth (2012) identified distinct patterns of the trajectories of past-month powder cocaine use, crack cocaine use, and methamphetamine use. Results indicated 3-4 classes per substance. Trajectories of past month powder cocaine use resulted in the identification of 4 classes: Steady High (*n*=60), Declining (*n*=118), Steady Moderate (*n*=145), and Fast Low (*n*=387). Trajectories of past month crack cocaine use resulted in the identification of 4 classes: Steady High (*n*=119), Declining (*n*=165), Increasing (*n*=81), and Fast Low (*n*=345). Trajectories of past month methamphetamine use resulted in the identification of 3 classes: High to Moderate (*n*=58), Moderate to Low (*n*=148), and Fast Low (*n*=504). In a study that assessed patterns of cocaine use trajectories for different groups of adolescents (i.e., Delinquents who reported high levels of substance use and criminal activity, Partiers who reported high levels of substance use and low levels of criminal activity, Troublemakers who reported moderate levels of substance use and criminal activity, and Conformists who reported low levels of both substance use and criminal activity) relatively consistent patterns of cocaine use trajectories were identified across groups (Hamil-Luker et al., 2004). For the Delinquent and Troublemaker adolescents, the same three patterns of cocaine use were identified: Young Adult Peaked Users, Desisters, and Low-Risk/Non-Users. For both groups, Low-Risk/Non-Users were the most common pattern of cocaine use over time; however, Desisters were more prevalent than Young Adult Peaked Users among Troublemakers, whereas the reverse was true for Delinquents. Three patterns of cocaine use over time were also identified among Partiers: *Extended* Young Adult Peaked Users, Desisters, and Low-Risk/Non-Users, with Low-Risk/Non-Users being the most prevalent and Extended Young Adult Peaked Users being the least. Two patterns of cocaine use over time were identified among Conformists: Young Adult Peaked Users and Low-Risk/Non-Users. The studies that examine patterns of hard drug use seldom conform the patterns identified by studies of other substance users. However, this may be a result of sampling in that national datasets or datasets not specifically focused on recruiting hard drug users may have a hard time modeling and finding these patterns of use. Studies that incorporate pattern-analytic approaches to concurrent substance and include hard drugs, which will be discussed subsequently, often find patterns more similar to the identified patterns for alcohol, marijuana, and tobacco use. However, both of the two studies (i.e., Brooks-Russell et al., 2015; Chassin, Flora, & King, 2004) that incorporated hard drug use into concurrent substance use trajectories included marijuana use, which may account for the similarity between identified patterns in those studies and those found for marijuana and alcohol use. Research on patterns of concurrent substance trajectories that differentiates between marijuana and hard drug use and uses a more normative sample of users may help clarify patterns of hard drug use that are more applicable to a wider population.

Patterns of Concurrent Substance Use Trajectories

Because of the difficulty in modeling polysubstance use over time, studies that have assessed co-occurring substance use using person-centered approaches have often relied on latent class (i.e., cross-sectional person-centered approaches) or latent transition analyses (i.e., short-term longitudinal studies that examine transitions in profile membership over time). Tomczyk, Isensee, and Hanewinkle (2016) provided a comprehensive overview of 23 studies using person-centered approaches to assess patterns of concurrent polysubstance use among adolescents age 10-19. Results indicated 3-7 classes of identified patterns of substance use; although, 3- and 4-class solutions were most prevalent (i.e., 74% of studies). Patterns of low/non-use were identified across most of the studies and were consistently the largest class. Patterns of polysubstance use, assessed via concurrent use of at least two substances, were also consistently identified across all 23 studies and represented the smallest identified class. However, there was significant variation across these studies in terms of the substances used to assess co-occurring or polysubstance use, with only 11 of the 23 studies including measures of tobacco, alcohol, marijuana, and other illicit drug use. It should be noted that each of these 23 studies were limited by the reliance on retrospective rather than prospective measures of substance use (Tomczyck et al., 2016).

In an extensive review of the literature, four studies were identified that incorporated person-centered approaches to modeling trajectories of co-occurring substance use. Two studies assessed patterns of concurrent alcohol use and smoking (i.e., Jackson, Sher, & Schulenberg, 2005; Orlando, Tucker, Ellikson, & Klein, 2005), one study assessed concurrent alcohol and illicit drug use, which included marijuana use (i.e., Chassin, Flora, and King, 2004), and the fourth study assessed concurrent tobacco, alcohol, drug use (including marijuana) (i.e., Brooks-Russell et al., 2015). However, no study examined hard drugs separately from marijuana, which is highly problematic given that marijuana use is much more prevalent and not associated with as severe outcomes as other substances and likely drives the trajectory of the drug use category. Jackson, et al. (2005) used data from the nationally representative Monitoring the Future study and modeled patterns of co-occurring alcohol and tobacco use across emerging adulthood (age 18-26) and identified seven distinct classes: Chronic High Drinkers/Smoker (6%), Chronic High Drinker/Low Smoker (14%), Moderate Drinker/Developmentally Limited Smoker (5%), Moderate Drinker/Smoker (6%), Moderate Drinker/Late Onset Heavy Smoker (5%), Low Drinker/Chronic High Smoker (8%), and Non Drinker/Smoker (56%). Orlando et al. (2005) used past-year frequency of alcohol use and smoking among adolescents and emerging adults (aged 13-23) to identify five distinct patterns of use from mixture modeling, with one class of Non-Users (5%) specified prior: Normative Users (55%), Smoking Quitters/Drinking Maintainers (6%), Steady Increasers (13%), Early Increasers (12%), and Early Highs (9%). Although less common, some scholars choose to specify a non-user group (i.e., people who reported no use of any modeled substances) prior to estimating patterns of use in the remaining sample. Chassin, et al. (2004) modeled patterns of co-occurring alcohol and hard drug use (including marijuana) from early adolescence (age 11-14) to adulthood (age 27-30) and identified three distinct patterns from the growth mixture model (GMM), and a fourth pattern (i.e., Abstainers, *n*=74) that had been specified prior. The three identified patterns from the GMM were Light Drinking/Rare Drug Use (*n*=159), Moderate Drinking/Experimental Drug Use (*n*=295), Heavy Drinking/Heavy Drug Use (*n*=132). Although labeled Light

Drinking/Rare Drug Use and Moderate Drinking/Experimental Drug Use, the graphical representation indicated that drinking behavior was driving the distinction between these two classes rather than drug use. It is also likely that marijuana use rather than any of the other hard drugs in the drug use category was driving the patterns of drug use identified. The final study assessed patterns of tobacco, alcohol, and drug use trajectories in a nationally representative sample of 10-12th graders and identified five distinct patterns of use over time: “Nonusers (45.5%); tobacco, alcohol, and other drug users (9.2%); alcohol and other drug users (9.2%); increasing multiple-substance users (16.7%), and decreasing multiple-substance users (19.4%)” (Brooks-Russell et al., 2015, p. 962).

Another approach incorporated person centered analyses to the study of co-occurring problem behaviors, of which substance use was one. Mustanski et al. (2013) used a parallel process growth mixture model (GMM) to identify co-occurring patterns of adolescent (age 12-18) sexual risk taking, conduct problems, and substance use trajectories. Assessing substance use with a composite measure of past-month tobacco, alcohol, marijuana, and past-year cocaine use, four patterns of use were identified: increasing high-risk takers, adolescent-limited conduct problems and substance with high risky sex, early experimenters, and normative, low-risk. Another study using parallel-process growth mixture modeling assessing the co-occurrence of conduct problems and substance use (assessed via a composite indicator of past month tobacco and marijuana use, and past-year alcohol use) in adolescence (7th-12th graders) also identified four distinct patterns over time: High Conduct Problems/High Substance Use, Increasing Conduct Problems/Increasing Substance Use, Minimal Conduct Problems/Increasing

Substance Use, and Minimal Conduct Problems/Minimal Substance Use. However, because these two model assessed the co-occurrence of multiple problem behaviors in adolescence, and used composite measures of substance use, it is impossible to disentangle the trajectories of substance use for specific substances. Furthermore, treating substance use as a composite variable suggests that each substance contributes equally to the finally variable, which is problematic given that this likely an incorrect assumption that is overcome by modeling substance use using latent variables.

Classification Overlap or Comorbidity

Some studies that identified patterns of substance use over time for individual substances (i.e., tobacco, alcohol, and marijuana) compared classifications across substances. These comparisons underscore the comorbidity of substance use over time and highlight the need for studies assessing concurrent patterns of substance use trajectories. Tucker et al. (2005) compared the overlap of classification patterns of trajectories across substances (i.e., tobacco use, binge drinking, and marijuana use), finding greater levels of overlap among individuals classified as abstainers. Tucker et al. (2005) reported that "among those who abstained from at least one substance, 30% abstained from all three substances…those who were classified as a steady increaser on at least one substance, 5% were classified as a steady increaser on all substances… [and] among those who were classified as an early high on at least one substance, 3% were classified as an early high on all substance" (p. 318). In comparing alcohol and tobacco classes, Jackson et al. (2008) found that individuals classified as Low Heavy-Drinkers were also more likely to be classified as Low-Smokers, Chronic Heavy Drinkers were more likely to be classified as Chronic or Moderate Smokers and less likely to be classified as Low-Smokers, Developmentally Limited Heavy Drinkers were more likely to be classified as Developmentally Limited Smokers and less likely to be classified as Low-Smokers, and Late-Onset Heavy Drinkers were more likely to be classified as Late-Onset Smokers. In comparing alcohol and marijuana classes, Jackson et al. (2008) found that Low Heavy-Drinkers were more likely to be classified as Low Marijuana Users and less likely to be classified as Chronic or Developmentally Limited Users, Chronic Heavy Drinkers were more likely to be classified as Chronic, Developmentally Limited, and Late-Onset Marijuana Users, and were less likely to be classified as Low Marijuana Users. Developmentally Limited Heavy Drinkers were more likely to be classified as Developmentally Limited Marijuana Users and less likely to be classified as Low Marijuana Users, and Late-Onset Heavy Drinkers were more likely to be classified as Late-Onset Marijuana Users. In comparing marijuana and tobacco use classes, Jackson et al. (2008) found that Low Marijuana Users were more likely to be classified as Low-Smokers and less likely to be classified as Chronic Smokers, Chronic Marijuana Users were more likely to be classified as Chronic or Moderate Smokers and were less likely to be classified as Low-Smokers, Developmentally Limited Marijuana Users were more likely to be classified as Chronic, Developmentally Limited, and Moderate Smokers and were less likely to be classified as Low-Smokers, and Late Onset Marijuana Users were more likely to be classified as Late Onset Smokers and less likely to be classified as Low-Smokers. In predicting past-month heavy drinking, Borders and Booth (2012) found that individuals in profiles who reported relatively high levels of powder or crack cocaine use reported significantly more past-month heavy drinking relative to individuals in profiles reporting relatively low levels of use. Furthermore, past-month use of other illicit substances was also significantly linked to higher levels of past-month heavy drinking. Overall, this body of literature demonstrates consistency and discrepancies of patterns of use across different substances. In general, abstainers or low users report this pattern of use across substances. However, for the other identified patterns (i.e., chronic, moderate, developmentally limited, late onset) there was more variability in patterns of use across substances, thus highlighting the need for approaches that can account for this variation by modeling substance use across substances simultaneously.

Although the preceding review is extensive, it is by no means an exhaustive account of every article modeling substance use trajectories using person-centered approaches. There is a substantial body of literature examining substance use trajectories for tobacco, alcohol, and marijuana use. As a comprehensive review of these studies already exists (i.e., Nelson, Van Ryzin, & Dishion, 2015), I have only highlighted some of the key studies. In general, results from this body of literature point to a fairly consistent pattern of identified substance use trajectories for tobacco, alcohol, and marijuana use including but not limited to Low/Non-Users, Chronic High Users, Adolescent Limited, Late Start or Increasing Users, and Decreasing Users, although there are some populations for whom variation in these commonly identified profiles are more prevalent (e.g., college students). However, the studies of hard drug use trajectories and concurrent use trajectories are more mixed evidencing considerable variation in identified patterns of use, potentially due to variation in sampling, measurement, and variable selection (i.e., which substances or which combinations of substances are being studied). Additional research may help clarify some of these patterns, particularly for trajectories of hard drug or concurrent substance use.

The current study fills the gap in the extant literature by assessing two innovative methods for analyzing patterns of substance use trajectories that simultaneously accounts for the use of multiple substances, albeit in different ways. The first model, the Multiple-Indicator Multilevel Growth Mixture Model (MIML GMM) incorporates latent variables that accounts for both (a) measurement error in the measurement of substance use and (b) the differential strength of relationship between the use of specific substances (i.e., alcohol, tobacco, marijuana, and hard drugs) and an underlying substance use variable. Modeling concurrent substance use with this approach will help define a normative pattern of use across substances and may help identify high-risk patterns that will be of use to practitioners as they account for overall patterns of concurrent substance use from adolescence to adulthood. The second, parallel processes mixture model approach, models patterns of trajectories for concurrent alcohol, tobacco, marijuana, and hard drug use. However, determining normative and high-risk patterns of use with this approach may not be as straightforward as with the MIML GMM approach as there will be variation in trajectories of specific substances within profiles. Not only is this a relatively novel approach to assessing substance use trajectories, it fills at least two gaps in the literature by examining concurrent substance use in a more comprehensive way (i.e., by distinguishing hard drug use from marijuana use) and across developmental periods from adolescence (age 16) to adulthood (age 28). In addition to filling gaps in the extant literature, the current study may lay the foundation for the identification of specific patterns of substance use that may and may not have long-term detrimental outcomes. Furthermore, although not assessed in the current study, this approach is the first step for future research to identify unique precursors and outcomes of specific combinations or patterns of substance use. Both of the models in the current study provide comprehensive approaches to assessing concurrent substance use over time that are lacking in the current literature. These approaches, will not only provide an understanding of the normative patterns of substance use, they will also provide a more complete picture of high-risk patterns of use that may help inform both clinical practice and legislative debates about substance use.

Individual and Family Background Predictors

Several studies have found differences in substance use based on several family background and individual characteristics (e.g., gender, race, family SES, and parental substance use). National studies of substance use (e.g., Monitoring the Future Study) have found several persistent gender differences in substance use among adolescents and young adults. In adolescence, Miech et al. (2016) noted that gender discrepancies in substance use are relatively small in 8th grade, but continue to diverge as individuals age, such that by 12th grade males report higher rates of substance use (i.e., tobacco, alcohol, marijuana, and other illicit substances) and heavy use than females. Johnston et al. (2016) noted that among young adults age 19-30, males evidence greater levels of substance use over a variety of measures and categories. Males report higher rates of any illicit drug use, marijuana use, any illicit drug use not including marijuana over the past year, as well as higher levels of each specific illicit substance use (i.e., heroin, methamphetamine, ketamine, etc.) over the past year. There were also differences found for daily use of alcohol, marijuana, and episodes of binge drinking with males reporting higher levels of use across all categories. Although there were fewer gender differences in tobacco/nicotine use among young adults in the 1980's, recent reports indicated that males have higher rates than females of tobacco/nicotine use for all substances (e.g., cigarettes, smokeless tobacco, cigars) and reported higher levels of past-month and daily use (Johnston et al., 2016). Therefore, based on both empirical and theoretical work supporting the notion of higher engagement in substance use by men than women, gender was included as a predictor of class membership to help determine the successful distinction of higher-risk patterns of concurrent substance use.

There are several studies showing racial and ethnic differences in substance use in adolescence. Miech et al. (2016) reported that African Americans generally report lower levels of illicit and licit substance use relative to Whites and Hispanics, and this is especially true for hallucinogens, tranquilizers, and methamphetamines. Miech et al. (2016) also reported that Hispanics in early adolescence (i.e., 8th grade) evidenced the highest rates of use for several substances (e.g., marijuana, binge drinking, crack/cocaine), but by 12th grade the discrepancy between Whites and Hispanics had narrowed and even reversed for some substances. However, Miech et al. (2016) postulated that the reversed trend in 12th grade, with Whites reporting highest level of use for some substances, might be due to dropout rates being higher among Hispanics. Another study examining racial and ethnic differences in trajectories of substance use from adolescence to adulthood, found that Hispanics evidenced highest initial levels of alcohol use, heavy drinking, smoking, and marijuana use in early adolescence, whereas Whites evidenced more steep increases in the use of all substances from adolescence to adulthood relative to African American, Hispanic, and Asian individuals (Chen & Jacobsen, 2012). Furthermore, declines in marijuana use among African Americans occurred relatively later into adulthood relative to the other racial and ethnic groups (Chen & Jacobsen, 2012). For these reasons, the model will condition the substance use classes and growth factors on race.

There are mixed findings linking SES with substance use, with some work demonstrating links between family SES and substance use, whereas others (e.g., Juon et al., 2011) have found no such association. Furthermore, the studies that have found associations have often reported contrasting effects. For example, Casswell, Pledger, and Hooper (2003) found positive associations between income and the frequency of alcohol use and negative associations between education and the quantity of alcohol consumed. Huckle, Quan You, and Casswell (2010) found SES related to both quantity and frequency of alcohol use, albeit in contrasting directions such that higher SES was associated with increased frequency of alcohol use whereas lower SES was associated with increased quantity of alcohol use. Another study found that family SES was indirectly related to adolescent smoking through parental smoking (Madarasová Gecková et al., 2005). Miech et al., (2016) reported that in early adolescence, family SES (assessed using only parents' average level of education) was inversely related to substance use (i.e., substance use was evidenced in higher rates among lower SES families). However, Miech et al., (2016) noted that by 12th grade family SES was did not predict using illicit substances in the past year and furthermore, that this finding has been consistent for decades. The current study may be able to further clarify the links between family SES and patterns of substance use as it accounts for the trajectories of different substances concurrently that may or may not align with theoretical perspectives and previous empirical work. Furthermore, as participants in the current sample may evidence increased rates of substance use due to recruitment procedures (i.e., paternal SUD), results linking family SES to patterns of substance use frequency trajectories may find varying results to those observed in nationally representative samples.

There is a long history of research into the etiology of substance use, with a large body of literature focusing on the impact of parental substance use. Several studies have demonstrated that parental substance use of both alcohol and illicit substances is linked with offspring use (for a review See Hawkins, Catalano, & Miller, 1992). Because parental SUD represents an increased risk for their child's substance use (which may operate through a number of different mechanisms), paternal substance use was treated as a predictor of class membership to help differentiate between higher and lower-risk patterns of substance use trajectories. The CEDAR data is uniquely suited to address the the influence of paternal SUD on patterns of substance use trajectories in their offspring by oversampling fathers with SUD such that this group represented approximately half of the sample.

Current Study

The current study tested two models for examining patterns of concurrent substance use over time and assessed individual and family background variables as predictors of class membership. The first model used latent variables to capture the interrelated nature of substance use and modeled patterns of growth based on the latent substance use factor (See Figures 1 & 2). The second model captures the interrelated nature of substance use through the incorporation of multiple trajectories for different substances that form unique patterns over time (See Figure 3). The following are hypotheses for the current study, separated by model.

Although the individual and family background predictors are hypothesized to predict membership into high- and low-risk patterns of substance use consistent with previous research, the findings may be more salient as the patterns of substance use account for concurrent substance use from adolescence to adulthood. Furthermore, because of the mixed findings, no hypotheses are made regarding the links between race and profile membership or household SES. However, should race or household SES predict class membership, findings may help clarify the discrepancies in the theoretical and empirical literature.

MIML GMM Hypotheses

1. Different profiles of substance use trajectories will emerge. Consistent with previous literature, there will likely be 4-6 identified profiles encompassing non/low use, chronic/high use, decreasing, late-onset or increasing, and adolescent-limited.

2. Family background and individual predictors will differentially predict membership into each of the identified profiles.
    a. Based on previous research men will be more likely to be classified in patterns of use considered high risk relative to women.
    b. Paternal SUD (a dichotomous variable accounting for whether the recruited father had a diagnosed SUD or not) will also increase the risk of membership in high-risk substance use patterns.

PP LCGA Model Hypotheses

1. Different profiles of substance use will emerge that reflect unique patterns of substance use. However, because this would be the first study of this kind, it is challenging to predict what patterns of substance use trajectories will emerge. Although the expectation is that different patterns of polysubstance use will emerge.
2. Consistent with expectations of person-centered approaches, I hypothesize that the family background and individual predictors will differentially predict membership into the substance use profiles.
    a. Based on previous research men will be more likely to be classified in patterns of use considered high risk relative to women.
    b. Paternal SUD will also increase the risk of membership in high-risk substance use patterns.

CHAPTER IV

METHODS

The overarching goal of the current study was to use the prospective design of the Center for Education and Drug Abuse Research (CEDAR) data to further delineate and clarify the links between different patterns of substance use trajectories from adolescence through adulthood and the differential probabilities of membership into each profile using family background and individual predictors. The CEDAR data is uniquely suited for the current research study as families were recruited for the study using the high risk paradigm and sampling from populations at high and low risk for subsequent substance use problems (e.g., parental SUD versus no parental SUD). This recruitment strategy is likely to promote a more diverse pattern of substance use in participants relative to probabilistic recruitment mechanisms. However, there were demographic differences between the recruitment groups such that Black participants were unequally represented in the SUD group relative to the non-SUD group. There were also SES differences such that participants in the SUD group and Black participants reported lower household SES. Although not assessed in the current study, Clark et al., (1997) also noted that fathers with a SUD were younger, had fewer years of education and lower IQ’s than fathers without a SUD.

Dataset, Recruitment Procedures, and Participant Characteristics

The overall project and data collection were funded by a grant from the National Institute on Drug Abuse (grant number 2 P50 DA05605) awarded to the Center for Education and Drug Abuse Research at the University of Pittsburgh. Due to the low prevalence of diagnosed substance use disorders in the general population, the CEDAR researchers utilized a high risk paradigm to ensure an analyzable sample of participants with diagnosed SUDs (Tarter & Vanyukov, 2001). Fathers with and without diagnosed substance use disorders (SUD) were the probands (the starting point in a study of family genetics or lineage) used to recruit families in to the study in 1989 (Center for Education and Drug Abuse Research, CEDAR, 2015) in the Pittsburgh metropolitan area. The overall research design includes longitudinal data collected from 775 families (344 with paternal SUD, 350 with no paternal SUD, 81 with mental health disorders, MHD) from 1989 until 2009 using multiple informants within a family (i.e., mothers, fathers, and the index child). The index child (i,e, the participant of interest in the current study) was assessed from age 11-12 to age 30 with eight waves of measurement across this time period. The current study included demographic data collected at the initial assessment (i.e., household SES, gender, race, paternal SUD) and substance use data collected across five waves of measurement from age 16 to age 28 with 3 year intervals between assessments. For the SUD group, fathers with a SUD aside from alcohol, caffeine, or nicotine were eligible. Horner, Tarter, Kirisci, & Clark (2013) reported that “exclusion criteria for the fathers included an IQ lower than 80, English not spoken as the first language, and poor health or severe chronic disability that would compromise validity of responses" (p.476).

The analytic sample resulted in 721 participants. Fifty-four participants were excluded from data analyses: 53 participants were missing data on substance use and were not included in the models assessing substance use trajectories. An additional participant was missing data on household SES and was excluded for the models including family background and individual predictor of class membership. The demographic features (i.e., gender and racial composition, paternal SUD, and household SES) of the analytic sample were nearly identical to that of the full overall sample. Of the final sample (N = 721), 75.5% of participants were White, 21.8% were Black, and 2.8% reported a different racial category 70.3% were male, and 43.6% were children of fathers with diagnosed SUDs (10.7% MHD, 45.8% Non-Disordered). Of the participants who reported an "other" racial identification, the majority identified as bi-racial (African American and White). Because of the low sample sizes in the "other" racial category and relatively small sample of MHD fathers, these groups were collapsed with Black and No SUD, respectively.

Because the sample was not recruited through probability sampling techniques, previous work with this dataset compared the recruited sample with samples from other epidemiological studies (Tarter & Vanyukov, 2001). The structure and severity of substance use disorders, and socioeconomic statuses among the proband recruited fathers with SUDs were also shown to be similar to other men with SUDs from the Epidemiologic Catchment Area (ECA) sample (Clark et al., 2006; Tarter & Vanyukov, 2001). There were also similarities in terms of socioeconomic status among men without SUDs in the ECA sample and the CEDAR sample (Clark et al., 2006; Tarter & Vanyukov, 2001). However, eligibility criteria for fathers in the non-SUD group included having no history of psychiatric disorders, and were therefore less likely to report having psychiatric disorders than community samples (Clark et al., 1997). Substance abuse rates among children of the probrand fathers have also been compared with large-scale community samples (i.e., Methods for Epidemiological Research on Children and Adolescents, MECA). Children of substance abusing fathers evidenced higher rates of substance abuse compared with a community sample, whereas children of non-substance abusing fathers were similar to children in the MECA sample (Tarter & Vanyukov, 2001).

Participants from the CEDAR dataset were compared with data from the 2010-dicentennial census of the Pittsburgh metro area (where the data were collected), the state of Pennsylvania, and the U.S. more generally. Racial characteristics in 2010 of the Pittsburgh metro area evidenced a higher percentage of African Americans compared with state and national levels, with the percentage of African Americans and European Americans being similar to the SUD-group in the CEDAR dataset. The racial demographic of Pittsburgh is primarily White (66%), compared with 81.9% and 72.4% at the state and national levels, respectively. In 2010, 26.1% of Pittsburgh residents identified as African American with an additional 1.1% reporting African American and another racial identification, compared with 11.5% and 13.2% at the state and national levels, respectively. The overall racial makeup of the CEDAR has similar rates of White participants as national levels, higher percentages of Black participants, and lower rates of every other racial/ethnic group comparatively. Although the CEDAR sample may not be nationally representative, the demographic makeup is representative of the Pittsburgh metro area and generalizations may be appropriate to similar samples in other metropolitan areas with similar demographic make-up (e.g., Tampa, FL and Winston-Salem, NC).

Measures

Substance Use

Substance use was assessed at each time point using the average monthly frequency of use for a number of substances over the past year. The following substances were assessed: alcohol, amphetamines/stimulants/ "uppers", cocaine/crack, prescription diet pills, over the counter diet pills, heroin/morphine/ opiates, methadone, prescription pain killer pills, barbiturates, Quaaludes, tranquilizer pills, LSD/hallucinogens, ecstasy, PCP, marijuana, glue, gasoline or other fumes, smoking tobacco, chewing tobacco, and anabolic steroids. For each substance, participants were asked, "Ordinarily, how many times each month have you used each of the drugs listed on the right in the last year." Responses ranged from 0-4 (0=0 times, 1=1-2 times, 2=3-9 times, 3=10-20 times, 4=more than 20 times) with higher values reflecting more frequent use of each substance. Substance use was differentiated into four categories: tobacco use, alcohol use, marijuana use, and hard drug use. Prescription and over the counter diet pills, methadone and anabolic steroids were not included in the construction of hard drug use measure.

Individual and Family Background Predictors

Participants reported their gender/sex (male, female) and race (White, Hispanic or Latino, Black or African American, American Indian, Asian, and other). Family SES was reported by the parents of the participants and was calculated using the highest level of education and Hollingshead Occupational Prestige for the primary householder. The Hollingshead Occupation Prestige scale ranges from 0 (homemaker, student) to 9 (higher executives, major professionals, and proprietors of large businesses) with higher values indicating more prestigious occupations. Recruitment group was assigned to each participant based on their fathers' diagnosis, or lack thereof, at time of recruitment, resulting in three categories (0 = fathers without psychological or substance diagnosis, 1 = fathers with only psychological diagnosis, and 2 = fathers with substance abuse diagnosis). A dichotomous variable was created that differentiated between whether fathers had a diagnosed SUD or not (i.e. paternal SUD). Paternal mental health disorder (MHD) was collapsed with fathers with fathers with no disorders primarily for statistical reasons as the low sample size of MHD fathers would make comparisons with this group unfeasible. In addition, because the primary outcome of interest was substance use, conceptually it is more appropriate to compare fathers with and without SUDs.

Plan of Analysis

The current study assessed the ability of two person-centered growth mixture models to capture the complexity of concurrent substance use over time and the extent to which family background and individual variables differentially predict membership into the identified patterns of use. According to Wang and Bodner (2007) "mixture modeling generally refers to modeling with categorical latent variables that represent mixtures of subpopulations in which population membership is not known but is inferred from the data" (p. 638). Several scholars have highlighted the benefits of person-centered approaches (e.g., Laursen & Hoff, 2006; Masyn, 2013), with some scholars arguing that person-centered approaches (i.e., mixture models) to identifying patterns of substance use over time may be more appropriate than traditional variable-centered growth curve approaches, as there are likely naturally existing typologies of users (e.g., Muthén & Muthén, 2000). Research on both longitudinal and cross-sectional data has highlighted different patterns of substance users (For a review see Tomczyk, Isensee, & Hanewinkel, 2016; Nelson, Van Ryzin, & Dishion, 2015), thus supporting this assertion. The first model is a multiple-indicator multilevel growth mixture model involving latent variable indicators of growth factors and class membership, whereas the second model is a parallel processes mixture model involving four classes of substance use (i.e., tobacco, alcohol, marijuana, and hard drugs). The first model enables the assessment of general patterns of substance use over time, whereas the second model enables the assessment of specific patterns of co-occurring substance use over time. Although several features of these two models will be similar, as they incorporate person-centered approaches to modeling longitudinal trajectories (e.g., handling missing data, estimating and interpreting growth factors, selecting the appropriate number of classes), each model provides a unique way of modeling concurrent substance use. Missing data will be handled using FIML in accordance with recommendations by scholars (e.g., Acock, 2005).

Model 1: Multiple-Indicator Multilevel Growth Mixture Model

The multiple-indicator multilevel growth mixture model incorporated several components. First, there is a measurement model that describes the latent factor of substance use. Indicators of this latent variable included tobacco use, alcohol use, marijuana use, and hard drug use. To move on to estimating trajectories of substance use using the described latent factor, measurement equivalence across time points must first be established. Second, using the latent substance use variable, trajectories (i.e., growth factors) are estimated. Previous research on substance use trajectories has often found evidence of quadratic growth, or upturn or downturn of the trajectroy (e.g., Johnson et al., 2015; Passarotti, Crane, Hedecker, & Mermelstein, 2015; Tucker et al., 2005). Therefore, in estimating the growth factors quadratic growth will be modeled. Once the growth curve model is successfully modeled, and if there is non-trivial variance around the estimates, the mixture model component is added, which identifies subpopulations (or classes) using the estimated growth factors. Finally, predictors of the growth factors and class membership are added to the model. Predictors are regressed on both the growth factors and the categorical latent variable denoting class membership. Muthén (2004, 2015) highlighted that if the predictors of the growth factors are significant, not modeling those associations distorts the relationship between the growth factors and class membership which leads to “incorrect class probability estimates and incorrect individual classification” (p. 354). Additionally, Muthén (2014) stated that constraining the regression of the predictors on the growth factors across classes is a more parsimonious approach. Although allowing the regression of the predictors on the growth factors to freely estimate across classes is also a correct model specification, Petras and Masyn (2010) underscored that this model specification "results in latent classes which are defined not only by heterogeneity in growth trajectories but also heterogeneity in the effect of those covariates on the growth trajectories" (p.83). Therefore, the current study regressed categorical latent class variable and the growth factors on the predictor variables, while constraining them to equality across classes.

The first step in estimating this model is to assess the applicability of the latent substance use variable and test for measurement equivalence of the latent substance use variable across time. First, a confirmatory factor analysis (CFA) was conducted to assess the adequacy of the latent substance use variable. Previous work has suggested that a latent substance use variable is a more parsimonious way to model substance use, and has supported the identification of a substance use latent factor (e.g., Bentler, 1980, 1986; Newcomb, 1994; Newcomb & Bentler, 1987, 1988). Model fit statistics were used to determine the adequacy of the latent substance use variable. Wu et al. (2010a) highlighted that because of the repeated assessment of individuals over time, the residual errors of the same observed indicators are likely to covary across time beyond what is explained by the latent variable. To avoid misspecifying the model, Wu et al., (2010a) suggests explicitly modeling the residual dependence. Therefore, in the MIML GMM, the residual errors of the same observed indicators were correlated across time (e.g., the residual errors of tobacco use will be correlated for each wave of measurement).

When the indicators of the latent growth factors are also latent, establishing measurement equivalence is a prerequisite for assessing change over time (Wu et al., 2010a). Establishing measurement equivalence demonstrates that the meaning of the construct does not change over time. Because the latent substance use factor has the same indicators at each time point, and the pattern of factor loadings will be assessed similarly for each (e.g., constraining the first factor loading to 1 to set the scale), the model will have met configural invariance (Dyer, 2015). To assess weak invariance, factor loadings across each time point were constrained to equality (Dyer. 2015). If the chi-square difference test does not reveal a significant decrease in model fit, weak invariance is established. To assess strong measurement equivalence, item intercepts were constrained to equality across time points, and assessed via a chi-square difference test (Dyer, 2015). Scholars have argued that strong measurement equivalence (i.e., equivalent item intercepts across time) is a minimum standard for establishing construct equivalence (e.g., Brown, 2006; Wu, Li, & Zumbo, 2007; Wu et al., 2010a). As strict measurement invariance is often unrealistic for longitudinal studies (e.g., Brown, 2006; Wu et al., 2010a), strong measurement equivalence will be evaluated, although it is likely it may only partially be met as one might expect alcohol use, in particular, to be lower on average before participants are legally allowed to drink.

Once measurement equivalence is established a growth model assessing the intercept, slope, and quadratic will be run before incorporating the mixture model (see Figure 2). The factor loadings on the intercept factor will all be constrained to 1. As a typical approach for estimating these models, factor loadings for the slope will be constrained in a linear fashion in accordance with the waves of measurement. This is essentially scaling time so that baseline substance use indicates average use at the first wave of data (i.e., age 16). The waves of data in the CEDAR dataset are equally spaced (e.g., age 16, age 19, age 22, age 25, age 28) so the linear growth factor loadings are 0, 1, 2, 3, 4. The factor loadings of the quadratic growth factor will be constrained to estimate quadratic growth (i.e., the squared value of the constraints on the linear growth factor). Previous research (e.g., Muthén & Muthén, 2000) has indicated that quadratic growth is often a good fit for modeling trajectories of substance use.

Once the appropriate growth curve model is identified, the mixture model will be added to the analyses. In their seminal article on incorporating person-centered longitudinal trajectories in research, Muthén & Muthén (2000) highlighted an approach that first assessed all possible typologies using latent class growth analysis (LCGA), which is a special case of GMM in which variation around the growth factors within each class are constrained to 0, and then reduced the number of typologies using GMM to allow for variation around the growth factors. In addition to practical considerations, both theoretical and empirical indicators will be used in selecting the appropriate number of classes (e.g., Lanza, Bray, & Collins, 2013; Masyn, 2013; Muthén & Muthén, 2000). Muthén and Muthén (2000) highlighted that "examining the trajectory shapes for similarity, the number of individuals in each class, and the differences in predictions of consequences based on different numbers of class" can further delineate the appropriate number of classes (p. 889). In other words, determining the appropriate number of classes will involve examining class separation (are the identified classes evidencing distinct patterns or different mean levels), whether the sample size within each class allows for subsequent analyses, and whether the identified profiles are useful in differentiating between outcomes. Several additional empirical indicators are used to determine the appropriate number of classes. Some scholars (e.g., Nylund, Asparouhov, & Muthén, 2007) recommend using the BIC as the best information criterion and the BLRT as it outperforms the other likelihood ratio tests. However Wang & Bodner, (2007) highlighted that the AIC and BIC are sensitive to sample size as well, and that these indicators of model fit favor more complex (i.e., less parsimonious) models. Furthermore, previous work has suggested that best practices for class enumeration for mixture models involves determining the correct number of profiles prior to the addition of covariates or predictors, as their misspecification may lead to over-extracting classes (e.g, Nylund & Masyn, 2016; Petras & Masyn, 2010). Therefore, once the appropriate number of classes was established, the family background and individual variables (i.e., race, gender, paternal SUD, and household SES) were added to the model as predictors of the growth factors and class membership for the reasons discussed above.

Model 2: Parallel Processes Latent Class Growth Analysis

Parallel processes mixture modeling, an extension of the basic parallel process model, is a person-centered approach allowing for the modeling of subpopulations using simultaneous growth trajectories. The first step in estimating this model is assessing the growth factors for the four trajectories of substance use. The intercept, slope, and quadratic were assessed. Once the appropriate growth factors have been identified, and if there is significant variance around the estimates, the mixture model component will be added. Unlike the multiple-indicator multilevel GMM, which identifies distinct patterns of *one* trajectory of substance use, each identified pattern in the parallel processes LCGA will include *four* trajectories (i.e., one for each substance modeled). The estimation procedure for the parallel processes LCGA will be similar to the procedure discussed in the previous model.

CHAPTER V

RESULTS

Descriptive Statistics

Means, variances, distributional properties of assessed variables, and correlations are in Table 1. The most amount of skew was evident across substances at age 16 and was higher among hard drug use relative to the use of other substances. Because of the non-normality of the data, maximum likelihood estimation with robust standard errors was specified when not used as the default estimation (e.g., in mixture models).

In general, bivariate correlations indicated relatively strong positive correlations across time for each substance, with those for alcohol use being slightly lower. Correlations with use at more proximal time points were stronger than for use at more distal time points. When examining substance use across substances, correlations within the same time point were generally stronger than for cross time point cross substance correlations. A similar pattern emerged with cross substance correlations having stronger effects with more substance use at more proximal relative to more distal time points. Correlations across substances ranged from small to moderate effects (.02 - .62). Correlations across time points ranged from moderate to large effects (.11 - .79) with larger effects found for tobacco and marijuana use across time points.

As demonstrated through simple bivariate correlations, substance use (both across different substances and across time) is highly related. These preliminary analyses further highlight the need for comprehensive approaches to studying substance use over time that can simultaneously account for the use of multiple substances.

Missing Data

Of the total sample (N = 775) from the CEDAR dataset, 53 participants were missing on all substance use indicators and were not included in the analytical sample. Furthermore, one person was missing data on household SES and was dropped from the analyses that included predictor variables. The most prevalent pattern of missingness following the pattern of no missing data, which accounted for approximately one third of the participants, was participants who were only missing substance use data at age 28, which accounted for 13.57% of the sample. Covariance coverage indicates the amount of missingness for each variable with higher values indicating less missing data. Substance use indicators ranged from .86 at age 16 to .51 at age 28. Full-information maximum likelihood estimation was used to account for missing data in accordance with recommendations in the field (Acock, 2005).

Model 1: Multiple-Indicator Multilevel Growth Mixture Model (MIML GMM)

For the first, MIML GMM, model, I assessed the measurement model using confirmatory factor analyses to determine the adequacy of the latent substance use variable. The first model simultaneously and freely estimated the substance use latent variable for each of five wave of data (ages 16, 19, 22, 25, and 28). Covariances were specified among each of the indicators of specific substance use at each time point (e.g., alcohol use at age 16 was correlated with alcohol use at each of the other time points). Maximum likelihood with robust standard errors was used to estimate the model due to skewness in the indicators of substance use. The resulting model was a good fit for the data. Although the chi-square was significant (χ^2 (120, N = 722) = 230.58, p < .001), this is often the case with samples >400. The additional indicators of model fit, including RMSEA (.04 90% CI [.03, .04]), CFI (.96), and SRMR (.06) indicated a good fitting model. I next constrained the factor loadings across the five time points to assess metric invariance of the substance use construct. The indicators of model fit also indicated that this was a good fit to the data (χ^2 (132, N = 722) = 318.56, p < .001; RMSEA = .04 90% CI [.03, .04]; CFI = .93; SRMR = .09). However, using the formula associated with the scaling correction for chi-square difference testing necessitated by MLR estimation for Mplus[1], results indicated that this model fit the data significantly worse than the freely estimated model ($\Delta\chi^2$ (12, N = 722) = 84.96, p < .05). Modification indices suggested freeing the constraint on the drug use factor loading at age 16 would significantly improve model fit. The removal of this constraint resulted in a model that did not fit significantly worse than the freely estimated model ($\Delta\chi^2$ (11, N = 722) = 48.00, p > .05). Substantively, the removal of this constraint suggested that hard drug use was a better predictor of the latent substance use variable at later ages relative to age 16. I next constrained the intercepts of each of the indicators of substance use to equality across the five time points, while still allowing the factor loading on the drug use indicator at age 16 to freely estimate, to assess strong or scalar invariance. Model fit indices indicated this model was a marginal-poor fit to the data (χ^2 (147, N = 722) = 853.57, p < .001; RMSEA

[1] https://www.statmodel.com/chidiff.shtml

= .08 90% CI [.08, .09]; CFI = .78; SRMR = .14) and fit significantly worse than the model with partial metric invariance ($\Delta\chi^2$ (16, N = 722) = 338.76, $p < .05$). Using an iterative process of examining modification indices and adjusting model specifications, partial scalar equivalence resulted as the model involved freeing the constraints on alcohol use at age 16 and age 19, as alcohol use was significantly lower at these time points than the three subsequent time points. Modification indices also suggested allowing the mean of the latent substance use variable at age 16 to freely estimate. This model specification involved a structural parameter, and indicated that substance use was lower at age 16 than the other four waves. The final model (see Table 2), which included a freely estimated factor loading between drug use and age 16 substance use, freely estimated intercepts for alcohol use at age 16 and 19, and a freely estimated mean value for substance use at age 16, was a good fit for the data (χ^2 (144, N = 722) = 338.61, $p <$ .001; RMSEA = .04 90% CI [.04, .05]; CFI = .93; SRMR = .08) and did not fit significantly worse than either the partially invariant metric model ($\Delta\chi^2$ (16, N = 722) = 45.03, $p > .05$) or the freely estimated model ($\Delta\chi^2$ (24, N = 722) = 91.26, $p > .05$).

Next, a LGCM was estimated using the created latent variables as indicators of the growth parameters. Due to estimation errors resulting from a negative residual covariance of the substance use latent variable at age 28, this residual covariance was constrained to 0. The resulting model was a good fit for the data (χ^2 (147, N = 722) = 334.734, $p < .001$; RMSEA = .04 [.04, .05]; CFI = .93) (see Table 3 and Figure 4). The mean of the intercept of this model is 0 which is the default setting for multiple indicators models in M*plus* (Muthén & Muthén, 1998-2012). The means of the slope and quadratic were both significant indicating growth over time that begins to taper downward between age 25 and age 28. The variance of the intercept was significant. Although the variances of the slope and quadratic were significant only at trend levels, the amount of variance was non-trivial, thus enabling the estimation of a latent class growth model.

Solutions estimating 3 – 6 classes were compared using the recommended statistical indicators of model fit: BIC and the bootstrapped likelihood ratio test (BLRT) (Nylund et al., 2007) as well as additional more substantive indicators including typology separation (see Table 4 and Table 5). The four-class solution (see Figure 5) was selected as the BIC was lower than the 3-profile solution and the BLRT was significant indicating it was a better fit than the 3-class solution. The 4-profile solution also evidenced high separation between latent classes (i.e., they were qualitatively different). Furthermore, this class solution was characterized by four distinct profiles (i.e., Stable High Users, Slight Increasing Low Users, Developmentally Limited Users, and High Baseline Decreasing Users[2]) which best-reflected trajectories of substance use in the extant literature.

A growth mixture component was added to the model allowing variance around the growth factors. Although this model allowed for variance around the growth parameters, the variance estimates were constrained to equality across classes by default. As this model included a mixture component, goodness-of-fit statistics were not available. The inclusion of variance estimates around the growth factors did not change

[2] Standard errors for the decreasing profile were high which led to the slope being non-significant; however, it is still indicative of a decreasing pattern

the meaning of the profiles although 8 people were reclassified. The estimates of several growth factors were large and non-trivial; however, they were non-significant because of inflated standard errors (see Table 6).

Predictors of both the growth trajectories and class membership (i.e., parental SUD, race, gender, and household SES) were added to the 4-profile MIML GMM. However, the addition of predictors changed the meaning of the profiles and reclassified 99 people. Furthermore, in two profiles the pattern of use was relatively similar with results suggesting relatively high baseline levels followed by generally stable use over time. Furthermore, the included predictors did not distinguish between membership in the two similar profiles. Because of the similarity of these two profiles with the addition of predictors (see Figure 6), it is possible that the number of profiles or patterns were overextracted and instead can be explained by the inclusion of the predictors.

Therefore, for the final model, I used a 3-profile MIML GMM that evidenced greater typology separation with the addition of the predictor variables (see Figure 7). The three identified profiles in this model were labeled: High Baseline Decreasing Users, Stable Moderate Users, and Increasing Low Users. The High Baseline Decreasing Users profile represented 10.4% of the sample and was characterized by highest rates of use at age baseline (age 16) followed by decreasing use over time. The Stable Moderate Users profile represented 11.79% of the sample and was characterized by moderate levels of substance use that were relatively stable from age 16 to age 28. The Increasing Low Users profile represented 77.8% of the sample and was characterized by the lowest use of any profile across time although there were increases in use from age 16 to age 28.

Individual (i.e., gender and race) and family background (i.e., paternal SUD and household SES) were assessed as predictors of both the growth factors (see Table 8) and class membership (see Table 9). The associations between the predictors and the growth factors were included to ensure the reliable classification of participants; however, the substantive question of interest was how these predictors influenced class membership.

The Increasing Low Users group was clearly the normative use profile representing approximately 78% of the sample, thus that profile was used as the primary reference group. Paternal SUD was the only distinguishing factor when comparing the ILU profile with the HBDU profile. Relative to the Increasing Low Users, individuals whose fathers had a diagnosed SUD were 116% more likely to be classified in the High Baseline Decreasing Users profile. Relative to the ILU profile, women were 62% less likely to be in the MSU profile, and individuals whose fathers had a diagnosed SUD were 70% more likely to be the MSU profile. Furthermore, for each unit increase in adolescence household SES, participants were 2% less likely to be in the MSU profile relative to the ILU profile. If we think about this in standard deviation units, for each standard deviation increase in household SES ($SD = 13.79$) participants were 27.58% less likely to be classified as Moderate Stable Users relative to Increasing Low Users. I also compared the High Baseline Decreasing Users and Moderate Stable Users profiles. At a trend level, women were more likely to be in the HBDU profile relative to the MSU profile. None of the other included predictors differentiated membership between these two patterns of use.

I also compared the 3-Profile MIML GMM with predictors to the 3-Profile GMM without predictors (see Table 7 and Figures 7 and 8) to determine if and how the addition of predictors changed the nature of the use patterns as well as the classification of participants. The pattern of substance use was somewhat different for the 3-profile GMM solution that included predictors compared with the pattern of use that did not include predictors. However, this discrepancy is likely due to the reclassification of 49 individuals, which made the sample size of the two higher risk profiles more similar.

Model 2: Parallel Processes Latent Class Growth Analysis (PP LCGA) Model

The first step in estimating the parallel processes model involved running the growth process for each substance separately. Maximum likelihood estimation with robust standard errors was used to account for non-normality and FIML was used to account for missing data. The alcohol use model was initially a moderate fit for the data (χ^2 (6, N = 722) = 35.22, p < .001; RMSEA = .08 [.06, .11]; CFI = .92). The means and variances of each growth factor were significant (see Figure 9). The model estimating tobacco use was a good fit to the data (χ^2 (6, N = 722) = 14.38, p = .03; RMSEA = .04 [.01, .07]; CFI = .99) and the means and variances of the growth factors were all statistically significant (see Figure 10). The model estimating drug use was a modest fit to the data (χ^2 (6, N = 722) = 14.31, p = .03; RMSEA = .04 [.01, .07]; CFI = .90). The mean estimates for the intercept, slope, and quadratic were significant and the variance estimates for the slope and quadratic were significant (see Figure 11). The model estimating the frequency of marijuana use was also a modest fit to the data (χ^2 (6, N =

722) = 26.04, $p < .001$; RMSEA = .07 [.04, .10]; CFI = .95). The estimates for the means and variances of the growth factors were all significant (see Figure 12).

After estimating the models separately, I next estimated a growth curve model including each of the four substance use trajectories. This model estimated with errors noting a linear dependency between two or more variables. The first recommendation to address this estimation error includes adding residual covariances between the frequency of use for each substance within each time point (e.g., specifying covariances between alcohol use at age 16 and tobacco use at age 16, marijuana use at age 16, and drug use at age 16) (e.g., Muthén, 2007). Although the addition of these residual covariances did not fix the linear dependency issue, it did improve model fit. In this model, the estimates of the variance for the intercept and quadratic growth variables for drug use frequency were non-significant. I re-estimated the model constraining the two non-significant growth variables to 0. This specification corrected the linear dependency issue and resulted in a good fitting model (χ^2 (113, N = 722) = 218.78, $p < .001$; RMSEA = .04 [.03, .04]; CFI = .96). The means and variances of the unconstrained growth factors were significant, suggesting overall modest increases in use over time that begin to decline by age 28 (see Table 10 and Figure 13).

I next added the mixture component. Constraining the variance of the growth factors to 0 across the classes (i.e., estimating a LCGA) assessing 3-to 7 class solutions. A latent class growth analysis allows for different estimated means for the growth factors within each profile while constraining the variances around those estimates to 0, whereas a growth mixture model estimates both the means and variances for the growth factors.

The seven-class solution did not converge after multiple attempts at increasing the random starting values. Therefore, 3- through 6-profile solutions were compared. The five-profile solution was deemed the best fit to the data. Although statistical indicators of class comparisons (e.g., BIC and BLRT) pointed toward a 6-profile solution (See Table 11), other considerations (e.g., graphical representation, typology separation, and sample size considerations) were considered as well. Sample sizes for the different profile solutions are presented in Table 12.

I graphically represented the models to determine if the differences between profiles for each solution were non-trivial. Graphically representing the profiles indicated a substantive change in profiles from the 4-profile solution to the 5-profile solution, such that the profile representing increasing alcohol, marijuana, and tobacco use formed two groups in the 5-profile solution: increasing alcohol and marijuana users and increasing alcohol, marijuana, and tobacco users. This change represented substantive changes in the meaning of the profiles. Only for the 6-profile solution were there two profiles that seemed potentially similar (i.e., both were characterized by stable high tobacco polysubstance use). Furthermore, the two similar profiles resulted from one consistent profile in the 5-profile solution. Representing these patterns of concurrent use graphically indicated there was better separation between the latent classes, and the sample size of the classes was relatively high thus allowing additional modeling using those classes in the 4- and 5-profile solutions. Therefore, because the 5-profile solution was a better model statistically than the 4-profile solution and resulted in non-trivial and substantive differences in profile membership, and had better typology separation, class sizes, and only a marginally smaller entropy than the 6-profile solution, it was deemed the best fit for representing the current data.

The first profile, labeled *Increasing Alcohol and Marijuana Users (IAMU)* (see Table 13 and Figure 14), represented 6.79% of the sample and was characterized by low tobacco and hard drug use over time, moderate initial levels of alcohol and marijuana use at baseline follow by sharp increases through emerging adulthood with a slight tapering of use between ages 25 and 28. The second profile, labeled *Increasing Alcohol and Tobacco Users (IATU)* (see Table 13 and Figure 15), represented 11.50% of the sample and was characterized by low marijuana and hard drug use over time, low baseline levels of tobacco and alcohol use followed by sharp and moderate increases, respectively, with a slight tapering of use between ages 25 and 28. The third profile, labeled *Increasing Alcohol Users (IAU)* (see Table 13. and Figure 16), represented 56% of the sample and was characterized by low levels of tobacco, marijuana, and hard drug use over time, low baseline levels of alcohol use with modest increases over time with a slight leveling off of use between ages 25 and 28. Alcohol use in this profile was also less frequent relative to alcohol use in the other profiles. The fourth profile, labeled *Increasing Alcohol, Marijuana, and Tobacco Users (IAMTU)* (see Table 13 and Figure 17), represented 10.11% of the sample and was characterized by relatively lower levels of use at baseline followed by steep increases in the use of alcohol, marijuana, and tobacco over time with a modest tapering of use between ages 25 and 28. Not only does the use of alcohol, marijuana and tobacco increase more rapidly over time, it is relatively higher than use in the other profiles (with the exception of tobacco use in the fifth profile). One might conclude that this profile represents a high-risk profile relative to the previously discussed profiles. The fifth and final profile, labeled *Stable High Tobacco, Polysubstance Users (SHTPU)* (see Table 13 and Figure 18), represented 15.65% of the sample and was characterized by stable high tobacco use across time pints, moderate baseline levels of alcohol and marijuana that peaked around age 22 returning to baseline levels around age 28. Most notable in this profile is the sharp increase in hard drug use over time resulting in comparable levels of use relative to alcohol and marijuana around age 28. Furthermore, this profile represented the highest hard drug use both at baseline and over time. Given the consistent high tobacco use and relatively high levels of hard drug use, one might postulate this profile representing the highest risk for later substance use related problems.

Predictors were then added to the model to determine whether the growth factors for each process (or substance) varied as a function of family background and individual characteristics (see Table 14) and whether these variables predicted differential odds of membership in each of the classes (see Table 15). Because the estimated model constrained the variances around the growth factors to 0 the coefficients for the regression of the growth trajectories on the demographic variables was also equivalent across classes. The addition of these predictor variables resulted in the reclassification of 4 individuals (one individual was dropped due to nonresponse on household SES) and increased the entropy (i.e., classification accuracy) from .918 to .921. Furthermore, the meaning and pattern of use in each profile remained relatively unchanged after the addition of the predictor variables.

Class membership was also regressed on the individual and family background variables to determine whether these variables predicted differential odds of membership in to one profile relative to another. Table 15 depicts odds ratios of class membership using each class as the reference group; however, because approximately 56% of the sample was classified as Increasing Alcohol Users, it is highly likely that this is representative of a normative pattern of use. Therefore, the Increasing Alcohol Users profile was first used as the reference group to aid in interpretation and understanding of the other four profiles.

Results indicated that women and non-White participants were less likely (52% and 61%, respectively) to be in the Increasing Alcohol and Tobacco Users profile relative to the Increasing Alcohol User profile. Furthermore, for each increase in household SES in adolescence, participants were 3% less likely to be classified in the IATU profile relative to the IAU profile. Women were 72% less likely to be the Increasing Alcohol, Marijuana, and Tobacco Users profile relative to the Increasing Alcohol Users profile. However, paternal SUD increased the odds of membership in the IAMTU profile relative to the IAU profile by approximately 148%. None of the included variables (i.e., gender, race, paternal SUD, and household SES) differentiated between participants in the Increasing Alcohol Users profile and individuals in the Increasing Alcohol and Marijuana users Profile, although there was a trend level effect suggesting women were less likely to be in the IAMU profile relative to the IAU Profile. Women were 51% less likely to be in the SHTPU profile relative to the IAU profile, and at a trend level non-White individuals were less likely to be in the SHTPU profile relative to the IAU profile.

Individuals whose fathers had a SUD were 93% more likely to be in the SHTPU profile relative to the IAU profile. There was also a significant effect of household SES such that for each unit increase in adolescent household SES participants were 3% less likely to be the SHTPU profile relative to the IAU profile.

I also examined differential odds of group membership using the other typologies as the reference group. Using the Increasing Alcohol and Tobacco Users as the reference group, Non-White individuals and individuals whose fathers had a SUD were significantly more likely (3.19 times and 2.61 times respectively) to be in the IAMTU profile relative to the IATU profile. Furthermore, for each unit increase in household SES individuals were 3% more likely to be in the IAMTU profile relative to the IATU profile. In comparing the Increasing Alcohol and Tobacco Users profile with the IAMU profile, results indicated that non-White participants were 4.26 times more likely to be in the IAMU profile. There was also a significant effect when comparing the IATU with the SHTPU profile indicating that participants whose fathers had a SUD were 103% more likely to be in the latter profile. Using the Increasing Alcohol, Marijuana, and Tobacco Users profile as the reference group, none of the included variables differentiated membership in the IAMU profile from the IAMTU profile. However, for each unit increase in household SES individuals were 3% less likely to be classified in the SHTPU profile relative to the IAMTU profile. At a trend-level, non-White participants were less likely (51%) to be classified in the SHTPU profile relative to the IAMTU profile. Lastly, using the Increasing Alcohol and Marijuana Users profile as the reference group, non-

White participants were significantly less likely (64%) to be in the SHTPU profile relative to the IAMU profile.

CHAPTER VI

DISCUSSION

Guided by person-centered analytical approaches and conceptual frameworks emphasizing heterogeneity and multiple developmental pathways of substance use over time, the goals of the study were to (a) successfully use latent variables to represent concurrent substance use and estimate a MIML GMM to demonstrate different patterns of substance use, (b) model the parallel processes of alcohol, tobacco, hard drug, and marijuana use in a mixture model framework (i.e., LCGA) to account for different patterns of trajectories of concurrent use of specific substances, and (c) examine family background and individual predictors of profile membership for both the MIML GMM and parallel processes LCGA model. In the following sections I will briefly summarize and discuss the identified profiles from the MIML GMM and the PP LCGA model, the links between individual (i.e., gender and race) and family background (i.e., household SES and paternal SUD) predictors of class membership, similarities and differences across methods for assessing concurrent substance use, consistency with past research, strengths, limitations, and future directions. Finally, I will discuss the contribution of the study to the substance use literature and some final conclusions related to the advantages of the analytic strategy.

Multiple-Indicator Multilevel Growth Mixture Model

In accordance with the first goal of the study, which was to assess concurrent substance use, I tested a multiple-indicator multilevel growth mixture model of substance use over time. This model used latent variables to assess general substance use over time using tobacco, alcohol, marijuana, and hard drug use indicators. I first estimated a latent variable to represent general substance use and assessed measurement equivalence across 5 waves of data collection ranging from assessments at age 16 to age 28. This approach allowed me to assess whether the construct measured the same thing over time. Marijuana use was the strongest predictor of the latent substance use variable across each measurement occasion. In other words, the factor loading was the highest for marijuana so it was constrained to 1 to set the scale for substance use. Results indicated that a latent variable is an appropriate method for capturing general substance use, although there was only partial measurement equivalence across time. Specifically, hard drug use was not as strong a predictor of substance use at age 16 as it was at the remaining 5 time points across emerging adulthood and adulthood. In addition, the intercept of alcohol use was lower prior to age 21 than at later time points, and the mean of general substance use was also lower at age 16 relative to the subsequent four time points. Although assessed somewhat differently and with a different sample, results from the CFA from the current study parallel findings from similar modeling of substance use in Newcomb's (1994) work. Although Newcomb (1994) included alcohol use rather than binge drinking similar to the current study he also separated cocaine use out from hard drug use and used that as an indicator of general substance use in addition to the inclusion of tobacco, alcohol, marijuana, and other illicit drug use. However, conceptually it would make more sense to include cocaine use with hard drug use, because overdose rates resemble that of other hard drugs such as benzodiazepines and heroin (National Institute of Drug Abuse, 2017). Results from both of these studies suggest there is an underlying substance use construct, which is indicated by use of different substances and that this construct has partial measurement equivalence over time with lower use being evident in adolescence. Furthermore, latent variables of substance use can be modeled over time to indicate general patterns of substance use.

With the incorporation of growth trajectories and a mixture model, a 3-profile GMM solution was deemed the best fit for the MIML model. However, this was determined after the inclusion of predictors as the predictors explained the variance between two classes allowing for the elimination of a spurious class. Patterns of substance use trajectories included Increasing Low Users (77.8%), High Baseline Decreasing Users (10.39%), and Moderate Stable Users (11.77%). Given that the Increasing Low Users profile represented approximately 75% of the sample, we might expect both of the other two identified profiles to be relatively high risk for negative outcomes.

Decreasing, stable, and normative low increasing patterns of use are consistent with previous research on patterns of use trajectories for work that assessed both concurrent and individual substance use trajectories (see Nelson et al., 2015 for a review); however, fewer patterns were identified using the current approach. The primary difference is that many studies identify abstainers or non-users as the normative class. In the current study, participants with no use are likely classified as part of the low users profile, indicating that non-use patterns may be conceptually similar to low-use patterns particularly when alcohol use rather than binge drinking is the construct assessed. Furthermore, it is likely that the normative pattern of use in the current study evidenced low- rather than non-use because the identification of this class relies on the measurement of constructs and nature of assessed substance use. For example, studies that assess tobacco use or binge drinking patterns over time are much more likely to find a pattern of abstainers than studies that assess alcohol use in general. As the current study included an assessment of alcohol use rather than heavy episodic drinking or binge drinking, it is expected that normative patterns of use will evidence some increases in alcohol use over time, based on previous research demonstrating normative patterns of alcohol use following that trajectory (e.g., Chen & Jacobsen, 2012; Chen & Kandel, 1995; Hicks & Zucker, 2014; Johnston et al., 2016; Miech et al., 2016; Muthen & Muthen, 2000b; Schulenberg & Maggs, 2002). In the other pattern-analytic approaches that examined alcohol-use alone rather than binge drinking or heavy episodic drinking, only high and low use groups were identified (e.g., Li et al. 2001). Furthermore, although these results support previous work demonstrating normative trends in substance use that increase until about age 25 and then begin to decline thereafter (e.g., Chen & Jacobsen, 2012; Chen & Kandel, 1995; Hicks & Zucker, 2014; Johnston et al., 2016; Miech et al., 2016; Muthén & Muthén, 2000b; Schulenberg & Maggs, 2002) the MIML GMM approach in the current study underscores that this normative trend may be applicable across substances.

Parallel Processes Latent Class Growth Analysis Model

Modeling the trajectories of alcohol, tobacco, marijuana, and hard drug use separately was an alternative approach to modeling concurrent substance use. This approach allowed for the disentanglement of patterns of trajectories of specific substances over time, rather than a single pattern that represented general use. A 5-profile solution was deemed the best fit for the data based on both substantive and statistical indicators. Patterns of substance use trajectories included Increasing Alcohol Users, Increasing Alcohol and Tobacco Users, Increasing Alcohol and Marijuana Users, Increasing Alcohol, Tobacco, and Marijuana Users, and Stable High Tobacco Polysubstance Users. Given that the Increasing Alcohol Users profile represented approximately half of the sample, it is reasonable to argue that this profile represents normative users. This pattern of users also likely includes non-users in addition to low alcohol users. Furthermore, although this profile indicates that alcohol use increased over time, the increase and frequency of use was still low to moderate relative to alcohol use in the other profiles. When thinking about the scale with which substance use was measured (1 = 1-2 times and 2 = 3-9 times) the highest average use in this normative pattern was approximately 1.5 indicating that on average, participants in this pattern are drinking alcohol a few times a month at most.

The results from the current study in some ways mirror past research on substance use, but because of the novel approaches to modeling concurrent substance use, there is limited research with which to compare current findings. Three of the four studies to-date that assessed concurrent substance use found relatively similar rates of membership in the normative low-use pattern (i.e., Increasing Alcohol Users, 56%) (e.g., Brooks-Russell et al., 2015; Jackson et al., 2008; Orlando et al., 2005). Furthermore, of the four studies that assessed concurrent substance use, one identified four patterns of use, two identified five patterns of use, and one identified seven patterns of use. The identified patterns of use from the current study are in line with findings from the other studies that assessed concurrent substance use. In the only other study that assessed concurrent substance use similar with the assessment in the current study (Brooks-Russell et al., 2015), 5 profiles were identified with four of the five being characterized by poly substance use patterns (e.g., increasing multiple substances, alcohol and other drug users). However, although representing similar proportions of the participants (i.e., approximately 50%) the normative users in the Brooks-Russell et al., 2015 study were non-users whereas the normative users in the current study were increasing alcohol users. This discrepancy is likely to due to the measurement of alcohol use. Whereas Brooks-Russell et al., (2015) incorporated heavy episodic drinking as well as frequency, the current study only assessed the frequency of alcohol use. However, unlike the current study Brooks-Russell et al. (2015) assessed illicit drug use as one category rather than examining marijuana separately. As results from the current study demonstrate, it is important to differentiate between marijuana use and other illicit drugs as the trajectories for marijuana use and hard drug use are quite disparate. Furthermore, the predictors of class membership, which will be discussed subsequently, varied for patterns evidencing higher rates of hard drug use relative to those evidencing higher rates of marijuana use. The approach taken by the current study (i.e., modeling concurrent trajectories of substance use and distinguishing between marijuana use and the use of other illicit substances) allows for the disentanglement of unique predictors and outcomes that may differentiate between polysubstance use patterns that include marijuana use and those that include use of other illicit drug use. Although findings from the current study point to some individual and family background differences, future research can provide further evidence for the uniqueness of each identified pattern of use by including additional predictor and outcome variables. This model may also be particularly relevant give recent policy discussions about the medicinal and recreational use of marijuana, particularly once additional indicators and consequences of these patterns of use are assessed.

Family Background and Individual Predictors

There were several significant findings linking family background and individual predictors with class membership. In the Parallel Processes LCGA model, women were more likely only to be in the normative use pattern (IAU) relative to each of the other substance use patterns. There were no racial differences in the MIML GMM meaning that race was not a significant factor in determining class membership. However, racial differences in likely class membership were found in the Parallel Processes LCGA model indicating that Non-White (predominantly African American) participants had higher likelihood of being in the normative use (i.e., IAU) profile and profiles characterized by high marijuana use (i.e., IAMU and IAMTU) and were less likely to be in the other two profiles (i.e., IATU and SHTPU). Although the findings that racial and ethnic minority participants were more likely to be in high marijuana use pattern relative to other polysubstance patterns, the results do not point to why these differences may be found, although future research may clarify remaining questions about why these findings emerge. These findings further underscore the benefits of the parallel processes approach as it allows for distinguishing between unique patterns of use over time and particularly differences in what predicts these unique patterns.

Greater consistency was found across models in the links between paternal SUD and class membership. In general, paternal SUD was linked with higher odds of membership into profiles that were characterized by heavier use of more substances for both the MIML GMM (i.e., HBDU and MSU) and the Parallel Processes LCGA model (i.e., IAMTU and SHTPU), providing limited evidence that those may be higher risk profiles. There were also some differences across the two approaches modeling concurrent substance use trajectories. Specifically, there were discrepancies between the two approaches in the links between household SES and class membership. In the MIML GMM, increases in household SES were linked with a decreased likelihood of classification into the MSU profile relative to the normative, ILU profile. In the Parallel Process LCGA model, increases in household SES were linked with decreased likelihood of classification into the IATU profile and SHTPU profile.

Consistent with previous theoretical and empirical work (e.g., Chen & Jacobsen, 2012; Nelson et al., 2015) findings from the current study also found that women more likely to be in the ILU profile relative to the MSU profile and in the Parallel Process LCGA model were more likely to be in the IAU (i.e., normative use) profile relative to each of the additional use patterns. The inclusion of gender overall supported the notion that women were less likely to engage in problematic patterns of substance use relative to men.

Previous research has supported the notion of racial differences in substance use over time (e.g., Chen & Jacobsen, 2012), although evidence is mixed similar to findings from the current study. In contrast to previous research, the MIML GMM did not find racial differences in class membership. However, racial differences were found using the Parallel Processes LCGA approach. Consistent with the finding from the current study Non-White participants, composed of primarily African Americans, were more likely to be classified into profiles with higher levels of marijuana use relative to other multi-substance use profiles. However, African Americans were also more likely to be the normative use pattern relative to poly substance profiles that did not include high marijuana use. As belonging to a racial/ethnic minority group did not uniformly predict membership into patterns of substance use with higher relative use, findings from the current study do not align with theoretical perspectives that hypothesize increased substance use among racial/ethnic minorities due to coping with stress resulting from living in a racialized society (e.g., Caetano et al., 1998), but instead, paint a more complex and nuanced picture of the links between race and substance use.

Previous research has demonstrated the impact of parental SUD on their child's use with numerous studies linking parental use to increased likelihood and use by their children (Hawkins, et al., 1992). Therefore, the findings linking paternal SUD with increased likelihood into higher risk substance use profiles is highly consistent with past theoretical and empirical work, although the current study is not able to clarify through which mechanism the influence of parental SUD operates.

Although there were significant effects of SES in predicting class membership for the Parallel Process Mixture Model and a trend-level effect of SES in the MIML GMM, the effect of SES on predicting class membership should still be interpreted with caution. Household SES could be a proxy for a number of different factors that were not included in the current study. For example, research has demonstrated varying levels of SES by family structure (which may or may not have involved transitions into different structures) (e.g., Barrett & Turner, 2006). Furthermore, household SES was linked with membership in some, but not all of the higher-risk profiles. Therefore, these findings also provide mixed evidence in support of theoretical assertions about economic disadvantage and coping with economic stress. Future research including additional variables related to SES (e.g., family structure) may be able to disentangle additional effects and the processes through which household SES may be operating.

Although the current study assessed basic individual and family background predictors of class membership, future research should also consider interaction terms between potential predicting factors. There may be specific combinations of factors that result in increased risk or that operate as protective factors for substance use. For example, future research might explore if household SES has a differential impact on substance use classification based on race/ethnicity or gender, particularly as some research has shown that tobacco products are more heavily marketed in low-income areas and areas with a higher proportion of Black residents (Rodriguez et al., 2013; Yu et al., 2010). Assessing the differential impact of parental SUD by gender may also provide greater insight into patterns of substance use over time. As women are less likely to engage in more problematic patterns of substance use in general, perhaps parental SUD may have a lesser impact than it does for men.

Comparison of Approaches

There were several consistencies and discrepancies across the two methods for assessing concurrent substance use trajectories. In terms of similarities, both methods similarly identified the normative or low-use group as being represented by increasing low use over time, and as characteristic of a majority of the sample. However, there were differences in the percentage of the sample the normative profiles represented. In the 3-profile MIML GMM, normative users accounted for approximately three-quarters of the sample, whereas they accounted for only 50% of the sample in the PP LCGA model. It is likely then that some of the individuals classified as increasing polysubstance users in the PP LCGA model would be classified as low users in the MIML GMM model. This begs the question of whether polysubstance patterns similar to overall low-use patterns are still at-risk for negative outcomes, such as SUDs. There were also discrepancies in the additional patterns of substance use identified by the two approaches. None of the identified patterns of use from the PP LCGA model were consistent with the HBDU profile identified by the MIML GMM, as none of the identified profiles evidenced a primarily decreasing pattern of use over time.

Both of the approaches in the current study provide more comprehensive assessments of substance use over time relative to patterns that incorporate only one substance. Each of these approaches identified unique subtypes of users that may have different background characteristics, risk factors, and outcomes later in life. However, there are some differences in the identified patterns of use between these approaches. Reconciling the differences between these two models represents a unique challenge for drawing conclusions about concurrent substance use over time. Although there are many strengths and limitations of the current approaches, the unique ability of these two approaches to account for concurrent substance use over time has far reaching implications for how researchers study and understand patterns of substance use over time. In addition, these models and particularly once they are applied more broadly to a variety of questions, may help inform work in applied settings as well (i.e., legislation about marijuana use, clinical work with substance users).

Strengths and Limitations

Strengths

The current study addressed gaps in the substance use literature (i.e., accounting for or only explicitly modeling the use of one substance) by proposing two alternate models to assess patterns of concurrent substance use trajectories and the differential likelihood of membership into use patterns over time based on family background and individual predictors. Not only did the current study address gaps in the substantive substance use literature, the models are innovate in that they demonstrated relatively novel ways for examining substance use over time using a person-centered framework.

There are several notable strengths of the current study. First, the CEDAR data is prospective and longitudinal with measurement waves ranging from adolescence to adulthood. Prospective data has many advantages over retrospective approaches as prospective reports do not rely on participants recalling their substance use many years prior. Furthermore, because data were gathered across multiple developmental periods (i.e., adolescence, emerging adulthood, and adulthood) a more comprehensive model of substance use patterns was assessed than is typically found in the extant literature. As peak rates of initiation for substance use range from approximately 16 for tobacco to 21-24 for cocaine (and potentially other hard drugs), with virtually no initiation in substance use past age 29 (e.g., Kandel, 1995), the CEDAR dataset was uniquely well-suited to address variation in patterns of substance use over time for multiple substances.

Second, the models used person-centered approaches to assess substance use trajectories that incorporate multiple substances. To date, studies that have incorporated person-centered approaches with multiple substances over time have primarily relied on latent transition analysis (LTA), with a few notable exceptions (Brooks-Russel et al., 2015; Chassin et al., 2004; Jackson et al., 2005; Orlando et al., 2005). Although important in expanding our knowledge of patterns of substance use over time, LTA models are used to answer different research questions (i.e., transitions in class membership) than the assessed models, which emphasize interindividual differences in intraindividual change.

There are also several advantages and strengths associated with mixture models. For example, Tomcyzk, Isenee, & Hanewinkel (2016) highlighted several advantages of mixture models including not being strongly influenced by distribution assumption, such as low cell frequencies or skewness. The authors emphasized that mixture models would likely still incorporate these variables into a profile or class that allows for additional testing. This is a big advantage particularly when studying substance use as these variables are often highly skewed. Tomcyzk et al. (2016) further underscored the flexibility of finite mixture models in that classes or profiles are determined by a combination of theoretical and statistical indicators, thus there is no definitive cut-off for the number of profiles or classes that can be identified. Some scholars have noted that an additional benefit of GMM over latent growth curve models (LGCM) is that GMMs allow for the assessment of whether change is multipath or unitary (e.g., Chan, 1998; Wang & Bodner, 2007). In other words, GMM (and LCGA) allows for the assessment of initial status and change over time (and variation around those mean estimates, for GMM only) for different *unobserved* subpopulations of a sample. Noteworthy, is that the identified patterns or subpopulations modeled in GMM are unobserved, whereas in LGCM only observed subpopulations can be explicitly modeled (e.g., never married vs. married) (Wagner & Bodner, 2007).

Strengths and Limitations of the MIML GMM

Assessing substance use within a latent variable framework also has distinct advantages over modeling trajectories of only one substance or composite measures of substance use. Primary benefits of the multiple-indicator multilevel growth mixture model over other models are a result of the inclusion of a measurement model. In particular, as highlighted by Wu et al. (2010a), the inclusion of a measurement model allows for (a) the ability to remove measurement error from the latent variable indicators of the growth factors, (b) increased flexibility in modeling residual dependence, and (c) the ability to assess temporal measurement equivalence over time. Furthermore, the MIML model may prove beneficial for clinicians as it provides an overall assessment of patterns of substance use over time while accounting for the use of each substance, which may help delineate problematic and normative patterns of overall substance use and specific predictors and outcomes that may allow for more comprehensive prevention efforts or treatments.

However, the main limitation of this model is that it does not allow for the assessment of specific effects of each substance, as they are considered underlying indicators of a more general substance use variable. For example, although general patterns of substance are identified (e.g., High Baseline Decreasing Users) there is not the level of specificity as other approaches might provide (e.g., Stable High Tobacco, Polysubstance Users). Another limitation of this model is that the modeling of trajectories, inclusion of the mixture model is contingent upon the establishment of measurement equivalence. However, establishing measurement equivalence may not be possible in every situation. Even in this study, measurement equivalence was only partially supported.

Furthermore, the pattern of findings for this model was more ambiguous. Several individuals were reclassified across different models resulting in changing patterns of substance use. Not only did this make identifying the appropriate number of classes more challenging, the lack of stability for the 3-profile solution (i.e., reclassification and changing substance use patterns) with the inclusion of covariates is cause for concern and highlights the need for replication of these patterns.

Strengths and Limitations of the Parallel Processes LCGA

The primary advantage of the parallel processes LCGA is that it allows for the simultaneous estimation of trajectories of multiple classes of substances. This model allows for the examination of specific patterns of concurrent substance use and how these patterns may be differentially predicted by family background and individual variables. The only study to date that has assessed patterns of concurrent tobacco, alcohol, and hard drug use over time was limited by combining marijuana and hard drug use as well as the inclusion of only three time points from 10^{th}-12^{th} grades, which is a restricted age range in terms of the developmental course of substance use. The design and data for the PP LCGA model are able to overcome both of the aforementioned issues by assessing trajectories of marijuana use and hard drug use separately and by incorporating measurement occasions across developmental time periods from adolescence to adulthood. The main limitation of this model is that the profiles which may be maladaptive are less clear; however, future research may clarify these patterns by including additional variables that may be indicative of patterns of use that have problematic short- and long-term consequences.

Additional Study Limitations

There are several additional limitations to the current study. One of the main limitations of the current study was the confounded nature of paternal SUD with the other predictors of the substance use patterns. Racial/ethnic minority members were overrepresented in the paternal SUD group and SES was lower in the SUD group relative to the non-SUD group. These confounds make it difficult to say paternal SUD alone predicts differential membership into patterns of substance use over time. However, these differences are likely naturally occurring and have been demonstrated in other samples (e.g., Tarter & Vanyukov, 2001). Furthermore, a demographically matched sample with SUD as the only difference would be artificial and not represent the true differences between those two groups.

The second limitation of the current study was the inability to assess heavy alcohol involvement. Alcohol use was assessed via past month frequency of alcohol use rather than through an assessment of more problematic patterns of drinking (e.g., drinking to intoxication, getting drunk, or binge drinking). This is likely somewhat problematic as previous research (Chassin, Pitts, & Prost, 2002) has been shown heavy alcohol use to be more indicative of problematic patterns of use relative to alcohol use in general.

The third limitation of the current study was its inability to disentangle simultaneous versus concurrent use of substances. Some studies (e.g., Earleywine & Newcomb, 1997) have highlighted larger effects of simultaneous compared to concurrent substance use. However, simultaneous use trajectories may be more difficult to capture or model effectively with the current approaches.

Furthermore, it is important to note that the relatively small sample size used in this study may be somewhat problematic for identifying small subpopulations of substance users. As studies using person-centered approaches to assess polysubstance use have consistently found that polysubstance use classes represent the least frequent classification (e.g., Tomczyk et al., 2016), it is possible that the current sample may not have identified these patterns. However, because the recruitment procedures sampled for adolescents at increased risk for using substances, there may be a more diverse range of users that enabled the identification of relatively infrequent patterns of use. Future research should replicate these patterns of use with additional samples to further support the identified patterns of users.

Another limitation of the current study was its inability to account for the context of substance use. Future research should replicate the demonstrated models and include additional variables in the model to account for contexts that indicate more problematic use. For example, mental health variables (e.g., depression, anxiety), personality variables (antisocial indicators), and abuse/dependence indicators may help differentiate between high and low-risk profiles to a greater extent than parental substance use disorders and individual-level demographic variables.

Model selection is also somewhat ambiguous in mixture modeling, particularly due to often-contradictory fit indices, and the human factors that are involved in determining the appropriate number of classes. For example, because recommendations for selecting the appropriate number of classes involves visual inspection and differential prediction of outcomes (e.g., Muthén & Muthén 2000), there may be significant variation in the extent to which researchers identify differences between classes as trivial versus substantial. Alternatively, there may be substantial variation in the identified classes depending on the predictors or outcomes being assessed.

Although mixture models have a low risk of Type II error, in some instances due to the high power of these models, overly complex models may appear better when in fact the data is being overfit (Wang & Bodner, 2007). To minimize overfitting the data I only modeled quadratic growth in accordance with recommendations by scholars who suggest that research in the psychological sciences lacks support for higher order growth terms (Wang & Bodner, 2007). In addition, consistent with further recommendations, I plotted and visually inspected the growth curves at each step to determine if the differences between classes were important or trivial (e.g., Muthén & Muthén, 2000; Wang & Bodner, 2007). Wang and Bodner (2007) also underscored the lack of research on the potential for Type I error as a limitation of mixture models. Although I have highlighted several limitations of growth mixture modeling, this analytic technique constitutes one of the most advanced methods for modeling substance use that enables research to more accurately capture and assess the true complexity of various patterns of use over time.

Contribution to the Substance Use Literature and Conclusions

The two assessed models add to the literature in several important ways. First, both models incorporate relatively novel methods for analyzing trajectories of substance use. Although some studies (e.g., Newcomb & Bentler, 1987, 1988, 1994) have incorporated latent variables of substance use, and others have included composite measures of the use of multiple substance in the assessment of use trajectories (e.g., Mustansk et al., 2013), no study to my knowledge has utilized a latent substance use variable to assess trajectories of use over time. Furthermore, although some studies (e.g., Mustanski et al. 2013; Wu et al., 2010b) have incorporated parallel-processes mixture models to study concurrent risk trajectories over time (of which substance use was one), and few others have modeled patterns of concurrent substance use over time (e.g., Brooks-Russell et al., 2015, Orlando et al., 2005), no study to date has examined classes of distinct trajectories for tobacco, alcohol, marijuana, and hard drug use across developmental periods spanning from adolescence to adulthood. Because these models demonstrate novel ways of assessing substance use over time, they may each contribute new knowledge about patterns of substance use from adolescence to adulthood and may help with the development of targeted and specific interventions.

Because the multiple-indicator multilevel model and parallel processes growth mixture model represent general and specific patterns of substance use over time, results from the two assessed models demonstrated how general patterns of use (e.g., High Baseline Decreasing Users) as well as specific patterns of use (e.g., Stable High Tobacco Polysubstance Users) are differentially predicted by family background and individual variables. Although there was a limited ability to identify high-risk profiles that result in more severe consequences from use, future research can incorporate these methods that more accurately depict individuals lived experiences and further delineate the general and specific outcomes for each pattern.

There are several pertinent areas for future research arising from the advancement of these two approaches. Because the included preliminary variables were basic demographic and family background variables, particularly for the parallel processes mixture model it is difficult to determine if each pattern of polysubstance use represents an increased risk for negative outcomes. Future research should examine additional predictors (e.g., family factors, education, mental health factors, etc.) and outcomes (e.g., SUDs, educational attainment, relationship functioning) that will help clarify the precursors and consequences of these different patterns of use. For example including indicators of education may show that college attendance differentially predicts membership into some but not all of the polysubstance use patterns, as previous research has demonstrated higher rates of use for some substances among college populations (e.g., National Institute of Drug Abuse, 2015; O'Malley & Johnston, 2002). Additional research should also focus on outcomes such as SUDs to determine if the general and specific patterns of substance use trajectories are linked with increased likelihood of disordered use. Additional research could focus on contextualizing patterns of concurrent substance use. For example, do neighborhood characteristics (e.g., crime, disorganization, availability) predict membership into some patterns of use polysubstance use and not others? The current study laid a basic foundation for the multitude of avenues with which we can further understand patterns of substance use over time.

Research incorporating additional predictors and outcomes that assesses both approaches to concurrent substance use may be able to further delineate the overlap in classifications across these two approaches. For example, perhaps the IATU and IAMU profiles in the parallel processes model that highlight two unique patterns of polysubstance use would be considered part of the low-use pattern in the MIML GMM approach. An important next step may also be to hard classify individuals in both of these approaches and specifically examine the overlap across classifications.

In addition to examining precursors and outcomes that may help identify high versus low-risk patterns of users, these models may be extended to additional substantive questions as well. For example, there is a large body of literature examining the links between substance use and marital outcomes including divorce, marital timing, and relationship satisfaction. Particularly for marital timing there is a diverse array of evidence suggesting contrasting associations between substance use and marital timing, potentially due to the differences in approaches and substances studied. Approaches like those used in the current study that account for patterns of concurrent substance use over time may be able to clarify seemingly discrepant links in the extant literature. Although this is only one example of how these models can address substantive questions, there are a plethora of other topics for which these approaches would be useful.

These models have important implications for intervention work as well as they allow for a more complete picture of the lived experiences of substance users. Models that can account for concurrent substance use provide a more holistic view of individuals and may promote more comprehensive prevention efforts or treatment plans particularly once future research examines additional variables that may predict specific patterns of use as well as consequence from specific patterns of use. For example, different treatments may be more or less effective depending on the specific combination of substances individuals use or based on general patterns of use. There could also be specific family factors (e.g., parental support, neglect, abuse, etc.) and mental health factors (e.g., internalizing, externalizing, antisocial behaviors) that differentially predict membership into patterns of substance use and understanding how these operate can help practitioners focus on different aspects of prevention and treatment.

Overall, results from the current study demonstrated two approaches to analyzing concurrent substance use over time. The first approach used multiple indicators and latent variables to capture general trends in patterns of substance use, whereas the second approach modeled trajectories of each substance (or group of substances) separately and identified specific patterns of substance use trajectories. Furthermore, basic individual and family background variables differentially predicted membership into the patterns of substance use across both approaches. These findings highlight the need for examination of additional variables that may further clarify the unique antecedents and consequences of these patterns of use as well as the need to utilize more comprehensive approaches to assessing conceptual questions about substance use over time.

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APPENDIX A

TABLES AND FIGURES

Table 1. Descriptive Statistics and Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1. AUF 16																								
2. AUF 19	.33																							
3. AUF 22	.23	.40																						
4. AUF 25	.23	.34	.49																					
5. AUF 28	.11	.25	.39	.59																				
6. TUF 16	.46	.28	.10	.12	.02																			
7. TUF 19	.35	.42	.24	.17	.08	.62																		
8. TUF 22	.25	.30	.31	.22	.17	.51	.72																	
9. TUF 25	.20	.30	.28	.26	.18	.48	.67	.75																
10. TUF 28	.25	.24	.24	.20	.17	.46	.64	.75	.79															
11. DUF 16	.21	.03	.03	.02	.05	.15	.11	.11	.10	.10														
12. DUF 19	.13	.32	.11	.09	.08	.25	.29	.20	.19	.16	.18													
13. DUF 22	.20	.14	.27	.03	.01	.28	.31	.31	.29	.33	.11	.32												
14. DUF 25	.28	.14	.17	.15	.03	.39	.37	.34	.37	.44	.13	.16	.51											
15. DUF 28	.26	.10	-.01	.10	.07	.31	.23	.30	.24	.35	.15	.18	.38	.40										
16. MUF 16	.62	.23	.15	.13	.06	.48	.42	.32	.29	.35	.22	.21	.32	.41	.37									
17. MUF 19	.33	.52	.26	.16	.15	.34	.49	.41	.35	.38	.04	.39	.32	.33	.24	.47								
18. MUF 22	.27	.35	.39	.22	.15	.27	.41	.45	.36	.47	.12	.19	.39	.30	.16	.41	.65							
20. MUF 25	.22	.25	.21	.23	.20	.24	.36	.35	.37	.38	.06	.10	.20	.35	.20	.32	.50	.66						
21. MUF 28	.16	.21	.15	.16	.21	.22	.27	.33	.29	.32	.05	.05	.22	.25	.27	.31	.47	.60	.76					
22. Gender	-.06	-.06	-.07	-.13	-.11	-.08	-.14	-.16	-.15	-.13	.07	-.02	-.07	.00	-.01	-.10	-.10	-.15	-.13	-.11				
23. Race	.02	-.08	-.11	-.09	-.10	-.05	-.11	-.06	-.04	.03	.05	-.05	-.03	-.01	-.03	.12	.15	.15	.12	.11	.07			
24. Parental SUD	.10	.14	.06	-.03	-.06	.10	.13	.13	.11	.17	.04	.12	.09	.12	.13	.11	.19	.21	.16	.12	-.03	.14		
25. Household SES	-.05	-.04	.04	.11	.11	.12	-.06	-.10	-.11	-.17	-.05	-.07	-.04	-.07	-.14	-.11	-.14	-.13	-.12	-.08	.02	-.32	-.30	
N	623	571	483	503	366	623	571	483	503	366	623	571	483	503	366	623	571	483	503	366	775	775	775	774
M	.41	1.12	1.82	1.74	1.68	.69	1.24	1.37	1.48	1.51	.12	0.23	.36	.36	.35	.77	.95	.99	.92	.84	.29	.25	.44	41.52
V	.54	1.21	1.25	1.15	1.35	1.89	2.87	2.95	3.18	3.34	.20	0.43	.77	.74	.81	.99	1.92	2.12	2.04	2.06	.21	.19	.25	191.25
Skew	1.96	.79	.08	.14	.23	1.35	.84	.67	.53	.52	4.30	3.51	2.92	2.79	2.82	2.42	1.24	1.17	1.26	1.40	.92	1.19	.23	-.10
Kurtosis	4.01	-.06	-.53	-.45	-.60	.84	-1.11	-1.36	-1.57	-1.62	20.11	13.68	8.23	7.60	7.19	5.02	.11	-.22	.02	.32	-1.16	-.60	-1.95	-.80

Note: AUF = Alcohol use frequency, TUF = Tobacco use frequency, DUF = Drug use frequency, MUF = Marijuana use frequency

Table 2. MIML Measurement Model

	b	SE	β	p
Substance Use Age 16				
Marijuana Use	1.00	.00	.81	-
Alcohol Use	.68	.05	.74	<.001
Tobacco Use	1.00	.08	.59	<.001
Hard Drug Use	.18	.03	.32	<.001
Substance Use Age 19				
Marijuana Use	1.00	.00	.75	-
Alcohol Use	.68	.05	.63	<.001
Tobacco Use	1.00	.08	.61	<.001
Hard Drug Use	.39	.04	.58	<.001
Substance Use Age 22				
Marijuana Use	1.00	.00	.70	-
Alcohol Use	.68	.05	.58	<.001
Tobacco Use	1.00	.08	.58	<.001
Hard Drug Use	.39	.04	.44	<.001
Substance Use Age 25				
Marijuana Use	1.00	.00	.60	-
Alcohol Use	.68	.05	.52	<.001
Tobacco Use	1.00	.08	.50	<.001
Hard Drug Use	.39	.04	.41	<.001
Substance Use Age 28				
Marijuana Use	1.00	.00	.55	-
Alcohol Use	.68	.05	.44	<.001
Tobacco Use	1.00	.08	.47	<.001
Hard Drug Use	.39	.04	.36	<.001
Latent Means and Variances				
Means				
Substance Use Age 16	-.58	.05	-.72	<.001
Variances				
Substance Use Age 16	.65	.08	1.00	<.001
Substance Use Age 19	1.04	.12	1.00	<.001
Substance Use Age 22	.99	.12	1.00	<.001
Substance Use Age 25	.76	.10	1.00	<.001
Substance Use Age 28	.66	.11	1.00	<.001

Table 3. Latent Variable Growth Curve Model Growth Factor Estimates

	Means			Variances		
	b	*SE*	*p*	*b*	*SE*	*p*
Intercept	.00	.00	-	.50	.12	<.001
Slope	.29	.06	<.001	.18	.09	.060
Quadratic	-.06	.01	<.001	.01	.00	.068

Table 4. MIML Mixture Model Comparisons

Model	AIC	BIC	ABIC	Entropy	-2LL Diff	VLRT p-value	BLRT *p*-value
Two-Profile LCGA Solution	26765.30	27145.61	26882.06	.947	720.18	<.001	<.001
Three-Profile LCGA Solution	26260.06	26677.02	26388.07	.940	517.52	<.001	<.001
Three-Profile GMM Solution	26158.82	26594.11	26292.56	.935	447.98	<.001	<.001
Four-Profile LCGA Solution	25668.01	26117.05	25805.87	.942	606.04	.207	<.001
Four-Profile GMM Solution	25568.50	26035.87	25711.99	.940	586.10	.211	<.001
Five-Profile LCGA Solution	25492.39	25973.50	25640.09	.912	189.63	.707	<.001
Six-Profile LCGA Solution	25419.62	25928.22	25575.77	.891	84.78	.456	<.001

Table 5. Class Size Comparisons for MIML Mixture Models

Model	1	2	3	4	5	6
Two-Class GMM Solution	91	631				
Three-Class LCGA Solution	53	105	564			
Three-Profile GMM Solution	570	50	102			
Four-Class LCGA Solution	34	569	57	62		
Four-Class GMM Solution	577	50	34	61		
Five-Class LCGA Solution	49	33	67	83	490	
Six-Class LCGA Solution	477	52	42	51	32	68

Table 6. Estimated Growth Factors – MIML Four-Profile Solutions

	b	*SE*	*p*	*b*	*SE*	*p*	*b*	*SE*	*p*	*b*	*SE*	*p*
LCGA	Class 1 (*n* = 34)			Class 2 (*n* = 569)			Class 3 (*n* = 57)			Class 4 (*n* = 62)		
Intercept	1.99	.73	.007	-.54	.11	<.001	1.52	.67	.022	.00	.00	-
Slope	-.72	.65	.266	.31	.09	.001	.11	.58	.854	.99	.15	<.001
Quadratic	.11	.13	.404	-.05	.02	.004	-.02	.11	.833	-.23	.03	<.001
GMM	Class 1 (*n* = 34)			Class 2 (*n* = 577)			Class 3 (*n* = 50)			Class 4 (*n* = 61)		
Means												
Intercept	2.06	.70	.003	-.59	.11	<.001	1.82	.60	.003	.00	.00	-
Slope	-.76	.62	.224	.32	.09	.001	-.09	.52	.866	.98	.15	<.001
Quadratic	.12	.13	.358	-.05	.02	.002	-.02	.01	.891	-.23	.03	<.001
Variances												
Intercept	.01	.01	.100	.01	.01	.100	.01	.01	.100	.01	.01	.100
Slope	.32	.07	<.001	.32	.07	<.001	.32	.07	<.001	.32	.07	<.001
Quadratic	.01	.00	.001	.01	.00	.001	.01	.00	.001	.01	.00	.001

Table 7. Growth Factor Estimates for 3-Profile MIML GMM

	b	*SE*	*p*	*b*	*SE*	*p*	*b*	*SE*	*p*
3-Profile GMM: Predictors									
	HBDU (*n* = 75)			ILU (*n* = 561)			MSU (*n* = 85)		
Means									
Intercept	1.82	.52	<.001	-3.00	.14	<.001	.00	.00	-
Slope	-1.48	.55	.007	.65	.18	<.001	-.39	.23	.096
Quadratic	.19	.11	.081	-.11	.04	.007	.08	.06	.187
Variances									
Intercept	.16	.03	<.001	.16	.03	<.001	.16	.03	<.001
Slope	.18	.10	.069	.18	.10	.069	.18	.10	.069
Quadratic	.01	.01	.313	.01	.01	.313	.01	.01	.313
3-Profile GMM: No Predictors									
	Class 1 (*n* = 50)			Class 2 (*n* = 570)			Class 3 (*n* = 102)		
Means									
Intercept	1.673	.59	.005	-.93	.13	<.001	.00	.00	-
Slope	-.23	.52	.660	.32	.10	.001	.72	.13	<.001
Quadratic	.04	.10	.679	-.05	.02	.003	-.17	.03	<.001
Variances									
Intercept	.03	.01	.003	.03	.01	.003	.03	.01	.003
Slope	.35	.07	<.001	.35	.07	<.001	.35	.07	<.001
Quadratic	.01	.00	.001	.01	.00	.001	.01	.00	.001

Table 8. Predictors of Growth Factors 3-Profile MIML GMM

	Gender			Race			Paternal SUD			Household SES		
	b	*SE*	*p*	*b*	*SE*	*p*	*b*	*SE*	*p*	*b*	*SE*	*p*
Intercept	-.02	.04	.646	.10	.06	.094	.02	.04	.694	.00	.00	.887
Slope	-.19	.09	.029	-.07	.11	.559	.18	.08	.026	.00	.00	.790
Quadratic	.03	.02	.137	.01	.03	.604	-.04	.02	.083	.00	.00	.881

Table 9. MIML GMM: Odds Ratios for Predictors of Class Membership

	Odds Ratio	*p*	Odds Ratio	*p*	Odds Ratio	*p*
Class 1: High Baseline Decreasing Users (HBDU)						
Sex			.79	.508	2.14	.095
Race			1.51	.239	.96	.933
Parental SUD			2.16	.020	1.28	.545
Household SES			1.00	.972	1.02	.199
Class 2: Increasing Low Users (ILU)						
Sex	1.26	.508			2.66	.005
Race	.66	.239			.64	.142
Parental SUD	.46	.020			.59	.043
Household SES	1.00	.972			1.02	.065
Class 3: Moderate Stable Users (MSU)						
Sex	.47	.095	.38	.005		
Race	1.04	.933	1.57	.142		
Parental SUD	.78	.545	1.70	.043		
Household SES	.98	.199	.98	.065		

Table 10. Parallel Process Growth Curve Model: Growth Factor Estimates

	Means			Variances		
	b	*se*	*p*	*b*	*se*	*p*
Alcohol						
Intercept	.43	.03	<.001	.24	.07	<.001
Slope	.80	.05	<.001	.24	.07	.001
Quadratic	-.12	.01	<.001	.01	.01	.006
Tobacco						
Intercept	.73	.06	<.001	1.40	.21	<.001
Slope	.59	.05	<.001	.66	.18	<.001
Quadratic	-.10	.01	<.001	.03	.01	.011
Hard Drugs						
Intercept	.12	.02	<.001	.00	.00	-
Slope	.16	.03	<.001	.04	.01	<.001
Quadratic	-.02	.01	.002	.00	.00	-
Marijuana						
Intercept	.48	.04	<.001	.67	.14	<.001
Slope	.48	.05	<.001	.58	.13	<.001
Quadratic	-.10	.01	<.001	.03	.01	<.001

Table 11. Parallel Process Latent Class Growth Analysis Model Comparisons

Model	AIC	BIC	ABIC	Entropy	-2LL Diff	VLRT p-value	BLRT *p*-value
Three-Profile Solution	26901.44	27304.66	27025.24	.919	871.25	<.001	<.001
Four-Profile Solution	26593.03	27055.81	26735.11	.910	334.42	.446	<.001
Five-Profile Solution	26204.46	26726.81	26364.83	.918	394.05	0.19	<.001
Six-Profile Solution	25781.68	26363.59	25960.33	.919	517.21	0.09	<.001

Table 12. Class Size Comparisons for PP LCGA Models

Model	1	2	3	4	5	6
Three-Profile Solution	155	448	119			
Four-Profile Solution	97	84	424	117		
Five-Profile Solution	49	83	404	73	113	
Six-Profile Solution	82	52	69	50	68	401

PP LCGA Solutions within timepoint covs

Table 13. 5-Profile PP LCGA Model: Growth Factor Estimates

	IAMU (n = 49)			IATU (n = 83)			IAU 3 (n = 404)			IAMTU (n = 73)			SHTPU (n=113)		
	b	*SE*	*p*	*b*	*SE*	*p*	*b*	*SE*	*p*	*b*	*SE*	*p*	*b*	*SE*	*p*
Alcohol															
Intercept	.65	.13	<.001	.29	.08	<.001	.18	.03	<.001	.56	.13	<.001	1.16	.10	<.001
Slope	1.38	.17	<.001	1.20	.12	<.001	.80	.05	<.001	1.29	.15	<.001	.84	.15	<.001
Quadratic	-.26	.05	<.001	-.21	.03	<.001	-.19	.01	<.001	-.22	.04	<.001	-.18	.04	<.001
Tobacco															
Intercept	.30	.13	.022	.16	.07	.014	.08	.02	<.001	.38	.12	.002	3.76	.06	<.001
Slope	.20	.21	.319	2.15	.20	<.001	.18	.04	<.001	2.35	.16	<.001	-.15	.12	.201
Quadratic	-.03	.05	.585	-.34	.06	<.001	-.04	.01	<.001	-.39	.04	<.001	.02	.03	.432
Hard Drugs															
Intercept	.01	.03	.787	.12	.06	.043	.10	.02	<.001	.15	.08	.049	.22	.06	<.001
Slope	.48	.12	<.001	.12	.11	.256	.00	.03	.894	.25	.12	.041	.53	.14	<.001
Quadratic	-.09	.03	.003	-.02	.03	.576	.00	.01	.854	-.04	.03	.206	-.07	.04	.060
Marijuana															
Intercept	.94	.32	.003	.18	.06	.003	.12	.03	<.001	.72	.18	<.001	1.58	.16	<.001
Slope	1.74	.27	<.001	.43	.15	.003	.10	.04	.009	1.99	.21	<.001	.39	.18	.033
Quadratic	-.36	.09	<.001	-.12	.04	.003	-.02	.01	.088	-.37	.07	<.001	-.11	.05	.015

Table 14. Family Background and Individual Predictors of Growth Functions

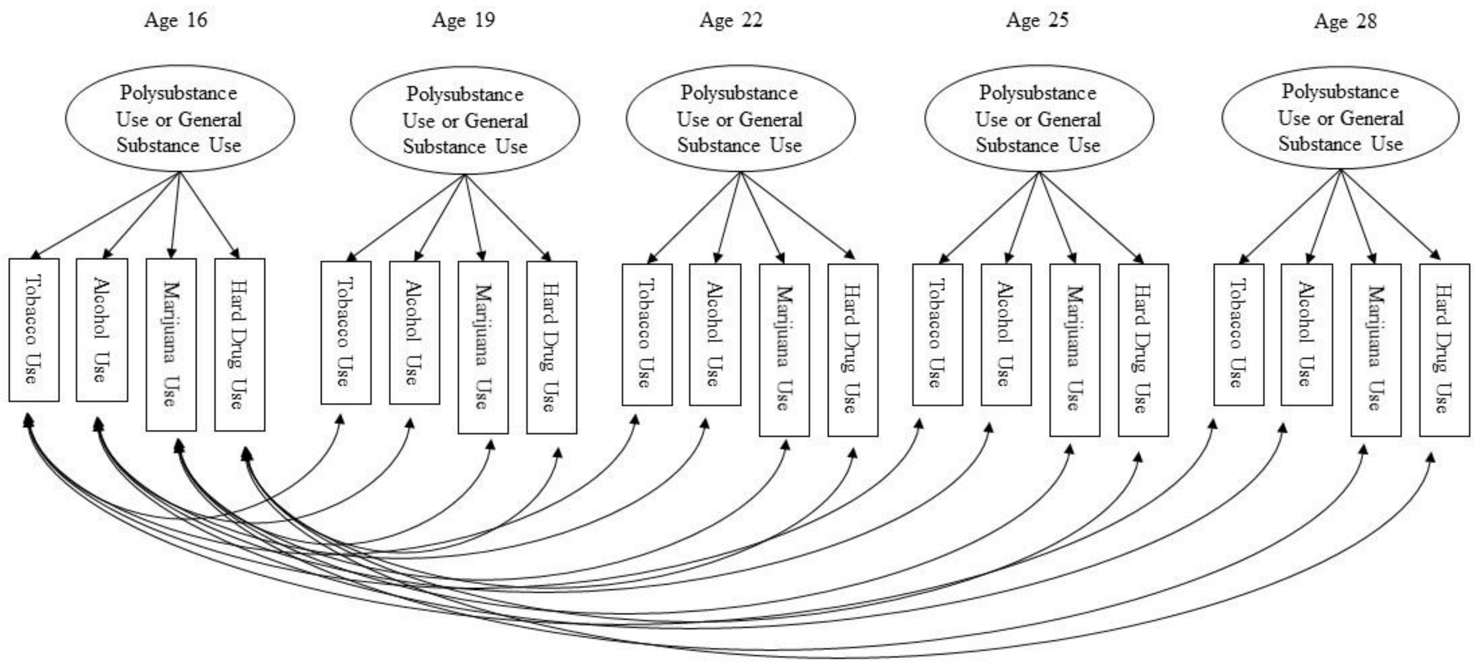
	Gender			Race			Paternal SUD			HH SES		
	b	*SE*	*p*	*b*	*SE*	*p*	*b*	*SE*	*p*	*b*	*SE*	*p*
Alcohol												
Intercept	.02	.06	.723	.03	.08	.696	.06	.06	.312	.00	.00	.499
Slope	.06	.09	.479	-.26	.11	.015	.09	.08	.282	.00	.00	.549
Quadratic	-.03	.02	.176	.06	.03	.053	-.04	.02	.092	.00	.00	.923
Tobacco												
Intercept	.00	.05	.942	-.11	.05	.047	-.04	.04	.278	.00	.00	.609
Slope	-.05	.10	.602	-.14	.11	.202	.05	.09	.569	.00	.00	.396
Quadratic	.02	.03	.495	.06	.03	.045	-.01	.02	.776	.00	.00	.292
Hard Drugs												
Intercept	.06	.04	.129	.02	.05	.653	.01	.03	.854	.00	.00	.398
Slope	-.05	.06	.414	-.10	.08	.214	.07	.06	.252	.00	.00	.296
Quadratic	.02	.02	.287	.02	.02	.469	-.02	.02	.387	.00	.00	.207
Marijuana												
Intercept	-.06	.06	.344	.28	.10	.003	.04	.08	.589	.00	.00	.939
Slope	.09	.09	.301	-.02	.11	.830	.13	.09	.157	.00	.00	.542
Quadratic	-.02	.02	.339	.00	.03	.985	-.03	.02	.146	.00	.00	.588

Table 15. Family Background and Individual Predictors of Class Membership

	Odds Ratio	p	Odds Ratio	p	Odds Ratio	p	Odds Ratio	p	Odds Ratio	p
Increasing Alcohol and Tobacco Users (IATU)										
Sex	.48	.022			1.68	.292	1.07	.919	.97	.930
Race	.39	.022			.31	.027	.19	.010	.65	.355
Parental SUD	.95	.864			.38	.023	.87	.788	.49	.031
Household SES	.97	.003			.97	.041	.98	.267	1.00	.987
Increasing Alcohol, Marijuana, and Tobacco Users (IAMTU)										
Sex	.28	.001	.59	.292			.95	.944	.57	.226
Race	1.23	.558	3.19	.027			.74	.551	2.08	.093
Parental SUD	2.48	.004	2.61	.023			1.57	.302	1.28	.492
Household SES	1.00	.830	1.03	.041			1.02	.307	1.03	.050
Increasing Alcohol and Marijuana Users (IAMU)										
Sex	.30	.054	.63	.495	1.05	.944			.60	.465
Race	1.67	.201	4.26	.004	1.35	.551			2.80	.023
Parental SUD	1.58	.188	1.67	.253	.64	.302			.82	.609
Household SES	.98	.279	1.02	.518	.98	.307			1.01	.521
Stable High Tobacco, Polysubstance Users (SHTPU)										
Sex	.49	.007	1.03	.930	1.75	.226	1.67	.465		
Race	.59	.083	1.54	.355	.48	.093	.36	.023		
Parental SUD	1.93	.007	2.03	.031	.78	.492	1.22	.609		
Household SES	.97	.002	1.00	.987	.97	.050	.99	.521		
Increasing Alcohol Users (IAU)										
Sex			2.10	.022	3.56	.001	3.35	.054	2.03	.007
Race			2.59	.022	.81	.558	.60	.201	1.68	.083
Parental SUD			1.05	.864	.31	.004	.63	.188	.52	.007
Household SES			1.03	.003	1.00	.830	1.02	.279	1.03	.002

Note: Missing values on the table indicate that that profile was used as the reference group.

Figure 1. MIML Conceptual Measurement Model



Note: Covariances were added across all time points. As representing each modeled covariance would over complicate the figure, only some were depicted for simplicity.

Figure 2. MIML GMM Conceptual Model

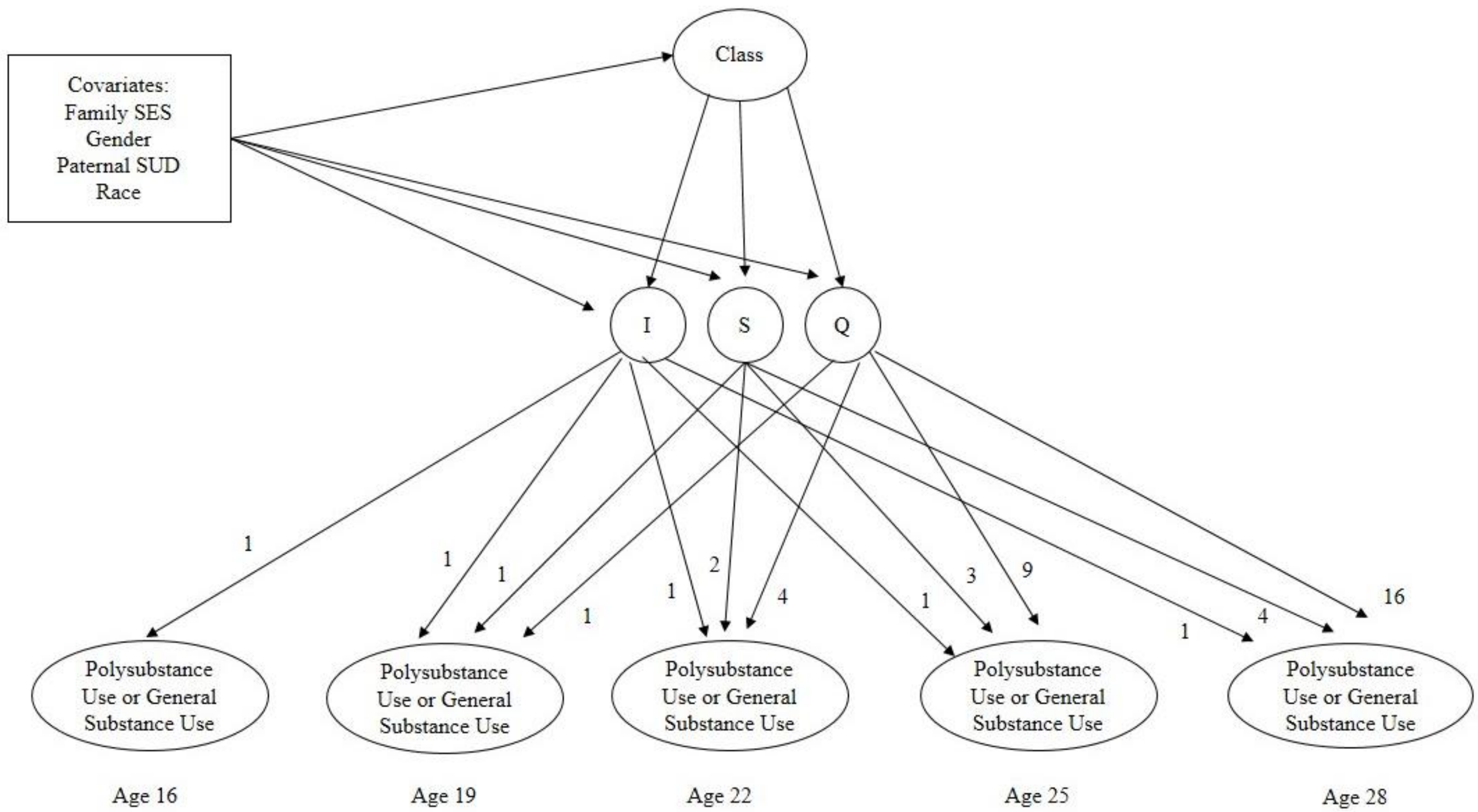
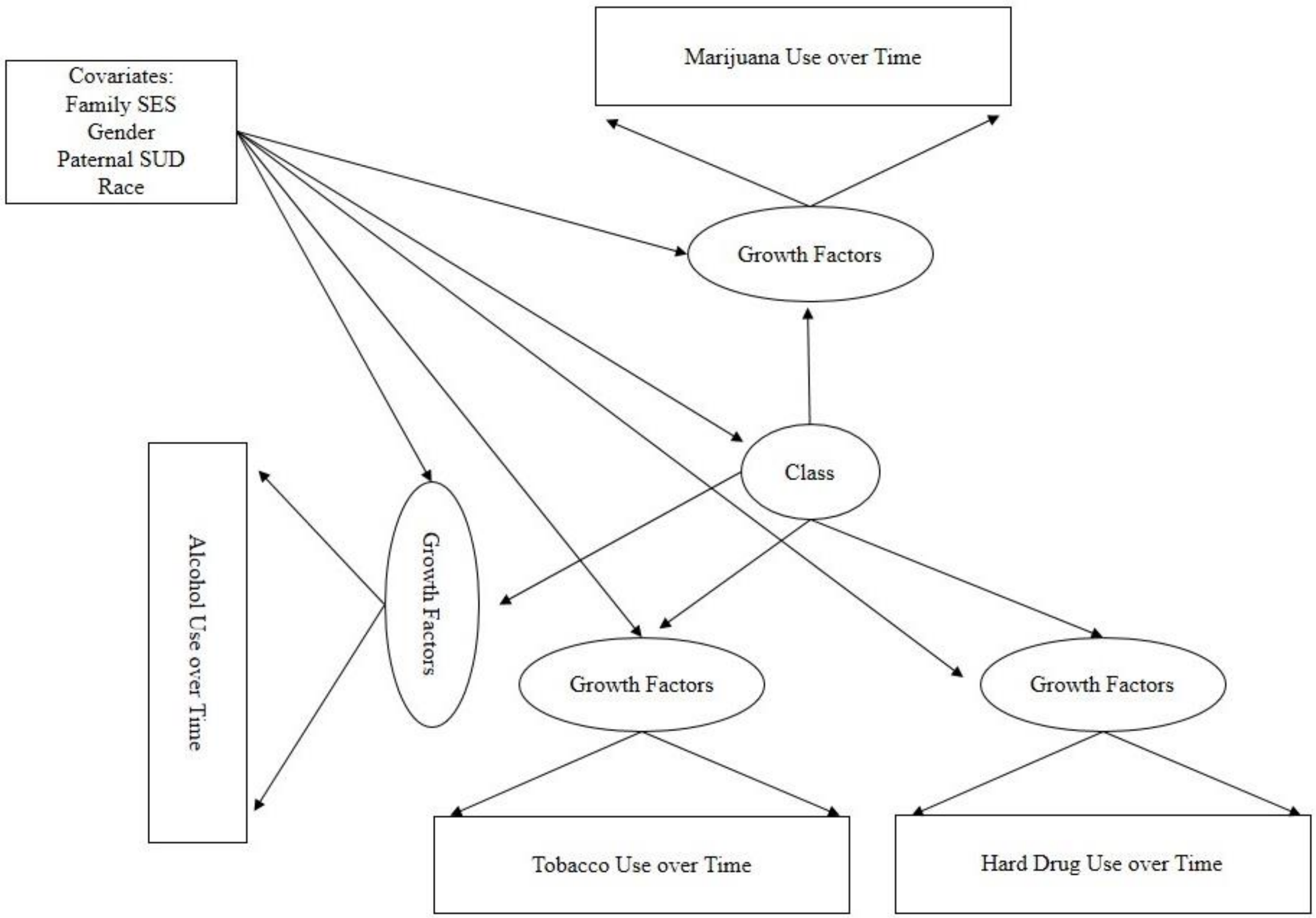


Figure 3. Parallel Process Latent Class Growth Analysis Conceptual Model



Note: Covariances were specified between the dimensions of substance use within each time point.

Figure 4. MIML Growth Curve Model

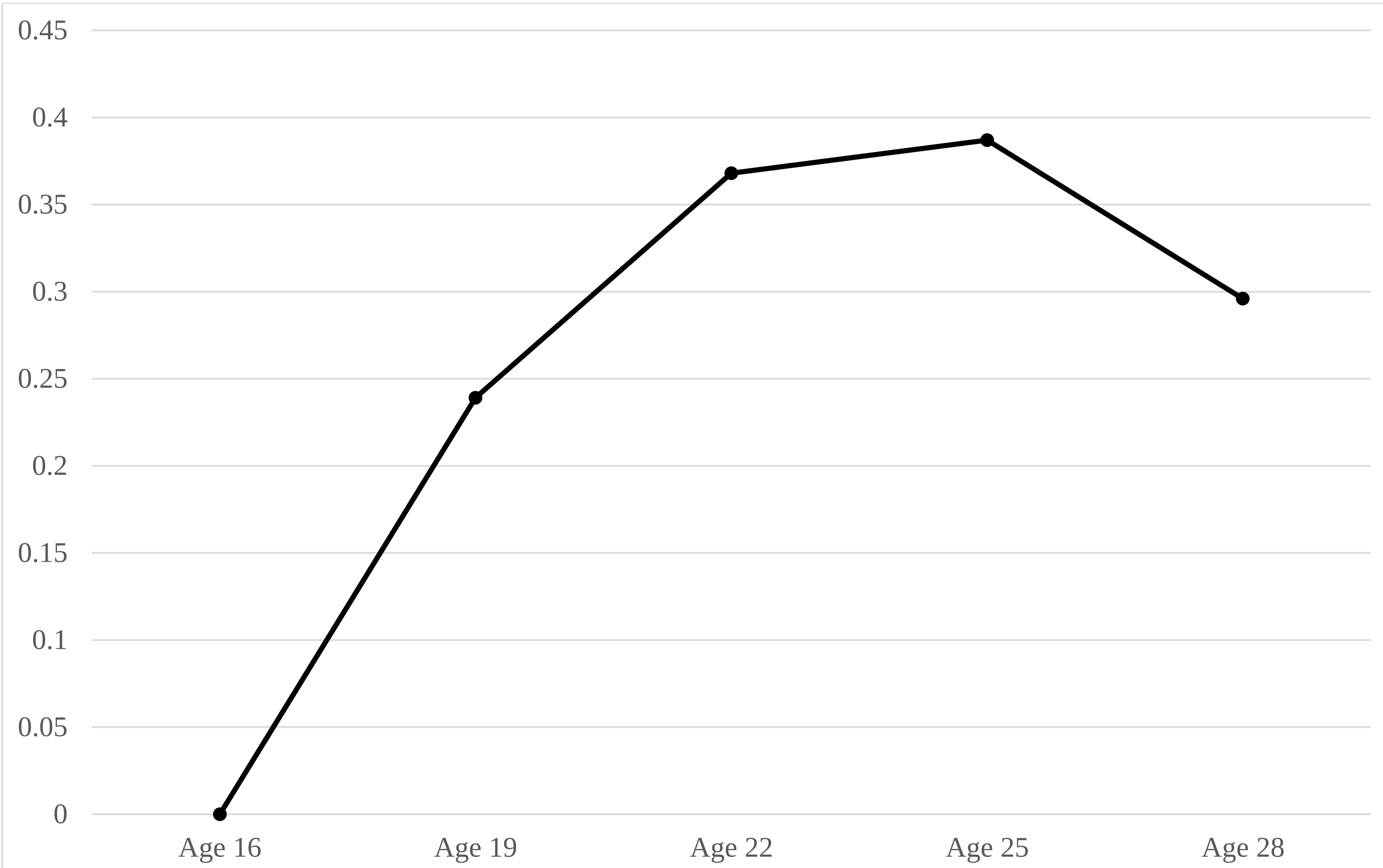


Figure 5. MIML LCGA 4-Profile Solution

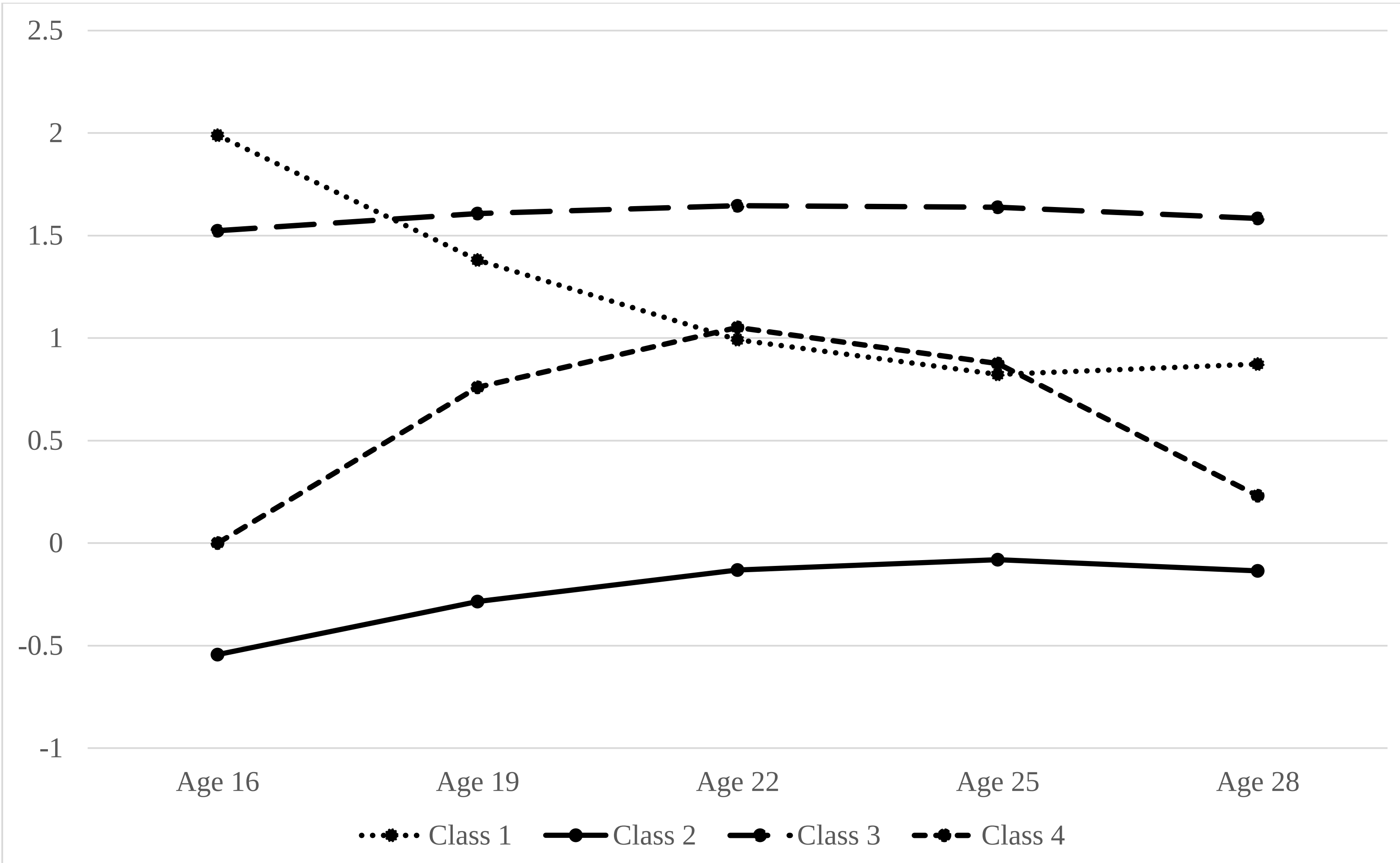


Figure 6. MIML GMM 4-Profile Solution with Predictors

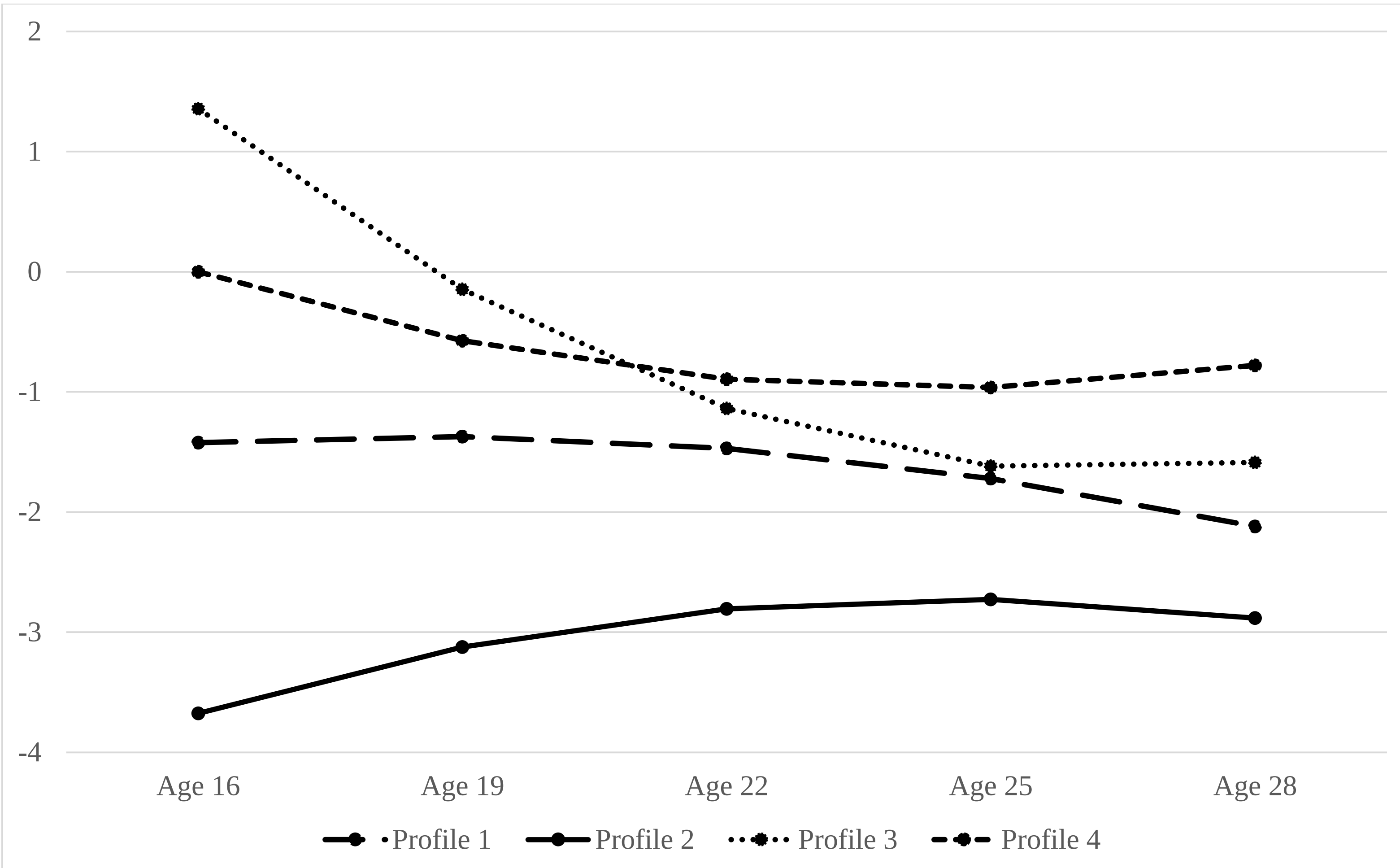


Figure 7. MIML GMM 3-Profile Solution with Predictors

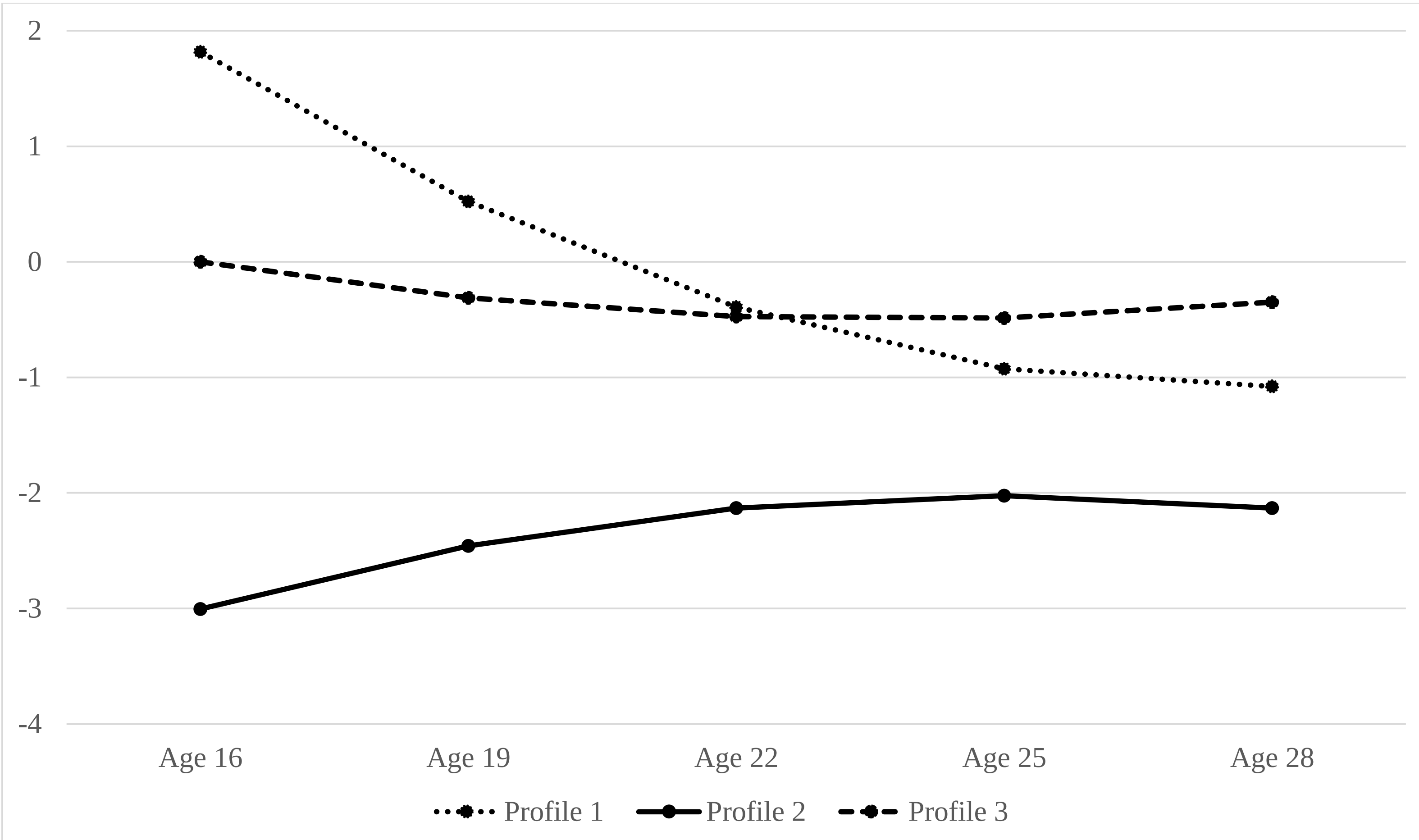


Figure 8. MIML GMM 3-Profile Solution

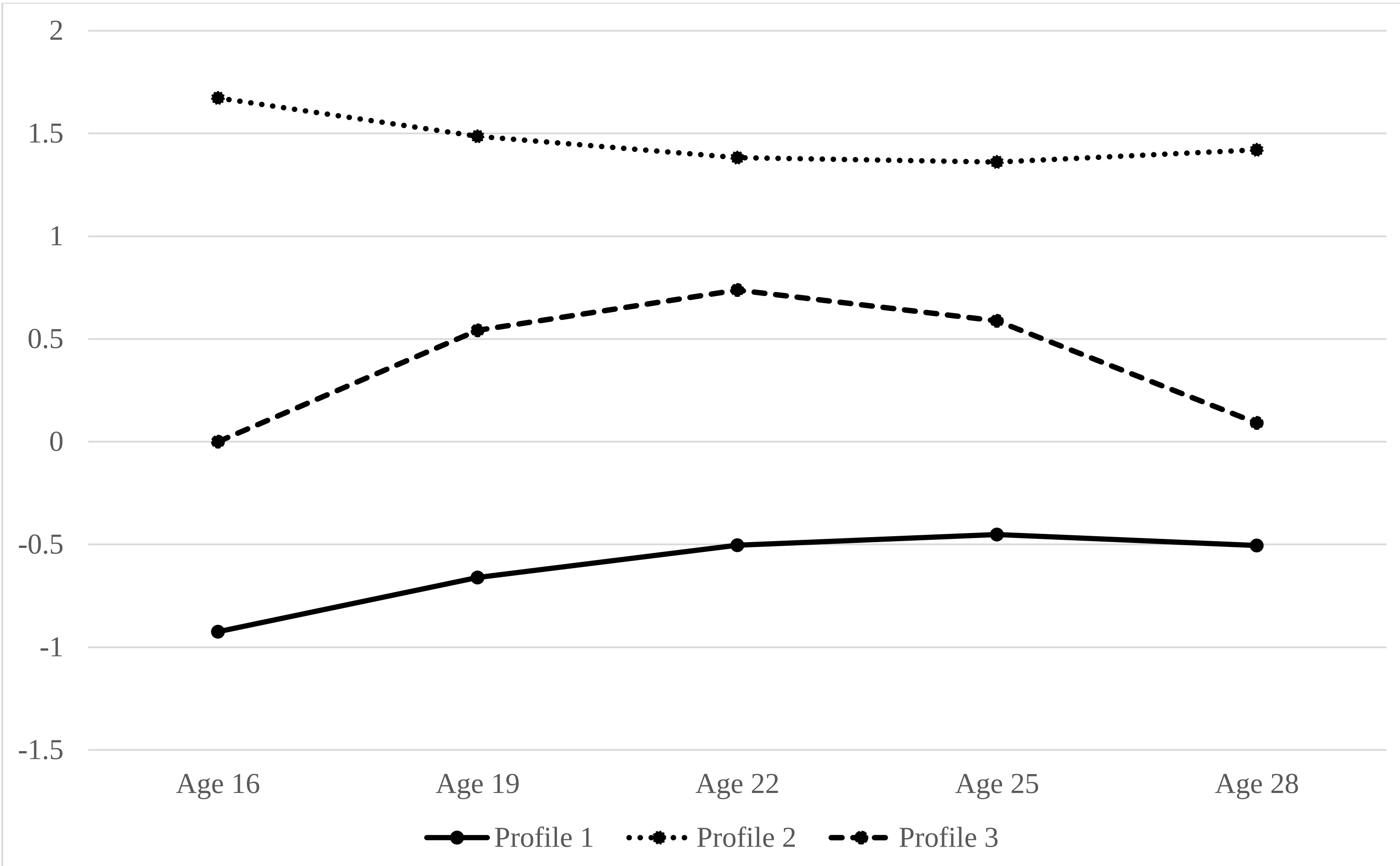


Figure 9. Alcohol Use Frequency Growth Curve Model

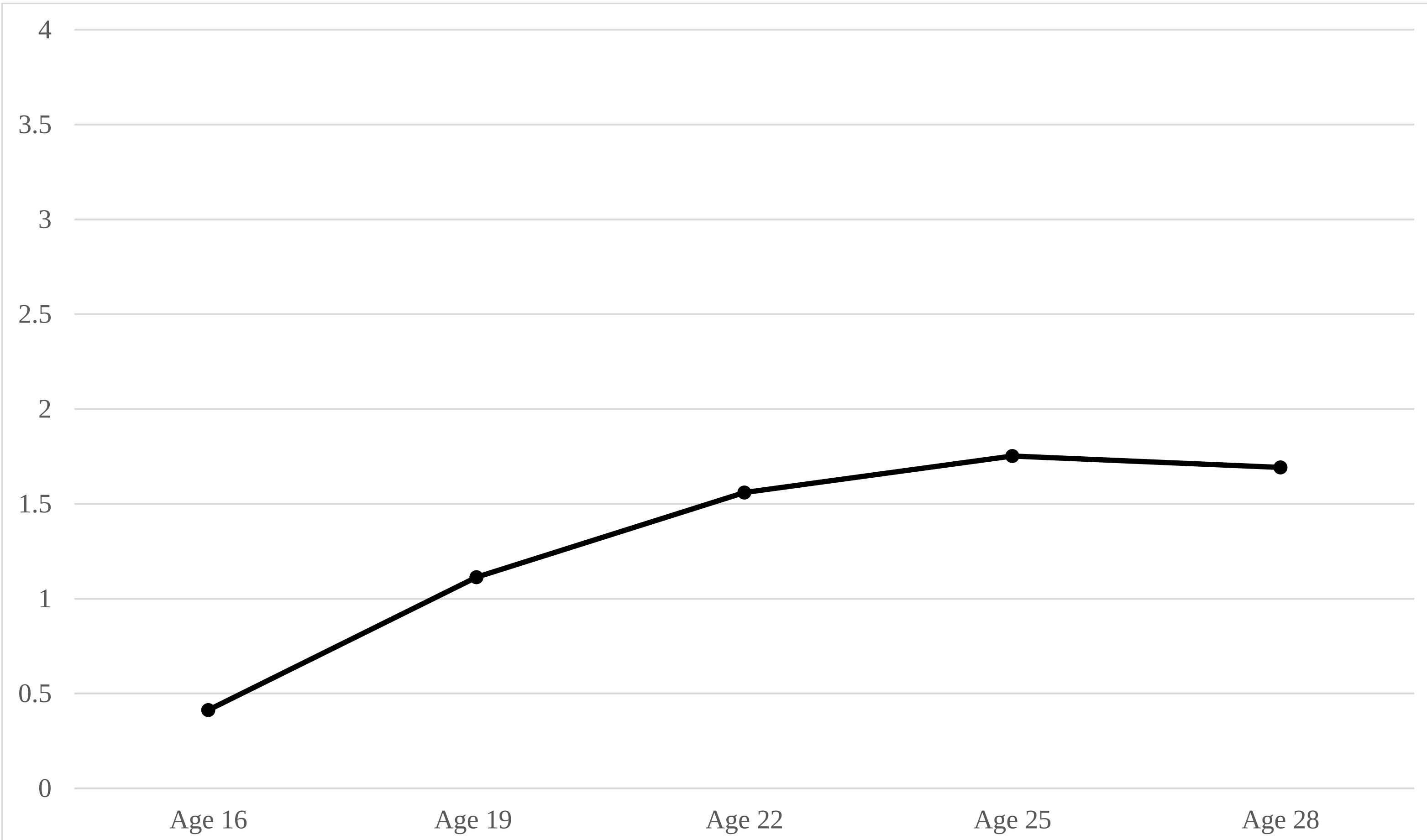


Figure 10. Tobacco Use Frequency Growth Curve Model

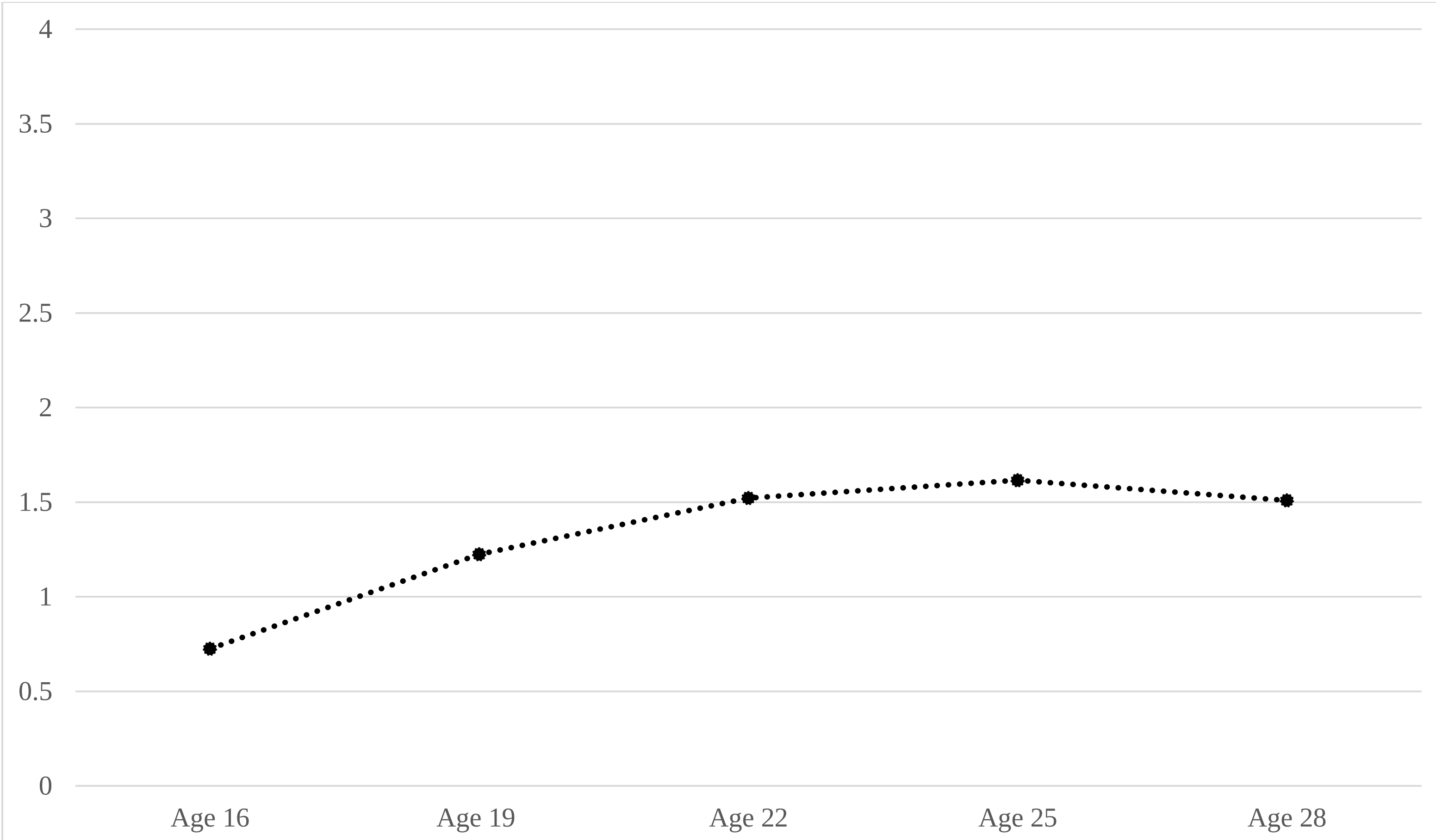


Figure 11. Drug Use Frequency Growth Curve Model

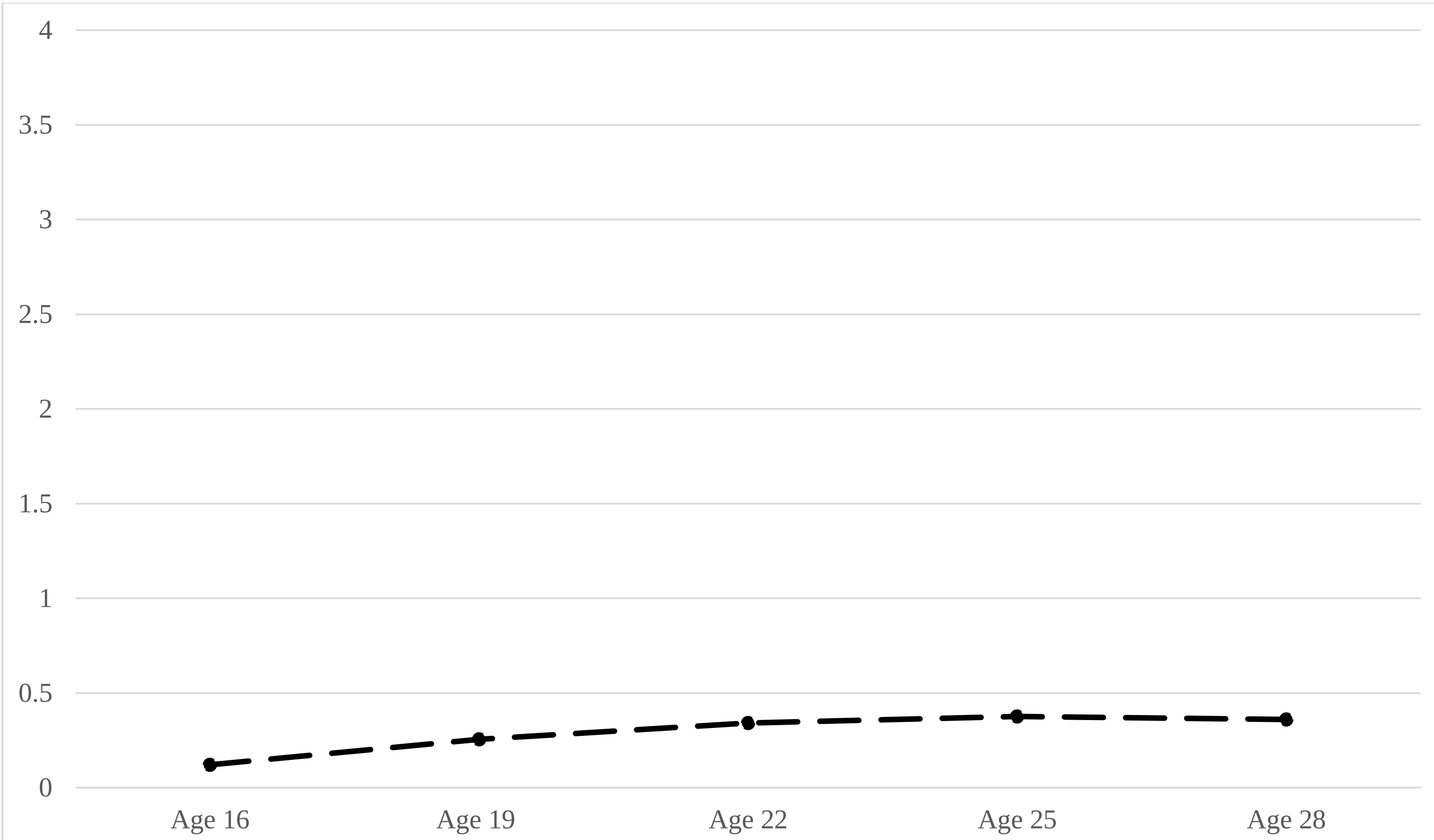


Figure 12. Marijuana Use Frequency Growth Curve Model

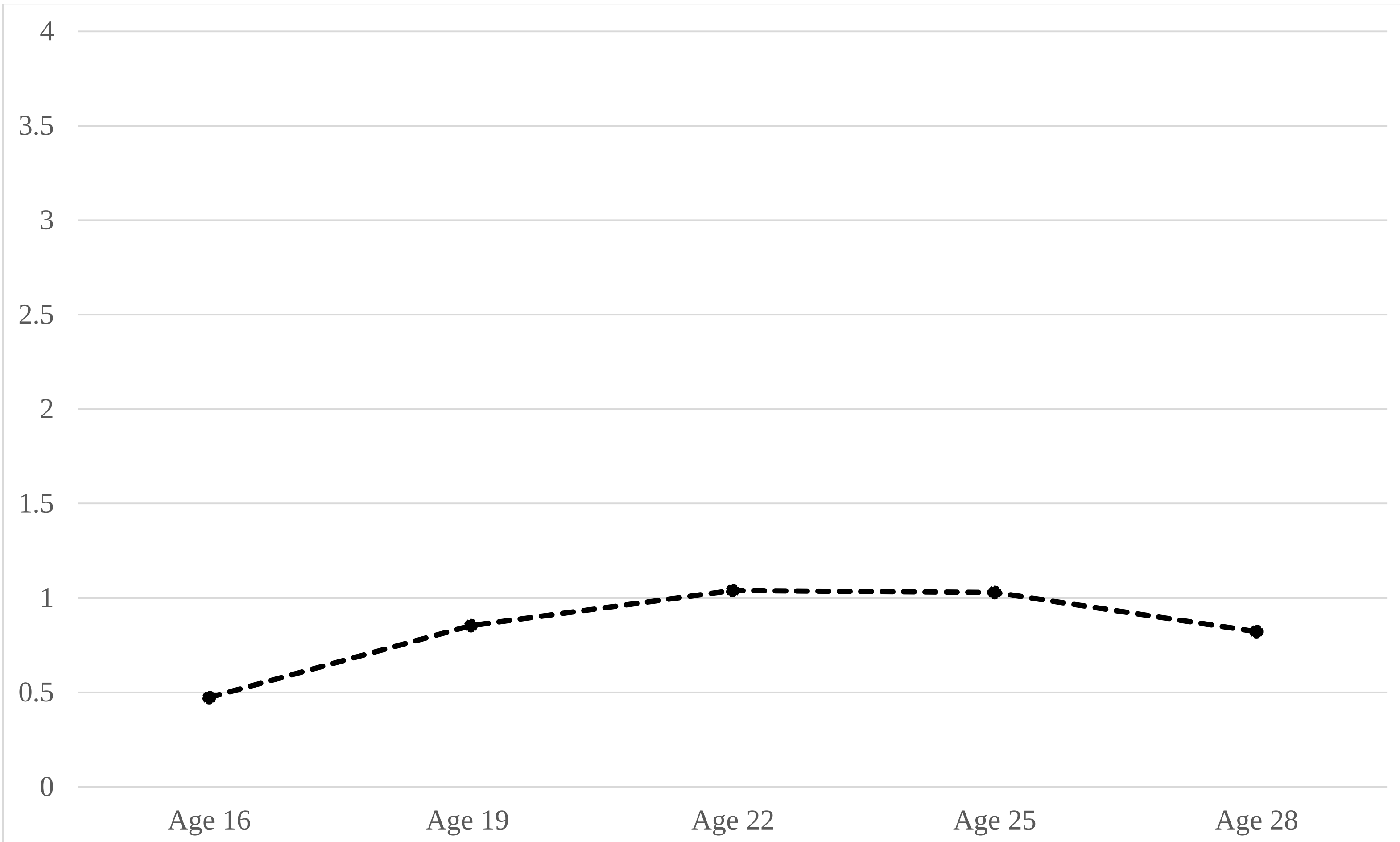


Figure 13. Parallel Process Growth Curve Model

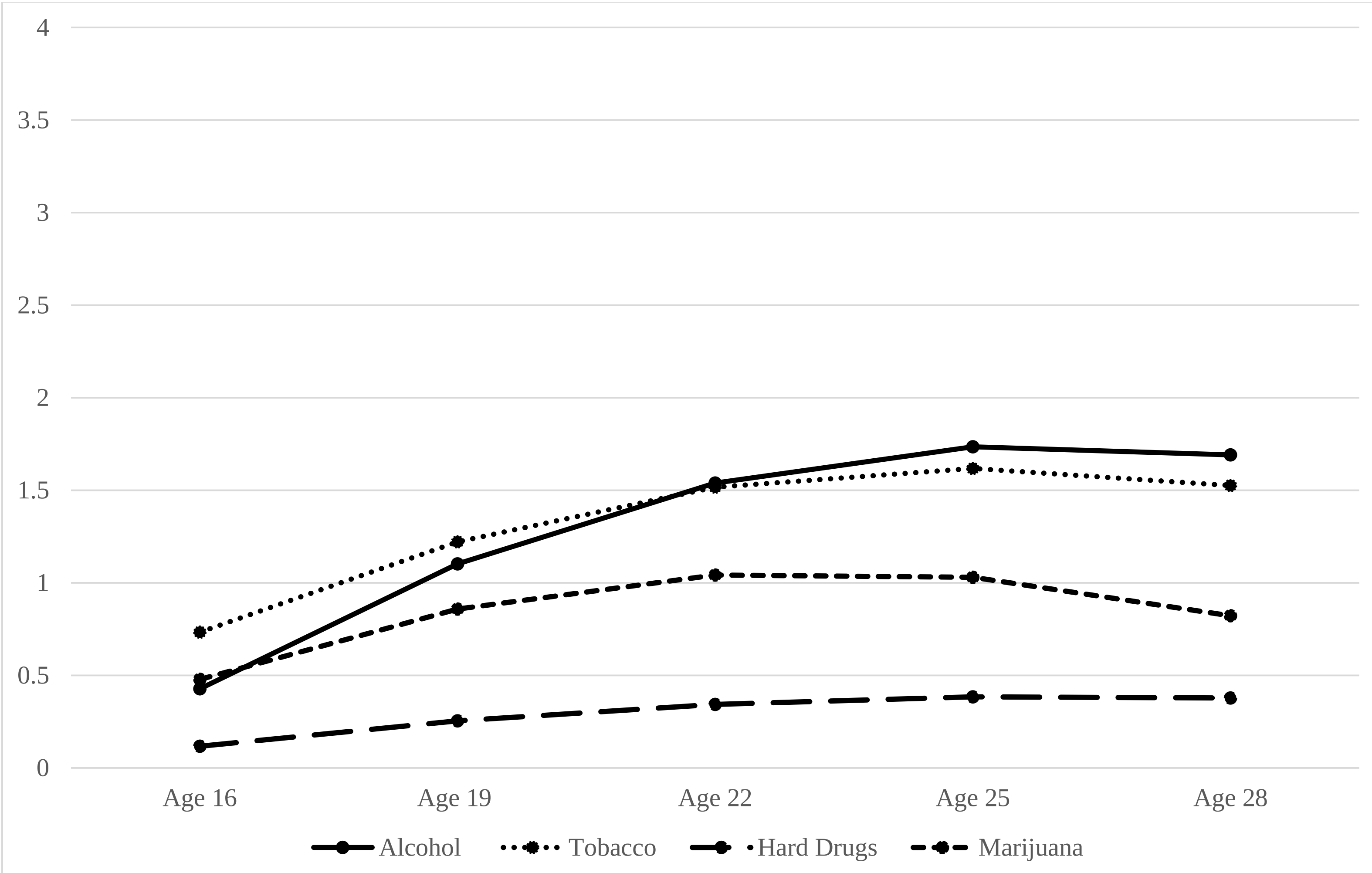


Figure 14. PP LCGA (Class 1: *Increasing Alcohol and Marijuana Users*)

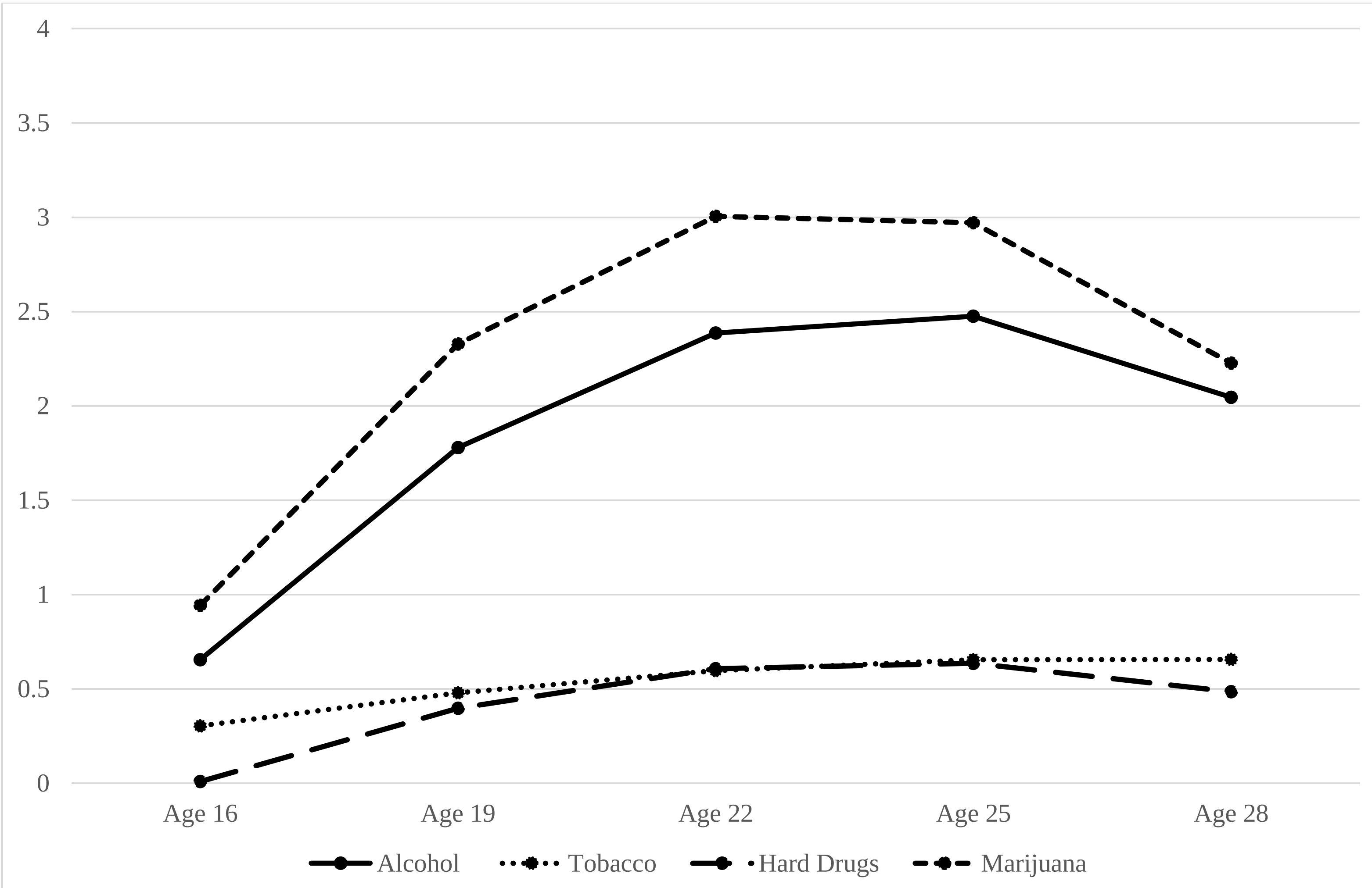


Figure 15. PP LCGA (Class 2: *Increasing Alcohol and Tobacco Users*)

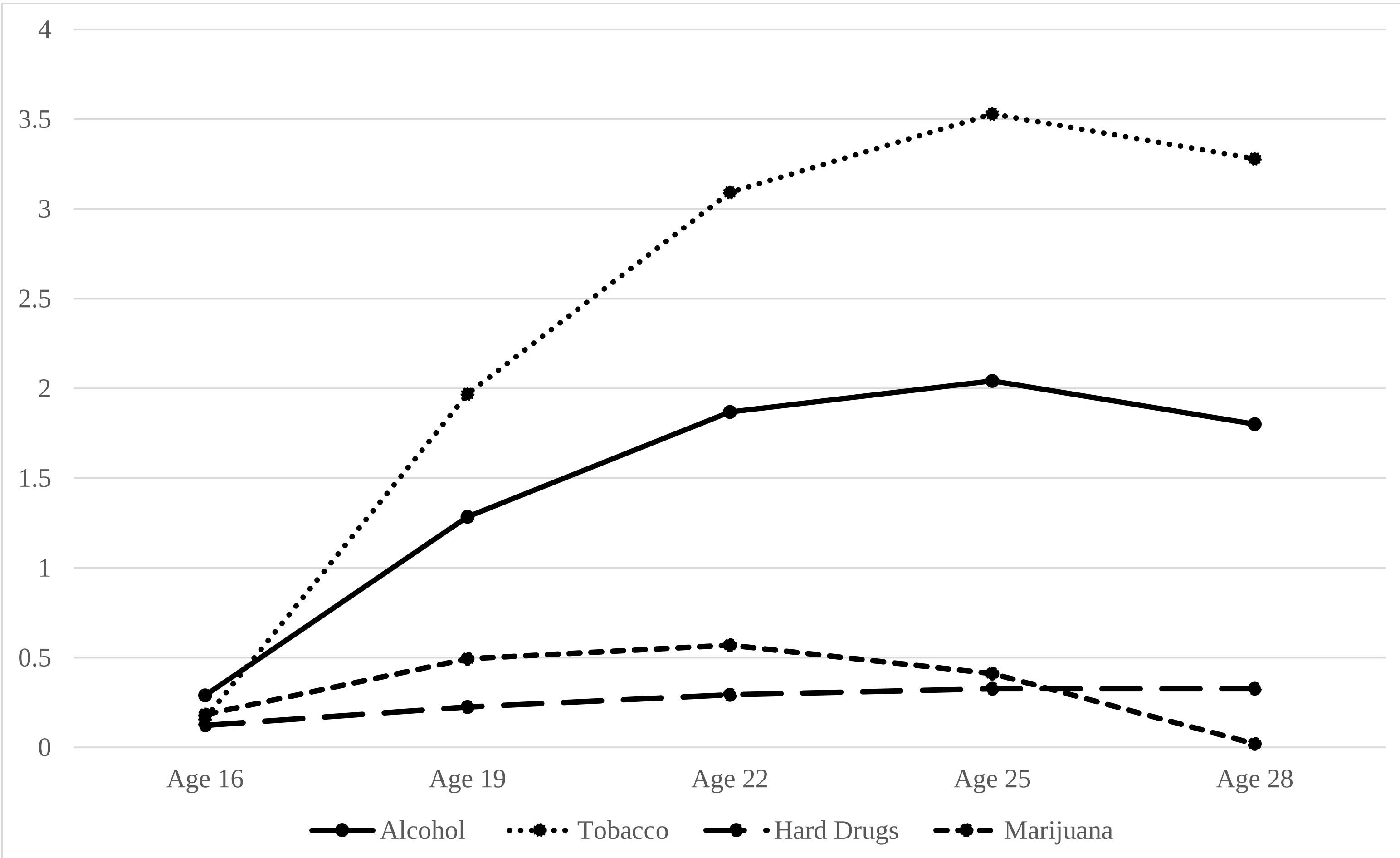
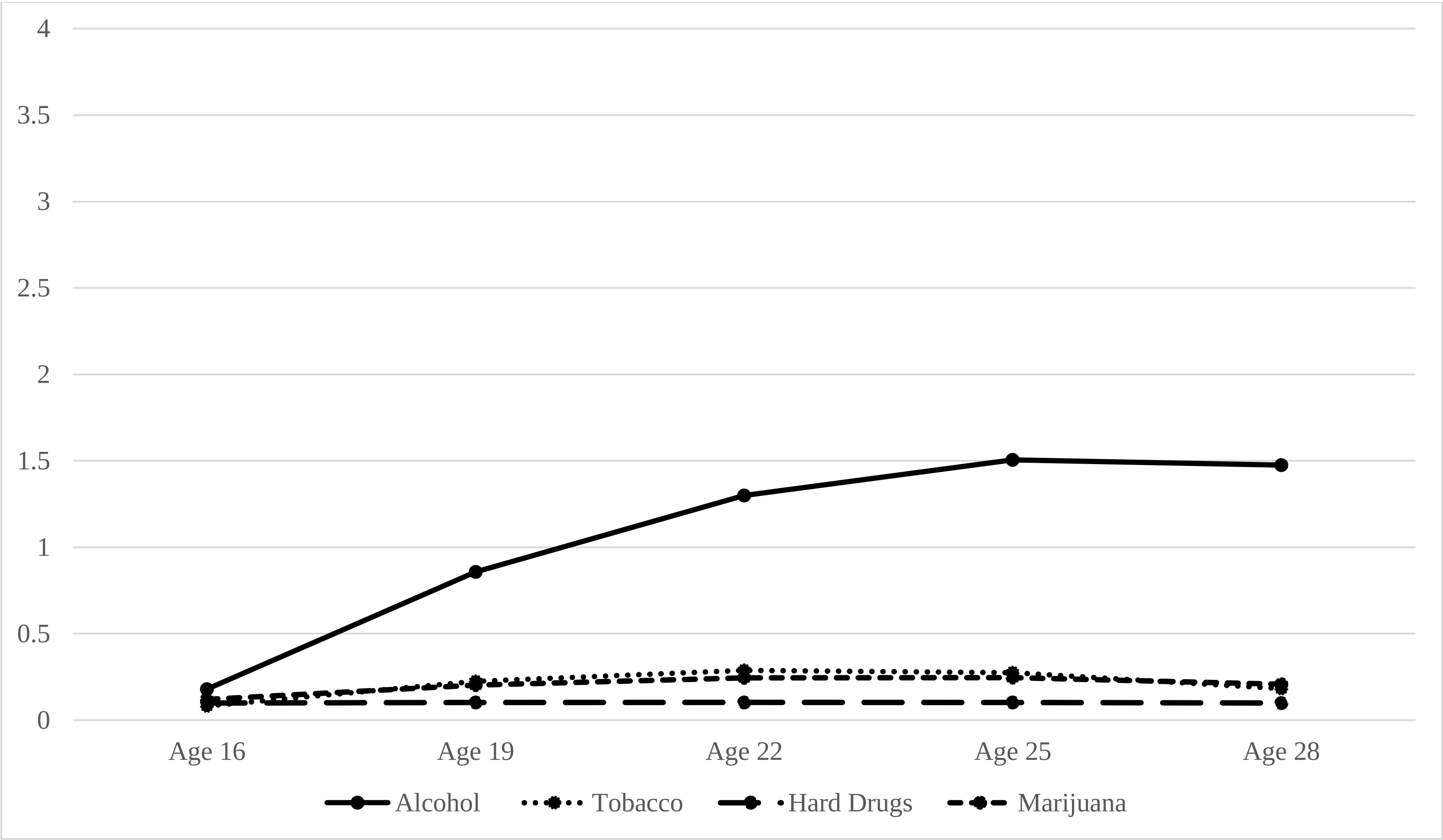


Figure 16. PP LCGA (Class 3: *Increasing Alcohol Users*)



Note: This is the normative use group

Figure 17. PP LCGA (Class 4 *Increasing Alcohol, Marijuana, and Tobacco Users*)

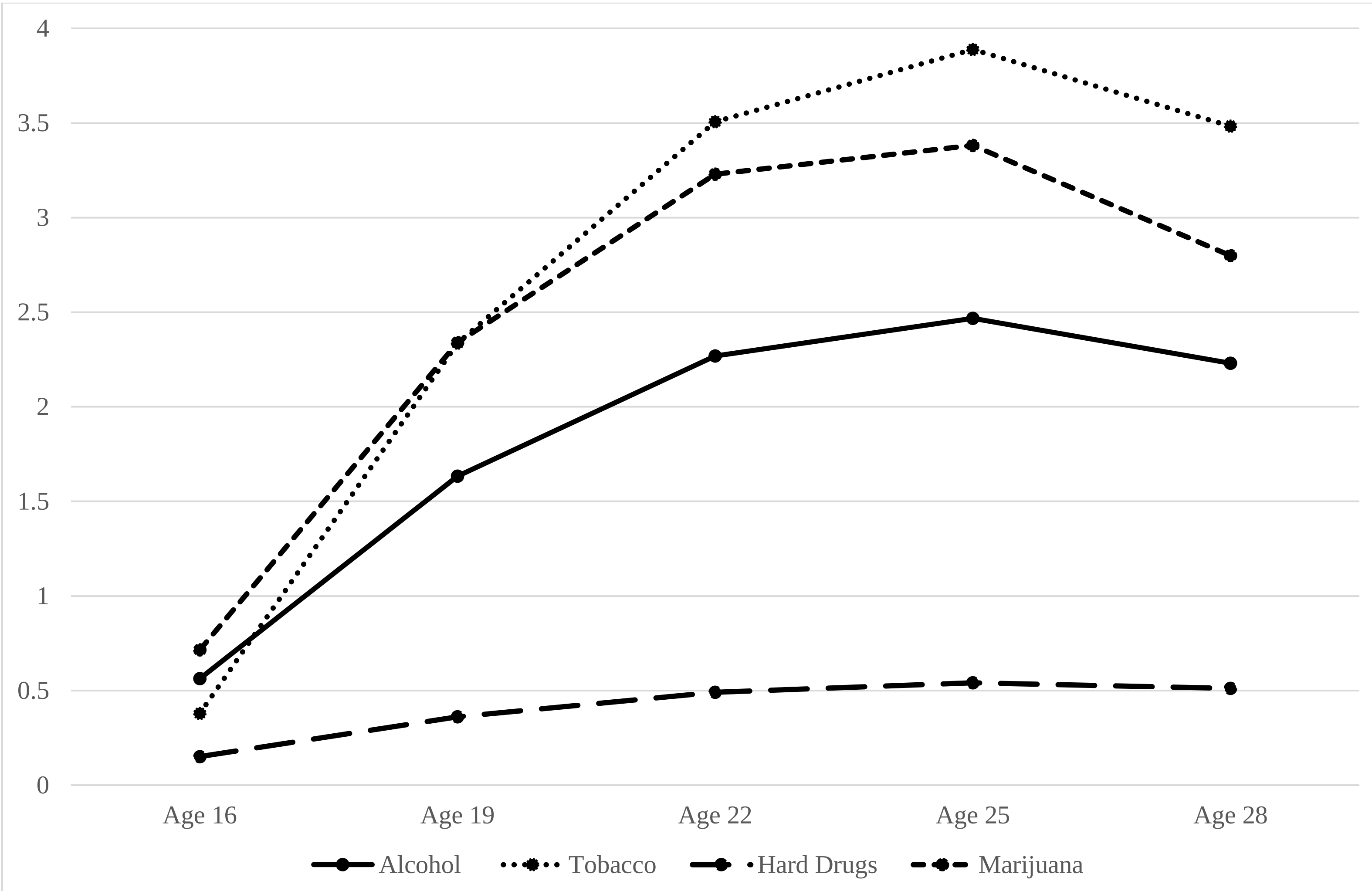


Figure 18. PP LCGA (Class 5: *Stable High Tobacco, Increasing Polysubstance Users*)