

Virginia Commonwealth University [VCU Scholars Compass](https://scholarscompass.vcu.edu/)

[Theses and Dissertations](https://scholarscompass.vcu.edu/etd) [Graduate School](https://scholarscompass.vcu.edu/gradschool) and Dissertations Graduate School and Dissert

2024

TRANSITIONS IN PATTERNS OF SUBSTANCE USE DURING EARLY ADOLESCENCE: BIDIRECTIONAL ASSOCIATIONS WITH EXTERNALIZING BEHAVIORS

Courtney B. Dunn Virginia Commonwealth University

Follow this and additional works at: [https://scholarscompass.vcu.edu/etd](https://scholarscompass.vcu.edu/etd?utm_source=scholarscompass.vcu.edu%2Fetd%2F7828&utm_medium=PDF&utm_campaign=PDFCoverPages)

© The Author

Downloaded from

[https://scholarscompass.vcu.edu/etd/7828](https://scholarscompass.vcu.edu/etd/7828?utm_source=scholarscompass.vcu.edu%2Fetd%2F7828&utm_medium=PDF&utm_campaign=PDFCoverPages)

This Dissertation is brought to you for free and open access by the Graduate School at VCU Scholars Compass. It has been accepted for inclusion in Theses and Dissertations by an authorized administrator of VCU Scholars Compass. For more information, please contact libcompass@vcu.edu.

TRANSITIONS IN PATTERNS OF SUBSTANCE USE DURING EARLY ADOLESCENCE: BIDIRECTIONAL ASSOCIATIONS WITH EXTERNALIZING BEHAVIORS

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University

> By: Courtney B. Dunn Bachelor of Arts, Cleveland State University, 2019 Master of Science, Virginia Commonwealth University, 2021

Co-Chairs: Albert D. Farrell, Ph.D., Professor Emeritus and Rosalie Corona, Ph.D., Professor Department of Psychology

Virginia Commonwealth University Richmond, Virginia April 22, 2024

List of Tables

List of Figures

Acknowledgements

I am filled with immense appreciation for everyone that has helped me get to this stage in my graduate career. To my graduate school advisor, F31 sponsor, and committee co-chair, Dr. Albert Farrell, I extend my deepest gratitude. Your consistent and thoughtful mentorship has helped me grow into a better analytic thinker, writer, and teacher. Your guidance has fostered my passion for prevention research, advanced statistics, and mentorship. I cannot express how thankful I am that you chose to advise one last student.

I am extremely grateful to my committee co-chair, Dr. Rose Corona for serving as my cochair and always being willing to offer her time and mentorship for myself and other students in the clinical psychology program. I would like to thank Dr. Corona for her guidance throughout graduate school in addition to bringing her research expertise to my committee. I would also like to express my sincere thanks to my committee members, Drs. Rashelle Musci, Terri Sullivan, and Dace Svikis. I truly appreciate your time and expertise, which has been invaluable throughout the process of completing my dissertation.

Many others have provided training and mentorship during my undergraduate and graduate education that have made this possible. My first research mentor, Dr. Liz Goncy, inspired me to pursue this career and taught me many fundamental skills that I still rely on. My fellow Farrell team members and academic sisters have provided instrumental informal mentorship and support that helped me pass each program milestone, submit a strong F31 application, and find my career path. I could not have done it without them. Each of my clinical supervisors have challenged me to take on new perspectives and motivated my desire to conduct research that aims to improve the lives of children and families.

vii

The research reported in this document was supported by the National Center for Injury Prevention and Control, Centers for Disease Control and Prevention (CDC; 5U01CE001956), the National Institute of Justice (NIJ; 2014-CK-BX-0009), and the National Institute of Drug Abuse (NIDA; F31DA057108). The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the CDC, NIJ, or NIDA. I offer my gratitude to the teachers and students who participated and the staff who implemented the project from which the data for this study were derived. I would like to thank Drs. Farrell and Sullivan for allowing me to use this data.

Lastly, I want to express my appreciation to my family and friends who have helped me through some of the most challenging and rewarding years of my life. I want to thank my cohort mates and closest friends, Carine, Rachel A., & Rachel H., for *many* hours of co-working, encouragement, and pure joy amidst the challenges of grad school. I am so grateful that this experience brought us together and am excited to see what we all achieve from here. To my parents, Charly and Susie, thank you for always believing in me and helping me grow into the person I am today. Thank you to my second family, Heather and Jerone, and sister, Helen, for all of your encouragement along the way. To my partner, Nathaniel, thank you for the never-ending love, security, and laughter that you bring to my life. Thank you for moving with me, making me close my laptop at the end of the day, and celebrating every little accomplishment over the past five years. Last, but certainly not least, I want to thank our cat (daughter), Phoebe, for bringing me more comfort and happiness than I could have imagined and being the best decision I made during grad school.

Abstract

Early adolescents who engage in polysubstance use, defined as the use of three or more different substances, are at particularly high risk of future substance use disorders and adverse psychosocial outcomes. However, little is known about the development of substance use patterns during early adolescence, particularly among youth living in urban settings. Although theory and research suggest that youth with greater externalizing behaviors (e.g., aggression, delinquent behavior) may be more likely to escalate to polysubstance use at an early age, few studies have examined bidirectional relations between externalizing symptoms and polysubstance use. The goal of this study was to (a) identify subgroups of middle school students based on their history of initiation and recent substance use and examine transitions in those subgroups across two waves, and (b) evaluate longitudinal bidirectional associations between externalizing behaviors (i.e., aggression, delinquency) and substance use subgroups. Participants were 1,811 early adolescents (72% Black, 53% female) attending middle schools in neighborhoods with high rates of violence and of residents with incomes below the federal poverty line.

I used latent class analysis to identify subgroups of adolescents with different substance use patterns at two waves of data that were 3 months apart. A 4-class model was identified as optimal at both waves based on fit indices. The subgroups included (a) *Non-use* (76% of sample at wave 1, 73% at wave 2), (b) *Initiation* (11%, 13%), reflecting high probabilities of initiation of 2 or more substances, (c) *Alcohol Use* (7%, 7%), reflecting high probabilities of past 30-day alcohol use, and (d) *Polysubstance Use* (6%, 7%), reflecting high probabilities of alcohol, cannabis, and cigar use in the past 30-days. I then used latent transition analysis (LTA) to examine changes in subgroup membership over time and their prospective bidirectional

associations with externalizing behaviors. LTA revealed longitudinal changes in substance use patterns among those early adolescents who had already initiated substance use. Whereas change in externalizing behaviors over time was not impacted by adolescents' substance use patterns, adolescents who reported more frequent externalizing behaviors were more likely to initiate substance use, particularly polysubstance use, 3 months later. Delinquent behavior predicted initiation of polysubstance use even after accounting for distress symptoms, providing support for the pathway to early substance use onset via delinquent behaviors. These findings indicate that early adolescents engaging in substance use are not consistently using the same number of substances across 3-month periods. This study's findings also suggest that selective prevention efforts for early adolescents with externalizing symptoms may be beneficial. Additional implications of these findings for theory and interventions are discussed.

Transitions in Patterns of Substance Use During Early Adolescence:

Bidirectional Associations with Externalizing Behaviors

Substance use among early adolescents is a significant public health concern. Drug and alcohol use and misuse costs over \$740 billion annually in the United States (U.S.; National Institute on Drug Abuse, n.d.). Substance use often begins during adolescence (Johnston et al., 2021). Initiation of substance use during early adolescence (i.e., ages 10 to 14 years old) in particular, is associated with adverse outcomes including the subsequent development of substance use disorders (Griffin et al., 2010; Hingson et al., 2006). Whereas substance use refers to any consumption of alcohol, cannabis, tobacco, or other drugs, polysubstance use refers to the use of three or more of these substances during a given time frame (Conway et al., 2013). Polysubstance use during adolescence has been associated with greater risk for adverse outcomes compared with single substance use (Conway et al., 2013; Johnson et al., 2020; Moss et al., 2014). Research suggests that engaging in polysubstance use during adolescence is associated with a greater likelihood of polysubstance use during young adulthood (Merrin & Leadbeater, 2018), development of substance use disorders (Moss et al., 2014), and other adverse psychosocial outcomes (Connor et al., 2014; Green et al., 2016). This makes it vital to understand developmental risk processes that occur during early adolescence when onset and escalation in substance use begins.

Effective prevention efforts require an understanding of factors that contribute to the development of substance use during early adolescence. A robust body of literature indicates that externalizing psychopathology is related to adolescent-onset substance use and misuse (for a review, see Patrick & Schulenberg, 2014). Externalizing symptoms include a spectrum of behaviors such as aggression, inattention, hyperactivity, and delinquent behavior (Achenbach &

Edelbrock, 1984). Developmental theories assert several explanations for the relation between externalizing and substance use, including the contention that they co-occur due to common risk factors (Jessor, 1991) and that externalizing behaviors play a causal role in substance use development (Dodge et al., 2009; Zucker, 2006). Other theories argue that substance use may also lead to exacerbated externalizing behavior, such that the behaviors are reciproccally related over time (Goldstein, 1985; Moffitt, 1993; Parker & Auerhahn, 1998). Research consistently supports positive associations between externalizing behaviors and adolescents' substance use (Farrell, Goncy, et al., 2018; Sacco et al., 2015), and indicates that youth with higher levels of externalizing behaviors are more likely to report early onset of substance use and increase their use during adolescence (King et al., 2004; Maslowsky et al., 2014). However, studies examining their bidirectional associations have yielded inconsistent findings (D'Amico et al., 2008; Turner et al., 2018). Although theory suggests that youth with externalizing behaviors are at greater risk for polysubstance use (Iacono et al., 2008), few studies have examined relations between externalizing behaviors and polysubstance use. Consequently, there is a need for robust research that examines longitudinal bidirectional associations between externalizing and patterns of polysubstance use among early adolescents. This would inform prevention efforts by elucidating the developmental sequence of these behavioral concerns and identifying youth who may be at high-risk for escalating to polysubstance use during early adolescence.

Youth with externalizing behaviors may be particularly susceptible to substance use initiation and escalation during the developmental stage of early adolescence. The externalizing pathway posits that youth with externalizing behaviors often initiate and escalate substance use at an early age, which increases their subsequent risk for substance use disorders (Zucker, 2006). These youths' difficulty with behavioral regulation, paired with developmental changes that

occur during the transition to adolescence, contribute to increased risk of substance use at this age. Biopsychosocial developments that occur during adolescence make it a period of elevated vulnerability for risky behavior such as substance use (Steinberg, 2007). The brain region involved in regulating behavior (i.e., prefrontal cortex) undergoes structural changes and begins developing, while the importance of reward and novelty seeking is simultaneously heightened (Caudle & Casey, 2013; Spear, 2000). Adolescents are particularly susceptible to peer influence due to amplified rewards from interactions with their peers. Indeed, a large portion of U.S. youth initiate substance use during adolescence (Johnston et al., 2021). Although the likelihood of substance use increases for all youth during early adolescence, theory suggests that those with externalizing symptoms are at particularly heightened risk of substance use onset and escalation.

A major limitation of the literature on substance use is that most studies examine only one particular substance at a time or use a composite measure of multiple substances. These approaches prevent researchers from describing developmental patterns that include co-occurring use of multiple substances, and from identifying risk factors for polysubstance use. Prior studies have used mixture modeling approaches, which identify subgroups of individuals with similar responses to a set of items (Masyn, 2013), to describe cross-sectional patterns of adolescents' substance use. Prior studies have typically identified three to four subgroups that vary in the type of substances used and frequency or quantity of their use (for reviews, see Halladay et al., 2020; Tomczyk et al., 2016). Although research suggests that substance use patterns vary across adolescents of different cultural or racial backgrounds (Chung et al., 2013), developmental stages (Rose et al., 2018), and settings (Goldstick et al., 2016; Schneider et al., 2020), few studies have examined substance use patterns among specific subpopulations. In addition, limited research has described how polysubstance use develops throughout early adolescence. A better

understanding of the timing and sequencing of escalation in polysubstance use during early adolescence is needed to effectively prevent early initiation of polysubstance use and associated adverse outcomes.

The primary aims of this study were to identify changes in substance use patterns among middle school students and examine the extent to which concurrent and prospective bidirectional associations exist between externalizing behaviors and substance use patterns. The focus of the present study was on a primarily Black sample of early adolescents attending middle schools serving urban communities with high rates of violence and where most residents' incomes were below the federal poverty threshold. Although youth living in underserved urban communities, especially Black and Latiné youth, are at disproportionately high risk of experiencing adverse outcomes as a result of substance use (Jackson, 2010; Kakade et al., 2012; Zapolski et al., 2014), few studies have examined the role of externalizing behaviors in their substance use development. The results of this study thus have implications for substance use prevention and intervention among early adolescents living in urban communities.

Competing Theories of Relations between Externalizing Behaviors and Substance Use *Theoretical Framework*

Developmental psychopathology provides a framework for understanding factors that contribute to the development of behavior across the lifespan (Cicchetti, 2006). A key premise of this framework is that developmental processes are complex and vary across and within individuals. The concept of multifinality asserts that not all children who experience risk factors for early-onset substance use necessarily begin using substances during adolescence (Cicchetti $\&$ Rogosch, 1996). Moreover, numerous interacting developmental pathways can lead to adolescent-onset substance use (i.e., equifinality). Two primary developmental pathways have

been proposed to explain the association between childhood psychopathology and adolescent substance use. The internalizing pathway posits that difficulties with emotion regulation and negative affect symptoms (i.e., depression, anxiety) during childhood predict elevated risk to use substances during adolescence as a means to cope with negative affect (Hussong et al., 2011; Zucker, 2006). The externalizing pathway, the focus of this study, posits that difficulty with behavioral control as indicated by childhood aggressiveness, impulsivity, and disruptive behavior leads to early-onset substance use (Iacono et al., 2008; Zucker, 2006). Though most theories focusing on externalizing symptoms contend that an underlying tendency for disinhibition contributes to the association between externalizing behavior and substance use, they propose different processes to explain the etiology and sequencing of these behaviors.

Co-development of Externalizing and Substance Use

Common cause models posit that externalizing behaviors and substance use co-occur because they have shared risk factors. Jessor's (1991) problem behavior theory maintains that risk and protective factors at the genetic, personality, behavior, and environmental levels contribute to adolescents' likelihood of engaging in delinquency, illicit drug use, and other health-compromising behaviors. Moffit's (1993) developmental taxonomy of antisocial behavior also considers substance use, aggression, and delinquent behavior to be manifestations of antisocial behavior that develop as a function of the child's personality and the caregiving and environmental context. According to this model, a large portion of youth on the "adolescentlimited" pathway begin to engage in delinquent behavior and substance use during adolescence but stop engaging in these behaviors during emerging adulthood (Moffit, 1993). Common cause models therefore argue that for a portion of the population, externalizing behaviors and substance use co-occur during adolescence and are largely a function of the same biopsychosocial

influences.

Consistent with these theories, externalizing behaviors and substance use commonly cooccur among adolescents and adults (Armstrong & Costello, 2002; Becker et al., 2021). Individuals with trajectories of high and increasing frequencies of externalizing behaviors across adolescence also tend to follow high and increasing substance use trajectories (Farrell, Goncy, et al., 2018; D. Y. C. Huang et al., 2012; Lynne-Landsman et al., 2011; van Lier et al., 2009). For example, Huang et al. (2012) identified multiple trajectories of alcohol use, cannabis use, and delinquency between ages 14 to 20 in a nationally representative U.S. sample. Youth in the low alcohol and cannabis trajectories were most likely to also be in the low delinquency trajectory, whereas those with high and high-increasing trajectories of alcohol and cannabis use had a greater probability of being in the higher delinquency trajectories. In another study focused on a primarily Black sample of early adolescents, Farrell et al. (2018) found that aggression and delinquency were positively correlated with substance use at the beginning of sixth grade. Youth with steeper subsequent increases in delinquency throughout middle school also tended to report steeper increases in their substance use. Change in aggression, however, was not related to change in substance use. These findings indicate that youth who engage in more externalizing behaviors tend to also engage in more substance use during adolescence, though these associations may vary across the form of externalizing behavior.

Causal Pathways Between Externalizing and Substance Use

Other theories have proposed a developmental, causal pathway from childhood externalizing behaviors to early-onset substance use. Researchers studying typologies of alcohol use disorder among adults described a subgroup of individuals with early onset alcohol use and externalizing behaviors (Cloninger, 1987; Zucker, 2006). For example, within a developmentalbiopsychosocial model of alcohol use and alcohol use disorders, Zucker (2006) defined "Antisocial alcoholism" as a subgroup of individuals with alcohol use disorders who presented with a childhood-onset trajectory of oppositional behaviors and conduct problems. In contrast, "developmentally limited alcoholism" represented individuals with comorbid antisocial behavior and alcohol use that was limited to adolescence. Similarly, Moffit's (1993) developmental taxonomy states that a small portion of the population display "life-course persistent" antisocial behavior, beginning as defiant behavior in early childhood and progressing to delinquent behavior and substance use during adolescence. According to these developmental theories, the child's behavior is a function of the interaction between their underlying tendencies and environmental contexts. In particular, interactions with caregivers and peers are considered highly influential in the progression from childhood externalizing to adolescent-onset substance use. A combination of ineffective caregiving styles (e.g., limited monitoring), rejection by prosocial peers, and affiliation with peers who engage in delinquent behaviors are thought to contribute to increasing opportunities and norms supporting substance use during adolescence (Dodge et al., 2009; Oetting & Donnermeyer, 1998; Reid & Patterson, 1989). These theories thus assert that youth who present with a trajectory of externalizing behavior from a young age are more likely to initiate substance use during early adolescence and are at greater risk for problematic substance use during adulthood.

In accordance with the externalizing pathway, research has typically found positive longitudinal relations between externalizing behaviors and initiation or increases in substance use during adolescence (e.g., Herrenkohl et al., 2009; King et al., 2004; Maslowsky et al., 2014; van den Bree & Pickworth, 2005; Windle, 1990b). King et al. (2004) examined associations between externalizing disorders (i.e., conduct disorder, oppositional defiant disorder, attentiondeficit/hyperactivity disorder) at age 11 and onset of alcohol, nicotine, and cannabis before age 14 (i.e., early onset) using data from the Minnesota Twin Family Study. After excluding children who reported substance use at age 11 and accounting for clustering within twin pairs, having an externalizing diagnosis predicted substantially elevated risk for early initiation of alcohol, nicotine, and cannabis use by age 14, as well as regular monthly use and heavy use (i.e., drunkenness, daily smoking). When King et al. (2004) examined associations with more specific diagnoses, conduct disorder and oppositional defiant disorder predicted all substance use outcomes, whereas attention-deficit/hyperactivity disorder only predicted greater risk of nicotine and cannabis use. Other studies have similarly found that externalizing problems predict subsequent increases in alcohol and cannabis use, but not tobacco use (Herrenkohl et al., 2009; Maslowsky et al., 2014; Windle, 1990). These findings suggest that externalizing behaviors predict increases in substance use, though they may have different relations with specific types of substance use.

Bidirectional Associations Between Externalizing and Substance Use

Several developmental theories maintain that externalizing behaviors and substance use, once initiated, may reinforce each other, and have positive bidirectional relations over time. Moffit's (1993) "snares" hypothesis contended that engaging in one deviant behavior can lead to a series of adverse consequences, seemingly narrowing opportunities for future prosocial behavior. For example, using substances might prevent an adolescent from participating in prosocial extracurricular activities, interrupt their educational attainment, and motivate them to maintain ties with deviant peers, thus "snaring" them into continued antisocial behavior (Hussong et al., 2004). In addition, substance use may relate to increased future aggression or delinquency because the psychopharmacological effects of substances increase the likelihood of

engaging in impulsive and aggressive behavior (Goldstein, 1985; Parker & Auerhahn, 1998). Each behavior may reinforce the need for the other over time, such that youth engage in delinquent activities to support purchasing of substances (Goldstein, 1985). Finally, peers may play a key role in bidirectional associations between externalizing and substance use. Adolescents with externalizing problems may join peer groups with similar behaviors, which leads them to initiate new behaviors, such as substance use, or engage in delinquent behaviors more frequently (Oetting, 1999; Oetting & Donnermeyer, 1998).

Empirical research has generally not supported bidirectional associations between externalizing behaviors and substance use. Most studies have found that externalizing behaviors predict change in substance use, whereas substance use does not influence future externalizing behavior (Bui et al., 2000; Dunn & Farrell, 2023; Farrell et al., 2005; Miller et al., 2016; Turner et al., 2018). For example, one study found that more frequent aggression in sixth grade predicted steeper increases in alcohol use across middle school among a large multisite sample (Dunn & Farrell, 2023). In contrast, the sixth-grade frequency of alcohol use did not predict change in aggression. Another study found that delinquency in the 10th grade predicted increases in the frequency of substance use in 12th grade among a primarily White sample of U.S. students (Bui et al., 2000). Substance use in 10th grade, however, did not predict change in delinquent behavior.

Although several studies have found partial support for bidirectional positive associations between externalizing behaviors and substance use, their findings have varied across the type of substance and the adolescents' individual characteristics. For example, one study found positive bidirectional relations between delinquency and the use of illicit drugs other than cannabis, but not cannabis use (Ford, 2005). Another study found positive bidirectional relations between

substance use and delinquency across four waves spanning 1 year among youth involved in the juvenile justice system, though the sample consisted primarily of male adolescents (i.e., 87%; D'Amico et al., 2008). Mason and Windle (2002) found that substance use and delinquency were reciprocally related for male high school students, but not female students. There is thus limited robust research that supports bidirectional associations, and the strongest evidence has found that these effects are limited to male adolescents. In conclusion, most research indicates that externalizing behaviors predict subsequent increases in substance use, but not vice versa.

Sex and Gender Differences in the Externalizing Pathway

A key premise of developmental psychopathology is that developmental risk pathways might vary based on sex assigned at birth or gender identity (Pickles & Hill, 2006). However, studies that have examined sex or gender differences in associations between externalizing behaviors and substance use have found mixed results. Several studies have found that these relations are generally consistent across sex (Farmer et al., 2015; Heron et al., 2013; B. Huang et al., 2001; Jun et al., 2015; McAdams et al., 2014; Miller et al., 2016; van den Bree & Pickworth, 2005; Windle, 1990). Other studies have found stronger relations between delinquent behavior and substance use for male adolescents than for female adolescents (Maslowsky et al., 2014; Mason & Windle, 2002; Skara et al., 2008; Windle, 1990). For example, two studies found positive longitudinal relations between delinquent behavior and substance use only for male adolescents, but not for female adolescents (Maslowsky et al., 2014; Mason & Windle, 2002). In contrast, another study found that concurrent relations between delinquent behavior and increases in alcohol use were greater for female adolescents (Gottfredson et al., 2019). Notably, sample characteristics varied across these studies, such that the studies included youth from rural areas (Gottfredson et al., 2019), primarily white suburban areas (Mason & Windle, 2002), and a

national sample (Maslowsky et al., 2014). Differences may be present only within certain contexts or specific age groups (i.e., among older adolescents but not early adolescents). In addition, it is not known whether studies that found non-significant sex differences had sufficient power to detect differences that exist in the population. These inconsistent findings warrant more research examining sex and gender differences in the association between externalizing behavior and substance use. To help clarify these relations, future research examining sex differences must address the issue of sample size and power to detect effects and employ robust analytic methods for testing moderation (e.g., Memon et al., 2019).

Polysubstance Use during Early Adolescence

Importance of Polysubstance Use in the Externalizing Pathway

A major limitation of theory and research focused on the externalizing pathway is that neither has attempted to account for the role of polysubstance use in this risk pathway. Polysubstance use among adolescents is associated with negative health outcomes, poor academic achievement, and legal involvement (Connor et al., 2014; Green et al., 2016). Relative to single substance use, polysubstance use is related to greater risk of continuing polysubstance use into adulthood (Merrin & Leadbeater, 2018) and developing a substance use disorder during young adulthood (Moss et al., 2014). Research consistently shows that among adolescents who have initiated any substance use (i.e., 38 to 74% of samples across studies), most have used two or more different substances (i.e., 29 to 43% of samples; Coulter et al., 2019; Lamont et al., 2014; Patrick et al., 2018). A smaller but meaningful percentage of adolescents have reported the use of three or more substances (i.e., polysubstance use; 7 to 10%; Coulter et al., 2019; Lamont et al., 2014). Despite considerable evidence of the potential harm of adolescent-onset polysubstance use, existing theories do not fully account for how externalizing relates to earlyonset polysubstance use (Dodge et al., 2009; Zucker, 2006). Iacono et al. (2008) argued that a greater degree of underlying vulnerability for behavioral disinhibition will be reflected in increasing comorbidity and more deviant behavior, such that adolescents who initiate polysubstance use at an early age may have a greater predisposition for disinhibition than those who initiate the use of only one substance. This implies that adolescents who have a greater underlying tendency for externalizing will display both greater externalizing behavior problems and be more likely than their peers to engage in polysubstance use at an early age.

Due to methodological limitations in the measurement of substance use, there is limited empirical evidence of the role of polysubstance use in the externalizing pathway. Most studies reviewed thus far have examined only one substance at a time (e.g., Lynne-Landsman et al., 2011; Sacco et al., 2015; Turner et al., 2018), or created a composite measure that aggregates multiple substances (e.g., Farrell et al., 2005; Farrell, Goncy, et al., 2018; Mason & Windle, 2002; McAdams et al., 2014). Examining only one substance overlooks co-occurring or polysubstance use, whereas composite measures preclude researchers from identifying differences in relations across specific patterns of co-occurring substance use. Both of these measurement approaches thus fail to inform the literature on the sequencing of different patterns of substances and their development over time. In addition, measures that average or sum scores across multiple substances treat all substances as equal, including types that may be developmentally normative versus deviant and those with varying levels of potential harm (e.g., initiation use of alcohol vs opioids). Measurement approaches that account for the co-occurrence of different substances are needed to improve knowledge of the impact of the externalizing pathway on riskier forms of substance use (e.g., polysubstance use) and inform developmental theory.

Patterns of Substance Use among Adolescents

Mixture modeling approaches such as latent class analysis (LCA) enable researchers to describe heterogeneity in the substances that adolescents use. LCA is used to group individuals with similar patterns of responses to a set of items into unique subgroups (Masyn, 2013). This analytic approach has been used to identify subgroups of individuals based on their patterns of use of multiple substances. Two prior systematic reviews have summarized the research examining substance use subgroups among adolescents. Across 23 studies focusing on adolescents ages 10 to 19, Tomczyk et al. (2016) found that most studies identified three or four latent subgroups characterized by no/low substance use, alcohol use only, and one to two polysubstance use subgroups. In an effort to update and expand upon the previous review, Halladay et al. (2020) reviewed 70 studies that used person-centered methods (i.e., mixture models and cluster approaches) to identify subgroups among adolescents ages 11 to 18 based on their substance use and mental health symptoms. The subgroups they identified typically consisted of (a) low substance use, (b) single or dual substance use, (c) moderate multi-use (i.e., polysubstance use), and (d) high multi-use. Single or dual substance use subgroups usually reported using alcohol, alcohol with cannabis, or alcohol with tobacco, whereas polysubstance use subgroups used alcohol, tobacco, cannabis, and, in some instances, other substances. Both Tomczyk et al. (2016) and Halladay et al. (2020) noted that most subgroups were based on binary indicators of either initiation (i.e., at any time during their life) or recent (i.e., past month) substance use, whereas few studies considered frequency or quantity of use. The largest portion of the adolescent samples typically fell within the no/low use subgroup, followed by single or dual substance use. In contrast, polysubstance use subgroups were generally found to represent the smallest percentage of the sample.

Although many prior studies have examined patterns of substance use in national samples (e.g., Conway et al., 2013; Merrin et al., 2018; Patrick et al., 2018), it is vital to consider how these patterns vary across specific subpopulations in order to inform relevant prevention initiatives. Prevalence rates of substance use in the U.S. vary across adolescents of different racial and ethnic backgrounds due to cultural differences in socialization to substance use. More specifically, daily alcohol and tobacco use is more common among White and Latiné adolescents than among Black adolescents, though these differences are less pronounced during early adolescence (Johnston et al., 2018). In contrast, cannabis initiation is more common among Black and Latiné eighth grade students compared with White students.

Several studies have found notable variations in patterns of polysubstance use across adolescents with different racial identities. For example, Chung et al. (2013) examined subgroups of polysubstance use separately for Black and White female adolescents (age 13 to 17) from Pittsburgh. A three-class model was optimal for both groups, consisting of "no use," "alcohol use," and "polysubstance use." However, despite their similar overall patterns, Black and White female adolescents differed in the substances they used. In the polysubstance use subgroup, both Black and White female adolescents had a high probability of alcohol use. Whereas Black female adolescents in the polysubstance use subgroup were more likely to endorse using cannabis (probability $= .89$) than cigarettes (probability $= .59$), White female adolescents had a high probability of cigarette use (probability $= .89$) and only a moderate probability of cannabis use (probability $= .60$). Banks et al. (2020) also examined separate patterns for White and Black high school students in a midwestern state. The four subgroups that emerged among Black youth included "nonuse" (88% of the sample), "alcohol and marijuana" (6%), "alcohol, marijuana, and cigarette" (4%), and "frequent polysubstance use" (2%). In

contrast, in the five subgroups identified among White adolescents, fewer adolescents reported no use (i.e., 73%), one subgroup represented predominantly alcohol use (14%), and three polysubstance use subgroups had a high probability of using three or more substances at different frequencies over the past 30 days (i.e., 9%, 2%, and 2%). Although these studies included primarily middle to late adolescents, the findings suggest that Black adolescents may be less likely to engage in polysubstance use and that their typical patterns of co-occurring substance use differ from White adolescents.

Because rates of substance use vary regionally and across settings in the U.S. (e.g., urban vs rural; Kogan et al., 2006; Mack et al., 2017), the study setting should also be considered when examining substance use patterns. Findings from past studies that focused on specific populations provide insight into developmental patterns for youth in different settings. For example, Rose et al. (2018) examined subgroups among a racially diverse sample of adolescents (26% American Indian, 26% African American, 29% White) in an economically disadvantaged rural setting. The subgroups they identified (i.e., nonuse, primarily alcohol use, low frequency polysubstance use, and moderate-to-high frequency polysubstance use) were fairly consistent with the typical patterns identified in prior literature reviews (Halladay et al., 2020; Tomczyk et al., 2016). In contrast, three studies focused on samples of youth living in urban settings, which primarily consisted of Black or African American adolescents. Among middle and high school students in Mobile, Alabama, less than 3% represented a polysubstance use subgroup (Johnson et al., 2020). Most students engaged in no use (48%), followed by those who engaged in alcohol and cannabis use (32%), and alcohol only (18%). After limiting their samples to youth who endorsed a history of substance use, Schneider et al. (2020) and Goldstick et al. (2016) both identified three subgroups. Among high school students in Baltimore, Maryland, subgroups

consisted of alcohol and cannabis use (67%), drugs and alcohol use (22%), and polysubstance use (9%; Schneider et al., 2020). Among adolescents presenting to the emergency department in Flint, Michigan who screened positive for substance misuse, subgroups included cannabis only (28%), alcohol and cannabis (16%), and polysubstance use (5%; Goldstick et al., 2016). These studies of youth in urban settings have generally identified subgroups with a lower prevalence of polysubstance use, and a larger proportion who report use of cannabis with or without alcohol use, compared with national samples (e.g., Connell et al., 2009; Conway et al., 2013; Lamont et al., 2014) and rural samples (Rose et al., 2018).

The developmental stage of early adolescence is highly relevant for the study of polysubstance use. Onset of substance use during early adolescence is less normative than in later stages of adolescence (Johnston et al., 2021) and any level of use at this age has been associated with adverse outcomes (Chen et al., 2009; Grant & Dawson, 1997). Focusing on this developmental stage may reveal patterns of substance use among youth at the highest risk for adverse outcomes and escalating substance use. However, most prior studies have focused on high school-aged adolescents (e.g., Patrick et al., 2018) or included a wide age range spanning adolescence (e.g., 12 to 18; Gilreath et al., 2014; Johnson et al., 2020). One exception is a study by Rose et al. (2018) that examined subgroups separately for middle school and high school students living in a rural, economically disadvantaged setting. Although similar subgroups were identified in the two age groups, the proportions in each subgroup varied. More middle school students reported no use (i.e., 63%) compared with high school students (i.e., 47%). In contrast, more high school students belonged to subgroups engaging in primarily alcohol use (i.e., 38%), low frequency use (i.e., 6%), and moderate-to-high frequency use (i.e., 10%) compared with

youth in middle school (i.e., 31%, 4%, and 3%, respectively). More research is thus needed to determine typical patterns of substance use that emerge during early adolescence.

Few studies have examined how substance use patterns develop over time among adolescents. The gateway hypothesis states that adolescents typically start using legal substances (e.g., alcohol, tobacco) and then progress to illicit substances (e.g., cannabis, cocaine, heroin; Kandel & Kandel, 2015). Researchers have argued that a longitudinal extension of mixture modeling, latent transition analysis (LTA), is well-suited to examine progressions in patterns of substance use over time (Maldonado-Molina & Lanza, 2010). This approach uses LCA to identify subgroups of substance users at two or more time points, and then examines the probability of transitioning from one subgroup to other subgroups over time. In a study designed to test the gateway hypothesis in a U.S. national sample of tenth grade students, Maldonado-Molina and Lanza (2010) found that subgroups of students who used alcohol were more likely to transition to using cigarettes over time than subgroups who did not use alcohol. Subgroups of youth who used cigarettes and alcohol were more likely to transition to cannabis use over time. However, this study was limited to patterns of alcohol, cigarette, and cannabis use, and only examined specific transitions from legal to illicit substances (e.g., cigarette use to cannabis use) that are hypothesized by gateway theory.

Other studies have more generally explored transitions in substance use subgroups over time. For example, Choi et al. (2018) examined changes in substance use subgroups across three annual waves of data between grades 10 to 12 in an ethnically diverse sample. Youth in all subgroups (i.e., low use, alcohol and cannabis, polysubstance use) were most likely to remain in the same subgroup over time. When youth in the low use subgroup transitioned over time, they had the highest probability of transitioning to alcohol and cannabis use (conditional probabilities $=$.18 from wave 1 to 2; .21 from wave 2 to 3). The alcohol and cannabis use subgroup had a higher probability of transitioning to polysubstance use (probabilities = .08 wave 1 to 2; .04 wave 2 to 3) than to low use (probabilities $= .00$ both transitions). Mistry et al. (2015) examined data from a primarily African American sample of adolescents in 10th grade and found high stability of membership in substance use subgroups 2 and 4 years later. However, adolescents who reported no use had a small probability of transitioning to alcohol and cannabis use (probabilities $= .10$ wave 1 to 2; $.19$ wave 2 to 3) and polysubstance use (i.e., alcohol, cannabis, and tobacco; probabilities $= .09$ wave 1 to 2; $.05$ wave 2 to 3). Alcohol and cannabis users had a small-to-moderate probability of transitioning to polysubstance use across waves (i.e., alcohol, cannabis, and tobacco; probabilities $= .37$ wave 1 to 2; .30 wave 2 to 3). Similar patterns of change were found in a sample of children and adolescents in Spain (Zych et al., 2020), and in a study that examined six transitions across 10 years in a sample that included adolescents and adults (i.e., ages 12 to 18 at baseline; Merrin et al., 2018). In contrast, in their study examining transitions in a high-risk sample of adolescents involved in publicly funded service systems (e.g., child welfare, juvenile justice), Shin (2012) found that nearly 92% of the sample changed subgroups over time. This suggests that adolescents exposed to higher levels of risk may be more likely to escalate their substance use patterns over time.

Although few studies have examined the development of polysubstance use during adolescence, existing research suggests several typical patterns. First, most studies agree that the majority of adolescents remain in the same subgroup over time, with only small to moderate probabilities (i.e., probabilities < .50) of changing subgroups across time (Choi et al., 2018; Merrin et al., 2018; Mistry et al., 2015; Tomczyk et al., 2016; Zych et al., 2020). The most common transitions that occur represent escalation in substance use. As predicted by the gateway hypothesis, youth engaging in no or low use are most likely to transition to subgroups reporting use of one to two substances, whereas single- or dual-use subgroups are relatively more likely to transition to polysubstance use subgroups (Choi et al., 2018; Maldonado-Molina & Lanza, 2010; Merrin et al., 2018; Mistry et al., 2015; S. Shin, 2012; Zych et al., 2020). Studies have found a small probability that youth in polysubstance subgroups de-escalate their substance use, and rarely transition to subgroups reporting no substance use once initiated (Choi et al., 2018; Merrin et al., 2018; Tomczyk et al., 2016). In addition, Mistry et al. (2015) found that transitioning from subgroups characterized by recent substance use to non-use subgroups became less likely during early adulthood, suggesting that substance use patterns become more fixed with age. More research in this area is urgently needed to inform effective and timely interventions to prevent escalation to polysubstance use at an early age.

Limitations in Polysubstance Use Research

Prior research has typically found three to four subgroups of adolescent substance use that differ in the types of substances and frequency or quantity of use (Tomczyk et al., 2016; Halladay et al., 2020). However, these studies have several notable limitations. Most have only considered adolescents' reported lifetime initiation (e.g., Johnson et al., 2020; Rose et al., 2018; Schneider et al., 2020) or recent substance use (e.g., past 30 days; Banks et al., 2020; Conway et al., 2013; Su et al., 2018) as indicators of subgroups. Exclusively considering initiation fails to provide information about whether adolescents continued using, or the extent or amount of their use. Focusing solely on recent use means that adolescents who have initiated use, but not used recently, are assigned to the "non-use" subgroup. A more representative depiction of adolescents' substance use patterns would be obtained by considering both their initiation of substances, and the extent of their recent use. The quantitative (i.e., the size of subgroups) and

qualitative (i.e., the types of patterns) differences across various settings and among youth of different ages and settings suggests the need to examine patterns of use within particular populations rather than focusing solely on overall patterns in nationally representative samples. In addition, more research to identify early adolescents' substance use patterns is needed to inform tailored, relevant prevention programming targeting this age group.

Regarding the research on changes in polysubstance use over time, prior studies have used methodologies that may limit their ability to effectively inform prevention efforts. First, no LTA studies to my knowledge have examined transitions in polysubstance subgroups among early adolescents (i.e., during middle school). Several prior studies have examined changes in samples of high school students (Choi et al., 2018; Maldonado-Molina & Lanza, 2010; Mistry et al., 2015). Others have included a wide age range at each wave of the LTA (Merrin et al., 2018; Shin, 2012; Tomczyk et al., 2016). For example, two samples included youth in early through late adolescence at the first wave (i.e., ages 12 - 18; Merrin et al., 2018; Shin, 2012). Because early adolescence is a critical period for initiation of substance use that is often the target of prevention programs, research examining the development of polysubstance use throughout this stage is needed. Moreover, most prior studies have focused on time points at least 1 year apart. Maldonado-Molina and Lanza (2010) argued that limitations of LTA can arise when the time points are too far apart to detect specific transitions in substance use. Research is needed that examines changes over shorter intervals of time to inform knowledge of how quickly changes in substance use patterns occur during early adolescence.

Associations between Externalizing Behaviors and Polysubstance Use

A small number of studies have used LCA or LTA to examine how externalizing behaviors relate to polysubstance use. Results of cross-sectional studies typically indicate that adolescents in substance use subgroups report greater externalizing problems than those who report no substance use (e.g., Chung et al., 2013; Goldstick et al., 2019; Shin et al., 2010), and polysubstance use subgroups tend to report more externalizing problems than those who use fewer substances. For example, among African American adolescents in an urban setting, those in the polysubstance use subgroup were more likely to report past year suspension or expulsion from school and arrest compared with those in the alcohol only subgroup (Johnson et al., 2020). Adolescents in the polysubstance use subgroup were also more likely to have been arrested than those who used only alcohol and cannabis. Similarly, a study focused on a primarily Black sample of adolescents found that subgroups with high and increasing levels of alcohol and cannabis use were more likely to report a criminal justice record than subgroups of youth who endorsed only alcohol use or no substance use (Green et al., 2016). A third study using a national sample found that a subgroup characterized by a high probability of heavy alcohol and cannabis use was more likely than three subgroups with less substance use to report past month truancy (Patrick et al., 2018). These findings suggest that delinquent behaviors occur more frequently among subgroups of youth who engage in polysubstance use versus those who abstain from use or use only one or two substances. However, these cross-sectional findings do not indicate how externalizing relates to development of substance use over time.

Only one study to my knowledge has examined the extent to which externalizing behavior predicts change in substance use patterns over time (Chung et al., 2013). This study found that conduct problems did not predict transitions in substance use subgroups across four waves between ages 13 and 17 among Black female adolescents living in an urban community. Because conduct problems did not relate to subgroup membership at the first wave for White female adolescents, the authors did not examine whether they predicted change in substance use over time. However, the conduct problems variable was a binary variable that indicated whether participants endorsed any conduct disorder symptom, and this study has limited generalizability due to its focus on female adolescents. Given the body of research supporting longitudinal associations between externalizing and substance use, more research is needed that investigates the extent to which externalizing behaviors predict changes in substance use patterns during early adolescence.

Statement of the Problem

Substance use during early adolescence poses significant risk for adverse mental and physical health outcomes (Griffin et al., 2010; Hingston et al., 2006). Adolescents who engage in polysubstance use, defined as the use of three or more substances, are at a particularly high risk of future substance use disorders and other negative psychosocial outcomes (Connor et al., 2014; Green et al., 2016; Merrin & Leadbeater, 2018; Moss et al., 2014). However, little is known about the development of early-onset polysubstance use. In order to inform effective prevention efforts, research is needed that examines longitudinal development of substance use patterns and factors that increase the risk of polysubstance use onset during early adolescence.

Theory and research support the externalizing pathway to adolescent-onset substance use, which asserts that childhood and adolescent externalizing behaviors predict subsequent initiation and escalation of substance use during adolescence (King et al., 2004; Maslowsky et al., 2014). Although several theories argue that the behaviors are reciprocally related over time (Moffit, 1993; Goldstein, 1985), most existing research has found that externalizing predicts increases in substance use, whereas substance use does not predict increases in externalizing behaviors (Bui et al., 2000; Farrell et al., 2005; Miller et al., 2016; Turner et al., 2018). A major limitation of research examining the externalizing pathway is that prior research has not addressed

polysubstance use. Studies that have used measures representing only a single substance (e.g., Turner et al., 2018), or a composite of multiple types of substances (e.g., Mason & Windle, 2002), are unable to determine how externalizing relates to the development of co-occurring substance use over time. In order to integrate polysubstance into developmental theory, there is a need for more research examining how risk factors such as externalizing behaviors relate to patterns of substance use among adolescents.

Prior studies that have used LCA to examine subgroups of polysubstance use among adolescents have typically identified three or four subgroups that vary in the type of substances used, and in their frequency or quantity of use (Halladay et al., 2020; Tomczyk et al., 2016). However, many of these studies have been limited by their assessment of substance use. For example, studies that only assess recent use of substances cannot capture all youth who have initiated use (e.g., Conway et al., 2013; Gilreath et al., 2014), and studies that only assess substance use initiation cannot determine whether youth continue use over time (e.g., Rose et al., 2018; Schneider et al., 2020). Studies that limit assessment to the most commonly used substances (e.g., alcohol, cigarettes, cannabis) may not identify the highest risk subgroups of adolescents who use substances such as hallucinogens, cocaine, and opioids. Moreover, very few studies have examined longitudinal transitions across substance use subgroups among adolescents. The longitudinal studies that exist have typically examined change over a period of 1 year or longer (Choi et al., 2018; Mistry et al., 2015; S. Shin, 2012; Zych et al., 2020), which cannot detect changes that occur more rapidly over the course of a year. A major limitation of the literature on polysubstance use development is that very few studies have examined polysubstance use in a sample comprised of early adolescents (e.g., Rose et al., 2018), a developmental stage when risk for substance use onset and escalation increases. More research is

needed that examines the development of polysubstance use during early adolescence.

The research on the externalizing pathway to substance use is also limited in its generalizability. Though researchers have called for more research on substance use within unique sociocultural settings (Kakade et al., 2012; Kulis et al., 2016), few studies have examined polysubstance use or its etiology among samples from underserved urban communities (Kakade et al., 2012). This population, which includes disproportionate numbers of Black and Latiné youth, may be at particularly high risk for adverse outcomes. Some research suggests that Black adolescents may escalate their drinking to daily heavy drinking more quickly than White youth (Jackson, 2010). Due to systemic racism in educational, legal, and other systems, Black youth and young adults are more likely to experience adverse consequences resulting from their substance use such as school dropout and legal involvement (Kakade et al., 2012; Mitchell $\&$ Caudy, 2015; Zapolski et al., 2014). Only a few of the reviewed studies have included samples with a significant proportion of Black youth (e.g., Farrell et al., 2018; Lynne-Landsman et al., 2011; Mustanski et al., 2013). In contrast, many studies have focused on primarily White samples (e.g., Bui et al., 2000; Ford, 2005; Huang et al., 2012; Lillehoj et al., 2005; Mason & Windle, 2002; McAdams et al., 2014). Moreover, many influential studies that support the externalizing pathway to substance use have focused on White adolescents (Dodge et al., 2009; Jessor, 1987), calling into question the generalizability of this pathway. A premise of prevention science is that prevention efforts will be effective only to the extent that they are able to reduce salient risk factors for a given population (Kellam et al., 1999). Research is thus needed that extends the literature examining polysubstance use and the externalizing pathway to substance use to Black youth living in urban settings.

Finally, the influence of other potential pathways to adolescent-onset substance use

should be considered. An alternative pathway to the onset of substance use during adolescence is via internalizing symptoms (Hussong et al., 2011). There is mixed evidence that internalizing and externalizing symptoms are uniquely related to substance use (Hussong et al., 2017). Findings from three studies indicate that externalizing behaviors positively predict substance use after controlling for internalizing symptoms (Bui et al., 2000; Farmer et al., 2015; Maslowsky et al., 2014). In contrast, two other studies found that associations were no longer significant after controlling for internalizing symptoms (Jun et al., 2015), or a combination of internalizing and other covariates (Huang et al., 2001). In order to inform developmental pathways to adolescent substance use, studies should examine both the impact externalizing symptoms alone on substance use, and the unique impact of externalizing behaviors after controlling for internalizing symptoms.

The Current Study

The overarching goal of this study was to advance research on the development of polysubstance use and its relations with externalizing behaviors among early adolescents. I addressed this goal by examining data from a primarily Black sample of middle school students living in urban communities. The first aim was to identify subgroups of early adolescents based on their initiation and recent substance use, and to examine transitions in those subgroups across two waves of data. To address methodological limitations of prior work, this study examined subgroups based on adolescents' initiation and recent use of legal (i.e., alcohol, cigarettes) and illicit substances (i.e., cannabis, inhalants, hard drugs). This study also examined transitions in substance use over time for groups of adolescents assessed at different times during the school year and summer to determine when transitions were most likely to occur. These analyses were designed to shed light on typical patterns of substance use development during early adolescence
and the timing of escalation in substance use among this age group. This study focused on a primarily Black sample of early adolescents attending middle schools that served communities with high rates of violent crime and where most residents' incomes were below the federal poverty threshold. Because notable variations have been identified across subpopulations in the types of substances, frequency of use, and prevalence of different subgroups, adding to the literature about substance use patterns among specific subpopulations of adolescents will help to facilitate development or modification of relevant substance use prevention programs for youth living in urban communities.

The second aim of this study was to evaluate the extent to which two forms of externalizing behaviors (i.e., aggression, delinquency) were concurrently and prospectively related to early adolescents' substance use patterns. To account for potential differences in development across subpopulations, the study examined differences in these associations across sex, grade, and the timing of the waves during the year. To my knowledge, only one other study has examined externalizing behavior as a predictor of transitions in substance use patterns over time (Chung et al., 2013). The current study aimed to extend this line of research by examining two forms of externalizing behaviors (i.e., delinquency, aggression) as predictors of transitions in substance use subgroups across two waves that are 3 months apart. These results contribute novel findings as to whether adolescents with high levels of externalizing behavior are at greater risk for initiating and escalating to polysubstance use during middle school, or whether externalizing behavior predicts particular patterns of substance use (e.g., alcohol use versus polysubstance use). The examination of bidirectional relations between externalizing behaviors and substance use also helps to clarify whether early adolescents who use substances are at greater risk for later physical aggression and delinquent behavior.

Although the focus of this study was on the externalizing pathway to substance use, I included sensitivity analyses that examined the unique impact of externalizing symptoms while controlling for distress symptoms. This analysis was designed to inform theory regarding the unique and intersecting influence of externalizing and internalizing pathways to substance use (Hussong et al., 2017). The findings of this study are relevant for informing targeted substance use prevention efforts for adolescents who engage in externalizing behaviors after the transition to middle school.

Aim 1

The first aim of this study was to examine longitudinal changes in substance use patterns among middle school students by identifying distinct subgroups that described heterogeneity in early adolescents' patterns of substance use (Aim 1a) and determining the probability of remaining in the same subgroup versus transitioning to a different subgroup across two waves of data that were collected 3 months apart (Aim 1b). The subgroups based on patterns of substance use will be referred to as "substance use subgroups," though each subgroup may not report engaging in substance use (i.e., no use). After identifying the substance use subgroups, I conducted tests of differential item functioning (DIF) to examine the extent to which substance use endorsement varied as a function of covariates (i.e., timing of waves, sex, grade, intervention phase; Aim 1c). Because the study involved analysis of data from a project that evaluated a bullying intervention, I also included intervention phase as a covariate to control for potential influences of the intervention on adolescents' behavior. Finally, I examined how covariates related to transitions in subgroup membership over time (Aim 1c).

Because LCA is an exploratory analysis, the number of subgroups and their patterns were not known in advance. However, results of a preliminary study using cross-sectional data from

the same project identified four substance use subgroups: non-use, alcohol use, initiation, and recent polysubstance use (Dunn & Farrell, 2021). Based on these hypothesized subgroups, I formulated general hypotheses prior to conducting any analyses for this study. After the subgroups were identified, I generated more specific hypotheses about each identified subgroup (see Formulating Hypotheses for the Subsequent Aims in the Results section). The hypotheses were registered with the Center for Open Science (https://doi.org/10.17605/OSF.IO/VBWJ9). I hypothesized that four subgroups similar to those found in the preliminary study (Dunn $\&$ Farrell, 2021) would be identified at both waves (Aim 1a). Regarding Aim 1b, I hypothesized that transitions would emerge across waves that represented escalations in the number of substances used. For Aim 1c, I hypothesized that participants' sex and grade would show evidence of DIF and significant associations with subgroup membership. Because the intervention did not focus on substance use, I hypothesized that intervention phase would not be associated with indicators (i.e., DIF) or subgroup membership. I also hypothesized that the probability of transitioning across subgroups over time would vary as a function of sex and grade. More specifically, youth in older grades versus younger grades, and male adolescents versus female adolescents, would be more likely to transition between subgroups over time that represented escalations in use. Associations between the timing of the two waves during the year (i.e., fall to winter, winter to spring, spring to summer) and the probability of subgroup transitions were examined in an exploratory analysis.

Aim 2

The second aim of this study was to examine longitudinal bidirectional relations between two externalizing behaviors (i.e., physical aggression and delinquency) and patterns of substance use. At each wave, I first examined concurrent differences in the mean levels of each

externalizing behavior across the substance use subgroups (Aim 2a). For Aim 2b I examined prospective bidirectional associations between each externalizing behavior and the substance use subgroups. I evaluated the extent to which the longitudinal associations between each externalizing behavior and substance use subgroups varied as a function of each covariate (i.e., sex, grade, timing of the waves, intervention phase; Aim 2c). Finally, I conducted sensitivity analyses to examine the extent to which externalizing behaviors were associated with substance use subgroups after controlling for distress symptoms (Aim 2d).

For Aim 2a, I hypothesized that subgroups that reported using a greater number of substances would also report more frequent physical aggression and delinquent behavior. For Aim 2b, I hypothesized that more frequent physical aggression and delinquent behavior at Wave 1 would predict a greater probability of transitions into Wave 2 subgroups that represented escalation in substance use, such as using a greater number of substances or illicit substances (e.g., cannabis, inhalants). Because most prior studies have found that substance use does not predict subsequent changes in externalizing behaviors, I hypothesized that subgroup membership at Wave 1 would not predict changes in adolescents' frequency of aggression or delinquent behavior across waves. I hypothesized that associations between externalizing behaviors and substance use subgroups would be consistent across sex, timing of the waves, and intervention phase, but would vary across grades (Aim 2c). More specifically, youth in seventh and eighth grade with high levels of externalizing behaviors would be more likely to escalate their substance use over time than youth in sixth grade with high externalizing behaviors. For the sensitivity analysis, I hypothesized that externalizing behaviors would uniquely predict substance use subgroups even after controlling for distress symptoms. I formulated more specific hypotheses regarding the associations between subgroup membership and externalizing behaviors after

completing Aim 1 and registered these hypotheses with the Center for Open Science prior to starting Aim 2 analyses (see Formulating Hypotheses for the Subsequent Aims in the Results section).

Method

Participants and Study Setting

This study used data from a project that evaluated a bullying prevention program at three urban middle schools (i.e., grades 6 through 8) in the Southeastern United States (see Farrell, Sullivan, et al., 2018; Sullivan et al., 2021). Schools were selected for participation in the project based on their high rates of truancy and location in neighborhoods with high rates of violent crime and households living at or below the federal poverty threshold. Data were collected in 3 month intervals between February 2011 and June 2018 from random samples representing 10 cohorts of students in grades 6, 7, and 8. The project used a planned missing design such that each student in the study was randomly assigned to participate in a maximum of two waves each project year. This study focused on participants from the evaluation project that were randomized to participate at two adjacent waves within a project year (i.e., fall and winter, winter and spring, or spring and summer). Data were randomly selected from one grade (i.e., grade 6, 7, or 8) for any participants who were randomly assigned to participate at adjacent waves during more than one grade.

Of the 2,755 students included in the evaluation project, 1,811 (66%) met criteria for inclusion in the current study (see "Procedures" for more information). The majority of participants (85%) had completed surveys at both waves to which they were randomly assigned, resulting in a sample size of 1,781 at Wave 1 and 1,574 at Wave 2. Missing data were addressed using full information maximum likelihood estimation, which uses all available information to

estimate the model. At their first wave of data collection, students' mean age was 13 years. Based on school records, over half (53%) were female adolescents and 47% were male adolescents. Eighteen percent of the sample identified as Hispanic or Latino/Latina ethnicity. Thirteen percent of the sample did not endorse any of the categories for race. The majority of those with missing data had identified their ethnicity as "Hispanic or Latino/Latina" (94%). Seven percent of the sample endorsed multiple categories for race. The majority of these (99%) endorsed African American or Black as one of the categories. The remainder of the sample endorsed a single category for race including African American or Black (72%), White (6%), American Indian or Alaska Native (2%), Asian (1%), and Native Hawaiian or Pacific Islander (1%). Most students at the participating schools (i.e., 74% to 85% across schools) were eligible for the federal free or reduced lunch program eligibility based on their income. Students most often reported living with two parents (27%), their mother (25%), their mother and stepfather (20%), or their mother and another relative (10%). The timing of the two adjacent waves of data collection for participants in this sample occurred during the (a) fall to winter (32%), (b) winter to spring (35%), and (c) spring to summer (34%).

Procedures

The study used data from a project designed to evaluate the implementation of the Olweus Bullying Prevention Program (OBPP; Olweus & Limber, 2010) at three urban middle schools. The OBPP is a school-based program that aims to reduce bullying and improve school climate. The project used a multiple-baseline design, such that the order and timing of the intervention was randomized across schools. During the first year of the project, a random sample of students was recruited from school rosters from each grade. In each subsequent year, a random sample of students was selected from the new sixth grade cohort, and new students in

grades 7 and 8 were randomly selected to replace those who left the school. Each student who consented to participate in the study was randomly assigned to complete measures at two of the four waves (i.e., fall, winter, spring, summer) during each year until they left middle school or chose to discontinue participation. Parents or guardians provided consent and students provided assent to participate in the study. Students completed measures using a computer-assisted interview administered at school during the school year and at their homes or another community location during the summer. Participants received \$10 gift cards for completing any part of the survey at each wave. The Virginia Commonwealth University Institutional Review Board approved all study procedures in the larger project and approved the use of anonymized data for secondary analysis in this study.

The project collected data every 3 months between 2010 and 2018 with several exceptions. Data collection began in the winter wave during the first year of the project and were not collected during the fall of the sixth year (i.e., 2016) due to a change in the funding source. The last wave of data collection was in the spring of the final year of the project. Attrition occurred over the course of the project. Of the students who participated in the project, data were missing from one or more wave from students who could not be scheduled to take the survey (7%), declined to complete the survey (6%), failed data checks (4%), did not complete the survey (3%) , would not be located (2%) , completed the surveys too fast (1%) , or for another reason (< 1%). Data were also missing from students who became ineligible because they left the school (32%), withdrew from the study (1%), or became ineligible for another reason (2%).

Measures

Substance Use

Three items on the Problem Behavior History Scale (PBHS) assessed the participants'

initiation of alcohol use, smoking cigars or cigarettes, and drug use (cannabis, inhalants, other hard drugs). For each item, the measure defined use as "more than a sip or taste." Responses were 0 (*never used*) and 1 (*initiated*). Adolescents who reported their history of initiation of use across the two waves inconsistently (i.e., changed from initiated to never used) were recoded such that "initiated" responses were carried forward to the second wave of data. Supplemental analysis indicated that carrying responses forward resulted in more subgroup consistency over time and did not alter the structure of the subgroups (see Appendix A).

The Problem Behavior Frequency Scale-Adolescent Report (PBFS-AR) assessed adolescents' frequency of problem behaviors in the past 30-days on a 6-point scale, with 1 (*never*), 2 (*1–2 times*), 3 (*3–5 times*), 4 (*6–9 times*), 5 (*10–19 times*), 6 (*20 or more times*). The PBFS-AR includes nine items that assess substance use: beer, wine, liquor, cigarettes, cigars (Black & Milds), cannabis, inhalants, other drugs (heroin, cocaine, ecstasy), and drunkenness. The measure defined alcohol use as "more than a sip or taste." Preliminary frequency analyses indicated that response options 3 (*3-5 times*) through 6 (*20 or more times*) were endorsed by less than 5% of the sample on each item. PBFS-AR items were coded as binary for analyses (i.e., 30 day use or no 30-day use) to eliminate potential estimation problems caused by empty cells. Twelve binary items that assessed participants' lifetime history of initiating substance use (i.e., 3 items) and past 30-day substance use (i.e., 9 items) were included as indicators of the subgroups.

Externalizing Behaviors

This study used the five-item PBFS-AR Physical Aggression subscale, which assesses acts of violence against others (e.g., "hit or slapped someone"), and the six-item Delinquent Behavior subscale, which assesses nonviolent delinquent behaviors (e.g., "stolen something," "purposely damaged property that did not belong to you"; Farrell et al., 2016). Responses to

subscale items were averaged to produce separate subscale scores for Physical Aggression and Delinquent Behavior. The PBFS-AR subscales have demonstrated concurrent validity with teacher- and self-reports of behavior, and strong measurement invariance across sex, grade, intervention condition, and the timing of waves (Farrell et al., 2017). Following the recommendations of results from an item response theory analysis of the PBFS-AR (Farrell et al., 2020), the items were recoded into a 4-point scale by collapsing the three highest response options (i.e., more than *6–9 times*). To account for skewness and kurtosis in the subscales, subscale scores were log transformed and then rescaled to the same mean and standard deviation as the original subscales. The Physical Aggression and Delinquent Behavior subscales demonstrated acceptable reliability in a random cross-sectional sample from the dataset (Cronbach's α = 0.80, 0.77 respectively).

Distress Symptoms

I included distress symptoms in a final sensitivity analysis to examine the unique effects of externalizing behaviors on substance use after accounting for distress symptoms. Participants reported their symptoms of distress on the 28-item Checklist of Children's Distress Symptoms (Richters & Martinez, 1990). Items on the Checklist of Children's Distress Symptoms are based on diagnostic criteria for Post-Traumatic Stress Disorder in the Diagnostic and Statistical Manual of Mental Disorders, third edition, revised (DSM-III-R; American Psychiatric Association, 1987) and represent the three clusters of Post-Traumatic Stress Disorder symptoms (i.e., hyperarousal, reexperiencing, and avoidance). The scale was designed to assess distress symptoms experienced by youth who were exposed to chronic community violence. Participants reported their frequency of symptoms in the past 6 months on a scale from 1 (*never)* to 5 (*most of the time*), and the responses across all items were averaged to create a total score. Prior research supported

the validity of the scale (Richters & Martinez, 1990). The measure demonstrated good reliability (Cronbach's α = 0.94).

Covariates

Participants' sex based on school records, grade, intervention phase, and timing of the waves were included as covariates. The timing of the waves during the year was represented by dummy-coded variables to examine differences in subgroups and transition probabilities across different times of year (i.e., fall to winter vs. winter to spring, vs. spring to summer). Intervention phase indicated whether the intervention was being implemented at the student's school during the year their data were collected. Because the intervention did not focus on substance use or delinquency, and no significant intervention effects were found on students' reports of their frequency of physical aggression in the original project (Sullivan et al., 2021), I did not expect to intervention phase to be associated with the study variables. Students' racial identity was not included as a covariate because the majority (75%) of participants identified as Black or African American and the remaining 25% represented a diverse group with no more than 10% endorsing any other single race. Dummy-coded variables for timing of the waves, sex, grade, and intervention phase were evaluated for measurement invariance (i.e., DIF) and included in each model as covariates.

Data Analyses

I used Mplus Version 8.8 statistical software (Muthén & Muthén, 2017) for all analyses and the Mplus Automation package for R to conduct mixture analyses (Hallquist & Wiley, 2018). I addressed missing data using full information maximum likelihood estimation, which uses all observed responses. One limitation of full information maximum likelihood estimation is that it does not include cases that are missing on all exogenous variables (i.e., independent

variables). This led to some missing data in LCA and LTA models. I accounted for nonnormality by using a robust estimator to compute standard errors and accounted for nesting of students by cohort and school using sandwich estimators (i.e., type=complex; Muthén & Satorra, 1995).

Aim 1

To address Aim 1, I identified subgroups of substance use at two waves and examined subgroup transitions across waves using the following methods:

Aim 1a. I conducted an LCA (Masyn, 2013) separately at Wave 1 and Wave 2 to identify subgroups that differed in their patterns of substance use based on 12 binary indicators (see Figure 1). I specified a one-class model and then increased the number of classes by one until the models were no longer well identified. I determined the optimal number of subgroups by comparing models on several recommended indices of model fit (Masyn, 2013), including the Bayesian information criterion (BIC; Schwarz, 1978), Consistent Aikaike information criterion (CAIC; Bozdogan, 1987), and approximate weight of evidence criterion (AWE; Banfield $\&$ Raftery, 1993). The model with the minimum value for the BIC, CAIC, and AWE was considered the best fitting model based on each criterion.

When the fit indices disagreed on the best fitting model, I weighed the model suggested by the BIC most strongly because the BIC more consistently identifies the optimal number of classes compared with other fit indices (Nylund et al., 2007). I considered the relative improvement (RI) of each model, which represents the change in model fit from model *K* to model *K*+1, relative to the greatest possible change (i.e., from a model with 1 to 2 classes; Moore, 2020). I visually inspected scree plots of the model fit indices for an "elbow," which indicated the model where the relative improvement in fit declined. I also examined indices to

determine if adding another class resulted in a meaningful improvement in model fit. The bootstrap likelihood ratio test (BLRT) and the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR-LRT) were used to compare the relative fit of models, where non-significant *p*-values indicated that adding an additional class did not improve model fit (Masyn, 2013). Based on these indices, likelihood ratio tests, and plots, I determined which contender models were supported by the strongest evidence. Finally, I interpreted the models under consideration based on their item response probabilities to determine whether each additional class represented a unique, qualitatively distinct pattern of substance use.

I evaluated the classification quality of competing models based on the average posterior class probabilities, odds of correct classification ratios, and model class assignment proportions. Models with average posterior class probability values greater than 0.7 and odds of correct classification ratios greater than 5.0 were considered to have well-separated classes and high accuracy in class assignment (Nagin, 2005). Model class assignment proportion values that fell within a 95% confidence interval for the model-based class proportions supported classification accuracy (Masyn, 2013). I also considered entropy values for the model, with values greater than 0.80 indicating good classification. Finally, I considered the size of the smallest subgroup, prior research, and model parsimony when selecting the optimal number of subgroups at each wave.

Aim 1b. I then evaluated longitudinal measurement invariance of the subgroups by estimating the latent classes at each wave simultaneously in the same model and comparing a model in which the item threshold parameters for each indicator were constrained across waves to a second model in which the item threshold parameters were allowed to vary across waves (Nylund-Gibson et al., 2022). Item threshold parameters represent the probability of endorsing each indicator within each subgroup. After evaluating longitudinal measurement invariance, I

conducted the LTA using an extension of the three-step BCH method to account for uncertainty in class assignment at each wave (Asparouhov & Muthen, 2021). I regressed the categorical latent subgroup variable at Wave 2 on the latent subgroup variable at Wave 1 (see Figure 1) to examine the probability of remaining within the same subgroup across waves (i.e., stability) or transitioning to a new subgroup across waves. I also calculated the odds of transitioning into subgroups with different patterns of substance use relative to remaining in the same subgroup over time.

Aim 1c. After identifying the subgroups at each wave and establishing longitudinal measurement invariance, I examined the covariates as sources of measurement invariance in the latent class indicators, known as differential item functioning (DIF). Recent developments in mixture modeling suggest that ignoring sources of DIF can lead to biased estimates of covariate relations with subgroup membership (Bettencourt et al., 2021; Masyn, 2017). I evaluated DIF by each covariate (i.e., sex, grade, timing of waves, intervention phase) using the stepwise methods recommended by Masyn (2017) and Bettencourt et al. (2021). Next, I incorporated all sources of DIF that were identified with the LCA models into the LTA model and examined the association between covariates (i.e., sex, grade, intervention phase, timing of waves) and subgroup membership in the LTA model. I specified a series of models to identify the optimal way to account for the covariate's effects on subgroup membership and/or transitions (Muthén, 2021). The optimal covariate structure for each covariate was retained to control for covariate differences in subgroup membership in Aim 2 analyses.

Aim 2

To address Aim 2, I examined cross-sectional and longitudinal relations between substance use subgroups and externalizing variables, with separate models for physical

aggression and delinquent behavior. The analyses included the following steps:

Aim 2a. I first examined cross-sectional associations between the externalizing variables and substance use subgroups. Within the LCA model at each wave, I used the three-step BCH approach (Asparouhov & Muthen, 2021) to examine mean differences in the frequency of each externalizing behavior across subgroups while controlling for the effects of covariates (i.e., sex, grade, intervention phase, timing of waves) on the externalizing behaviors.

Aim 2b. Next, I used a series of cross-lagged regression models to examine longitudinal bidirectional associations between each externalizing variable and substance use in separate onesided models to reduce their complexity (see Figure 2). The first one-sided model examined the extent to which each externalizing variable predicted transitions in subgroup membership while controlling for the covariate effects on subgroup membership (e.g., see Figure 2a). The second one-sided model examined the extent to which membership in each substance use subgroup predicted change in the frequency of each externalizing variable, while accounting for the autoregressive and covariate effects on the externalizing variables (see Figure 2b).

Aim 2c. For Aim 2c I evaluated whether the associations examined in Aim 2b differed across grade, sex, intervention phase, and timing of the waves. I examined the moderating effects of each covariate on these associations in separate models for each one-sided model, externalizing variable, and covariate.

Aim 2d. As a final sensitivity analysis, I incorporated the distress symptoms variable into the cross-lagged models from Aim 2b that evaluated the effects of the externalizing variables on transitions in subgroup membership (see Figure 2a). These analyses evaluated the unique effect of each externalizing behavior (i.e., delinquency, physical aggression) and distress symptoms on transitions in substance use subgroups.

Figure 1.

Latent Transition Analysis Model

Note. The initial latent class analyses were conducted separately for Wave 1 and Wave 2. The blue line indicates that regression of Wave 2 on Wave 1, which was added for the latent transition analysis.

Figure 2.

One-Sided Cross-Lagged Regression Models

Note. Effects of covariates and correlations among residuals within the same wave are not shown to reduce complexity of the figure. Red arrows depict cross-lagged effects. Black arrows depict autoregressive effects.

Results

Descriptive Statistics

Using full information maximum likelihood estimation to account for missing data, I examined the proportion of early adolescents who endorsed each of the latent class indicators separately within each wave (see Table 1). The percentage of participants that reported initiation of specific substances ranged from 11% to 20% at Wave 1 and 14% to 25% at Wave 2. Participants' endorsement of past 30-day use of specific substances ranged from 2% to 8% at Wave 1 and 2% to 7% at Wave 2. The descriptive statistics and correlations for the measures of physical aggression, delinquent behavior, and distress symptoms are reported in Table 2. Variables that had skewed and kurtotic distributions were log-transformed and the resulting values were rescaled to have the same means and SDs as the original scores to facilitate their interpretation. The log-transformed scores for physical aggression and delinquent behavior had large, positive correlations with each other within Wave 1 (*r* = .54) and Wave 2 (*r* = .51). The log-transformed scores for physical aggression were moderately positively correlated with distress symptoms within Wave 1 ($r = .31$) and Wave 2 ($r = 32$). The log-transformed scores for delinquent behavior showed small positive correlations with distress symptoms within both waves ($rs = .22, .24$).

Table 1.

Percentage of Participants at Each Wave Endorsing Each

Substance Use Indicator

Table 2.

Descriptive Statistics and Correlations Among Externalizing and Distress Symptom Variables at Wave 1 and Wave 2

		Minimum	Maximum	Mean	Skewness	Kurtosis		2	3	4
						Wave 1 $(n = 1778)$				
	Physical Aggression	1.00	4.00	1.40	1.84	3.38				
2	Physical Aggression (log)	0.94	3.25	1.40	1.13	0.46	$0.98**$			
3	Delinquent Behavior	1.00	4.00	1.14	4.03	19.71	$0.57**$	$0.53**$		
	Delinquent Behavior (log)	0.98	3.18	1.14	2.83	8.60	$0.57**$	$0.54**$	$0.98**$	
5	Distress Symptoms	1.00	5.00	1.95	1.00	0.67	$0.29**$	$0.31**$	$0.20**$	$0.22**$
		Wave 2 $(n = 1573)$								
	Physical Aggression	1.00	4.00	1.35	2.01	4.25				
2	Physical Aggression (log)	0.94	3.25	1.34	1.30	0.90	$0.98**$			
3	Delinquent Behavior	1.00	4.00	1.13	4.13	21.05	$0.52**$	$0.49**$		
	Delinquent Behavior (log)	0.98	3.18	1.12	2.93	9.28	$0.54**$	$0.51**$	$0.98**$	
	Distress Symptoms	1.00	5.00	1.83	1.15	1.09	$0.31**$	$0.32**$	$0.22**$	$0.24**$

Note. Log-transformed scores were rescaled to have the same means and standard deviations as the original scales.

Latent Class Enumeration

Removal of cases that were missing on all 12 latent class indicators within each wave resulted in a sample size of 1,778 at Wave 1 and 1,573 at Wave 2. Class enumeration of the 12 binary indicators resulted in proper solutions for up to seven classes at each wave. The four-class model was identified as optimal at both waves based on having the best fit as indicated by the minimum values for the BIC and the CAIC (see Table 3). Although the AWE supported the three-class model, I weighed the optimal model suggested by the BIC more strongly because the BIC more consistently identifies the optimal number of classes compared with other fit indices (Nylund et al., 2007). The VLMR-LRT indicated that the model did not improve with the addition of the sixth class, whereas the BLRT was significant in every case and did not suggest a point where adding an additional class did not improve model fit. However, inspection of scree plots of the loglikelihood values showed "elbows" at the four-class model, suggesting that improvement in model fit declined after the addition of the fourth class. The RI values similarly showed that improvement in model fit leveled-off after the four-class model. Because the fourclass model was supported by the BIC and the abundance of information, I evaluated its classification quality and item response probabilities to determine if the subgroups based on this model were accurately defined, quantitatively and qualitatively distinct, and consistent with theory.

At each wave the four-class model achieved adequate classification precision (see Table 4). Average posterior class probability values ranging from .85 to .96 and odds of correct classification ratios between 7 and 335 suggested that the classes were well-separated and the model had high accuracy in class assignment. The class proportions based on each individual's most likely class membership fell within a bootstrapped 95% confidence interval around the

model estimated class proportions, supporting classification accuracy. Finally, the entropy values at Wave 1 and Wave 2 (.88, .87, respectively) indicated good classification precision. The bivariate residual covariances between latent class indicators were examined to evaluate the assumption of local independence within the four-class models. Less than 5% of the 264 residuals were significant at $p < .05$ (i.e., 14 at Wave 1, 6 at Wave 2), supporting the assumption of local independence.

The unconditional item response probabilities suggested that the four-class models at both waves were interpretable and consistent with theory and prior research (See Table 5). The subgroup patterns were generally consistent across waves (see Figure 3). The largest subgroup (i.e., 76% of the sample at Wave 1, 73% at Wave 2) represented *Non-Use*, with low probabilities of endorsing any substance use initiation and past 30-day substance use (probabilities = .00 to .08). Adolescents in the *Initiation* subgroup (Wave $1 = 11\%$, Wave $2 = 13\%$) had moderate to high probabilities (probabilities $= .53$ to $.64$ across waves) of endorsing initiation of alcohol, drugs, or cigarettes/cigars, but low probabilities of endorsing any substance use in the past 30 days (i.e., probabilities = .00 to .22). Response patterns for the *Initiation* subgroup revealed that the majority of adolescents in this subgroup (i.e., 90% at Wave 1, 95% at Wave 2) had endorsed initiation of at least one substance. Initiation of two or more substances was endorsed by 55% of the subgroup at Wave 1 and 72% of the subgroup at Wave 2. However, adolescents in this subgroup varied in which specific substances they reported initiating, resulting in moderate response probabilities for each individual indicator of initiation at the subgroup level.

Adolescents in the *Alcohol Use* subgroup (Wave $1 = 7\%$, Wave $2 = 7\%$) had a high probability (.86) of endorsing initiation of alcohol use and small to moderate probabilities of alcohol use in the past 30-days (probabilities $= .11$ to .46 across items and waves). However, their probabilities of prior initiation of other substances (probabilities = .10 to .19) and past 30 day use of other substances (probabilities = .00 to .06) were small. Response patterns indicated that 100% of adolescents in the *Alcohol Use* subgroup at both waves endorsed either prior alcohol use initiation or use in the past 30-days. The majority of this subgroup (i.e., 81% at Wave 1, 77% at Wave 2) endorsed alcohol use initiation *and* one or more types of alcohol in the past 30-days. Varying patterns across the four types of alcohol they reported using in the past 30-days (i.e., beer, liquor, wine/wine coolers, got drunk) resulted in small to moderate probabilities for individual items at the subgroup level.

Finally, youth in the *Polysubstance Use* subgroup (Wave $1 = 6\%$, Wave $2 = 7\%$) had high probabilities of endorsing initiation of alcohol use (probabilities = .84, .88) and moderate to high probabilities of endorsing initiation of cigarette/cigar and drug use across waves (cigarette/cigar probabilities = .66, 63, drug use probabilities = .66, .70). The *Polysubstance Use* subgroup had moderate to high probabilities $(i.e., > .50)$ of endorsing past 30-day use of alcohol, cannabis, and cigars. Although probabilities were small to moderate for cigarette, inhalant, and illicit drug use (probabilities $= .23$ to .46 across waves), this subgroup had substantially larger probabilities of endorsing these items relative to both the entire sample (probabilities = .02 to .04) and all other subgroups. I examined the number of types of substances endorsed, considering initiation or past 30-day use of alcohol (i.e., wine/wine coolers, liquor, beer, getting drunk), tobacco products (i.e., cigars/cigarettes), and illicit drugs (i.e., cannabis, inhalants, other drugs) as different types of substances. At Wave 1, 97% of the *Polysubstance Use* subgroup endorsed at least two types of substances, and 65% endorsed all three types. At Wave 2, 99% of the subgroup endorsed at least two substance types, and 84% endorsed all three.

Table 3.

Fit Indices for the Latent Class Models Estimated Separately at Wave 1 and 2

						RI		Adj LMR	BLRT
K	LL	npar	BIC	CAIC	AWE	$(K, K+1)$	LRTS	<i>p</i> -value	<i>p</i> -value
					Wave 1 $(n = 1778)$				
1-class	-5147.50	12	10384.79	10396.79	10510.59	na	na	na	na
2-class	-3855.04	25	7897.16	7922.16	8159.24	na	2558.62	0.000	< .001
3-class	-3665.09	38	7614.54	7652.54	8012.90	0.15	376.03	0.000	< .001
4-class	-3591.57	51	7564.79	7615.79	8099.44	0.06	145.53	0.000	< .001
5-class	-3544.45	64	7567.82	7631.82	8238.75	0.04	93.29	0.000	< .001
6-class	-3505.96	77	7588.13	7665.13	8395.34	0.03	76.19	0.002	< .001
7-class	-3469.29	90	7612.08	7702.08	8555.57	0.03	72.59	0.417	< .001
	Wave 2 $(n = 1573)$								
1-class	-4895.35	12	9879.03	9891.03	10003.36	na	na	na	na
2-class	-3762.75	25	7709.52	7734.52	7968.54	na	2241.77	0.000	< .001
3-class	-3580.14	38	7439.98	7477.98	7833.69	0.16	361.46	0.000	< .001
4-class	-3509.66	51	7394.72	7445.72	7923.11	0.06	139.50	0.013	< .001
5-class	-3478.61	64	7428.30	7492.30	8091.39	0.03	61.46	0.000	< .001
6-class	-3451.12	77	7469.01	7546.01	8266.79	0.02	55.36	0.406	< .001
7-class	-3425.61	90	7513.68	7603.68	8446.15	0.02	51.47	0.512	< .001

Note. K number of latent classes, *LL* maximum likelihood value obtained for each model, *npar* number of free parameters in the model, *BIC* Bayesian information criterion, *CAIC* consistent Akaike's information criterion, *AWE* average weight of evidence criterion, *RI* relative improvement, *LRTS* likelihood ratio test statistic comparing row model with *K* classes to the model with $K + 1$ classes, *Adj. LMR p* adjusted Lo–Mendell–Rubin p-value for the LRTS, *BLRT p* parametric bootstrapped *p*-value for the LRTS. Values in bold for the BIC, CAIC, and AWE indicate the model with the minimum value.

Table 4.

	Estimated					
K	proportion	95% C.I.	mcaP	AvePP	OCC	
			Wave 1 $(n = 1778)$			
Class 1	0.76	(0.72, 0.79)	0.78	0.96	7.46	
Class 2	0.11	(0.05, 0.13)	0.10	0.85	48.03	
Class 3	0.07	(0.05, 0.14)	0.06	0.89	102.07	
Class 4	0.06	(0.05, 0.07)	0.06	0.94	249.29	
		Wave 2 $(n = 1573)$				
Class 1	0.73	(0.71, 0.76)	0.77	0.95	6.92	
Class 2	0.13	(0.11, 0.16)	0.11	0.90	60.71	
Class 3	0.07	(0.05 0.08)	0.06	0.96	335.19	
Class 4	0.07	(0.05, 0.09)	0.06	0.87	93.44	

Classification Quality of the Unconditional Four-Class Model at both Waves

Note. *C.I.* confidence interval; *mcaP* modal class assignment proportion;

AvePP Average Posterior Probabilities; *OCC* Odds of Correct Classification.

Table 5.

Item Response Probabilities for the Unconditional Latent Class Models Estimated Separately at Wave 1 and Wave 2.

		Wave 1 $(n = 1778)$				Wave 2 $(n = 1573)$				
		Non-	Initiation	Alcohol	Polysubstance	Non-	Initiation	Alcohol	Polysubstance	
		Use		Use	Use	Use		Use	Use	
		(76%)	(11%)	(7%)	(6%)	(73%)	(13%)	(7%)	(7%)	
Lifetime	Alcohol	0.04	0.53	0.86	0.88	0.08	0.64	0.86	0.84	
Initiation	Drugs	0.00	0.57	0.10	0.66	0.01	0.61	0.18	0.70	
	Cigarettes/Cigars	0.00	0.57	0.14	0.66	0.01	0.59	0.19	0.63	
Past 30-	Liquor	0.00	0.03	0.28	0.79	0.00	0.02	0.44	0.63	
Day Use	Beer	0.00	0.04	0.34	0.63	0.01	0.03	0.37	0.52	
	Got drunk	0.00	0.03	0.11	0.57	0.00	0.00	0.14	0.59	
	Wine/wine coolers	0.01	0.04	0.42	0.74	0.00	0.00	0.46	0.62	
	Cannabis	0.00	0.18	0.00	0.61	0.00	0.15	0.06	0.68	
	Inhalants	0.01	0.07	0.06	0.28	0.01	0.02	0.03	0.26	
	Illicit drugs	0.00	0.03	0.01	0.23	0.00	0.03	0.00	0.29	
	Cigars	0.00	0.22	0.00	0.65	0.00	0.19	0.00	0.76	
	Cigarettes	0.00	0.10	0.00	0.46	0.00	0.08	0.00	0.43	

Note. Bolded values indicate moderate to high probabilities (i.e., $> .50$).

Figure 3.

Plot of Response Probabilities for the Unconditional Four-Class Models Estimated Separately at Wave 1 and Wave 2

Note. Wave 1 *n* = 1778, Wave 2 *n* = 1573.

Formulating Hypotheses for the Subsequent Aims

After identifying the optimal number of subgroups at each wave and interpreting these subgroups, I formulated the following specific hypotheses for the remaining aims:

Aim 1b. Regarding transitions in subgroup membership over time, I hypothesized that individuals would be most likely to remain in the same subgroup over time (i.e., stability probabilities). When transitions occurred, I hypothesized escalation into more serious patterns of use would be most common, such that: (a) the *Non-Use* subgroup would have a greater probability of transitioning into *Initiation* and *Alcohol Use* subgroups than into the *Polysubstance Use* subgroup, (b) the *Initiation* subgroup would have a greater probability of transitioning into *Alcohol Use* than into the *Polysubstance Use* subgroup, and (c) the *Alcohol Use* subgroup would have a greater probability of transitioning into the *Initiation* than into the *Polysubstance Use* subgroup.

Aim 1c. Regarding the examination of DIF and covariate relations with class membership, I hypothesized that participant's sex and grade would show evidence of DIF and would be related to subgroup membership, but the timing of waves or intervention phase would not. More specifically, I hypothesized that male adolescents would be more likely than female adolescents to endorse substance use indicators after accounting for class membership. I also hypothesized that youth in seventh and eighth grade would be more likely to endorse substance use items than those in sixth grade after accounting for class membership. I did not hypothesize which specific indicators would show evidence of DIF. Regarding covariate associations with subgroup membership, I hypothesized that female adolescents and those in sixth grade would have greater odds of being in the *Non-Use* subgroup than male adolescents and those in the seventh and eighth grades. I

expected that male adolescents and seventh and eighth graders would have greater odds of being in the *Alcohol Use* and *Polysubstance Use* subgroup than sixth graders and female adolescents.

With respect to the associations between covariates and subgroup transitions, I hypothesized that students' sex and grade would relate to their transition probabilities, such that male and older adolescents (i.e., grades 7 and 8) would have greater probabilities of transitions that represent escalating use (i.e., *Non- Use* \rightarrow using subgroups; *Initiation* → *Alcohol Use* or *Polysubstance Use*; *Alcohol Use* → *Polysubstance Use*). I did not expect intervention phase to be related to transition probabilities. I conducted exploratory analyses to examine whether the timing of waves during the year relates to transitions in subgroups over time.

Aim 2a. I hypothesized that there would be differences in the mean levels of each externalizing behavior across all subgroups. More specifically, youth in the *Polysubstance Use* subgroup would report the highest frequencies on both externalizing behaviors, followed by *Alcohol Use, Initiation*, and *Non-Use* subgroups.

Aim 2b. I hypothesized that each externalizing behavior would predict transition probabilities. Youth who reported more frequent physical aggression and delinquent behavior at Wave 1 would be more likely to transition into subgroups at Wave 2 that represented escalation in substance use (i.e., *Non-Use* → using subgroups; *Initiation* → *Polysubstance Use*; *Alcohol Use* \rightarrow *Polysubstance Use*) relative to remaining in the same subgroup (i.e., stability). I hypothesized that substance use subgroup membership at Wave 1 would not predict change in adolescents' frequency of aggression or delinquent behavior at Wave 2.

Aim 2c. I hypothesized that the associations between externalizing behaviors and substance use subgroups would be consistent across sex, timing of the waves, and intervention phase. However, I hypothesized that the relations between externalizing behaviors and substance use subgroups would vary across grades (i.e., moderation), such that older youth (i.e., grades 7 and 8) with high levels of externalizing behaviors would be more likely to escalate their substance use over time than younger youth (i.e., grade 6) with high externalizing behaviors.

Aim 2d. For the sensitivity analyses, I hypothesized that adolescents who reported more distress symptoms at Wave 1 would be more likely to transition into subgroups at Wave 2 that represented escalation in substance use relative to remaining in the same subgroup (i.e., stability). I hypothesized that after controlling for distress symptoms, each externalizing behavior would still uniquely predict escalation in substance use subgroups (as stated in hypotheses for Aim 2b).

Latent Transition Analysis

After identifying the optimal number of subgroups at each wave, I visually inspected the LCA models to determine whether the classes at both waves had similar sizes and interpretations. Longitudinal measurement invariance is present when the likelihood of endorsing each indicator within a given subgroup is constrained to be the same at multiple time points. To evaluate longitudinal invariance in the subgroups, I incorporated the four-class LCA models from each wave into the same model but did not specify any structural associations between the two waves. In other words, the LCA models at both waves were estimated simultaneously but not regressed on each other. I evaluated longitudinal measurement invariance by comparing a model in which the item threshold parameters for each indicator were constrained across waves

to an unconstrained model in which the threshold parameters were allowed to vary across waves (Nylund-Gibson et al., 2022). The structural parameters (e.g., class sizes) were allowed to vary across waves in both models. I used the scaled log likelihood ratio difference test (Satorra & Bentler, 2010) to evaluate whether constraining the threshold parameters across waves decreased model fit. The sample size for this model was 1,810 because only one case was missing on all indicator variables at both waves and FIML estimation uses all available data. The LTA did not exclude cases that were missing data at only one of the two waves.

I determined that the four subgroups were conceptually similar at both waves based on the item response probabilities from the LCA models estimated separately at each wave (see Table 5). Because the subgroup patterns were similar, I evaluated longitudinal measurement invariance for all four of the subgroups. The model in which the item threshold parameters for each indicator within a given subgroup were allowed to vary across waves did not significantly improve upon the fit of the model that constrained these parameters across waves $(\chi^2(48))$ = 50.47, *p* = .376). This supported longitudinal measurement invariance. Constraining the subgroup parameters to be the same at each wave resulted in small changes in the class sizes and response probabilities but did not alter the overall interpretation of the subgroups or the structural parameters (see Table 6). Changes in the item response probabilities were not substantial enough to alter the substantive meaning of the subgroups. Longitudinal measurement invariance (i.e., subgroups constrained over time) was therefore assumed in all subsequent LTA models.

Within the longitudinal constrained model, I conducted the LTA using an extension of the three-step BCH method (Asparouhov & Muthen, 2021). This approach involved estimating the latent class variable for each wave in the same model and saving the joint BCH weights, which reflected measurement error in class assignment at each wave. I then used the joint BCH weights to estimate the LTA. The purpose of the BCH approach is to use weights (i.e., BCH weights) to account for the fact that there is uncertainty in individual classification to each subgroup. Most individuals do not have a probability of 1.0 of being classified into a particular subgroup. This approach thus provides an advantage over hard-classifying individuals into their most-likely subgroup by controlling for error in their subgroup assignment. Using the BCH approach also reduces the likelihood of the subgroups changing (i.e., individual cases moving to a different subgroup) when predictors are incorporated into the model. In the last step of the three-step method, I specified the structural associations of the LTA model by regressing the latent subgroup variable at Wave 2 on the latent subgroup variable at Wave 1 (see Figure 1). I identified the probability of remaining within the same subgroup across waves (i.e., stability) and transitioning to each other subgroup across waves using multinomial logistic regressions for the effect of Wave 1 subgroup membership on Wave 2 subgroup membership. I also used these estimates to calculate the odds of transitioning into subgroups with different patterns of substance use relative to remaining in the same subgroup over time.

Transition probabilities based on the unconditional LTA (i.e., model with no covariates) are presented in Table 7. As hypothesized, early adolescents were most likely to remain in the same substance use subgroup 3 months later. Adolescents in the *Non-Use* subgroup were unlikely (i.e., probabilities of .03 to .04) to transition to any other subgroup. That is, only about 10% percent of early adolescents who were in the *Non-Use* subgroup at the first wave reported initiation or past 30-day substance use 3 months later. Youth in the *Initiation* subgroup had a small probability (.08) of transitioning to the *Polysubstance Use* subgroup. The probability of transitioning from the *Initiation* to the *Alcohol Use* subgroup was zero. About 10% of early adolescents in the *Alcohol Use* subgroup at Wave 1 transitioned to the *Initiation* subgroup at

Wave 2. The transition from *Alcohol Use* to *Initiation* may represent early adolescents who began one or two new types of substances (i.e., other than alcohol) during the time period between waves, or those who had initiated alcohol use but reported no past 30-day alcohol use at the second wave. Another 10% of those in the *Alcohol Use* subgroup transitioned to the *Polysubstance Use* subgroup. Finally, youth in the *Polysubstance Use* subgroup were as likely to remain in this subgroup (probability $= .49$) as they were to de-escalate their use (probability $=$.49). They had a small-to-moderate probability (.37) of transitioning to the *Initiation* subgroup with no past 30-day use, and a small probability (.12) of reporting alcohol use only (i.e., *Alcohol Use* subgroup. This suggests that a large portion of youth who had initiated polysubstance use did not consistently use three or more substances during the past month. It should be noted that there were small probabilities that adolescents in subgroups that endorsed substance use at Wave 1 transitioned to the *Non-Use* subgroup at Wave 2. This transition pattern was allowed to occur in the model to account for naturally existing error in responses on measures and in model estimation. This was most likely to occur for the *Alcohol Use* subgroup (probability = .27).

Next, I evaluated my hypotheses regarding the likelihood of different transition patterns. I hypothesized that transitions to different subgroups over time would be more likely to represent escalation in substance use (i.e., transitioning to subgroups with use of more substances) rather than de-escalation (i.e., use of fewer substances). I also hypothesized that these transitions would be more likely to follow a sequential escalation in use (i.e., *Non-Use, Alcohol Use, Initiation, Polysubstance Use*) rather than escalating directly from no use to polysubstance use. To test these hypotheses, I calculated odds ratios for the odds of transitioning to the hypothesized subgroup relative to the odds of all other possible transition patterns (i.e., staying or transitioning

to any other subgroup). I then evaluated the significance of the odds ratios based on 95% confidence intervals with 5,000 bootstraps.

The hypothesized transition patterns were not supported. Early adolescents in the *Non-Use* subgroup were equally likely to transition to the *Initiation* subgroup and the *Alcohol Use* subgroup as they were to transition to the *Polysubstance Use* subgroup (respectively *OR*s=1.30, 1.02, 95% CI [0.60, 2.66], [0.54, 1.83]). An odds ratio could not be calculated to compare the likelihood of transitioning from *Initiation* to *Alcohol Use* versus *Polysubstance Use* because the model-estimated probability of transitioning from the *Initiation* to *Alcohol Use* subgroup was zero. Adolescents in the *Alcohol Use* subgroup were equally likely to transition to the *Initiation* (i.e., with no past 30-day use) subgroup as the *Polysubstance Use* subgroup (*OR* = .97, 95% CI [0.00, 8.92]). Adolescents in the *Polysubstance Use* subgroup were no more likely to transition to the *Initiation* subgroup than to the *Alcohol Use* subgroup (*OR* = 2.98, 95% CI [0.70, 15.99]).

Although early adolescents in the *Non-Use* and *Initiation* subgroups had small probabilities of transitioning into a different subgroup over time, there were more notable shifts for the adolescents in the *Alcohol Use* and *Polysubstance Use* subgroups across this 3-month period. Figure 4 displays data based on the estimated LTA model indicating the percentage of adolescents within each Wave 2 subgroup that had been in each of the four subgroups at Wave 1. Among youth in the *Polysubstance Use* subgroup at Wave 2, 45% had been in the *Polysubstance Use* subgroup at Wave 1, most of the rest (32%) had previously been in the *Non-Use* subgroup, and fewer had been in the *Initiation* (13%) or *Alcohol Use* (10%) subgroups. Although the *Non-Use* subgroup at Wave 1 had a smaller probability (.03) of transitioning into the *Polysubstance Use* subgroup at Wave 2 than the other subgroups, it represented a larger percentage of the *Polysubstance Use* subgroup at Wave 2 because the *Non-Use* subgroup represents a substantially larger portion of the total sample (see Figure 4). It is, however, noteworthy that 32% of adolescents who reported polysubstance use at Wave 2 had reported no substance use 3 months earlier. Among adolescents in the *Alcohol Use* subgroup at Wave 2, the majority (56%) had been in the *Alcohol Use* subgroup at Wave 1, and 33% had been in the *Non-Use* subgroup. Among youth in the *Initiation* subgroup at Wave 2, the majority (63%) had also been in the *Initiation* subgroup at Wave 1, and most of the rest were about evenly divided between the *Non-Use* (18%) and *Polysubstance Use* (15%) at Wave 1. There was far less change in the *Non-Use* subgroup at Wave 2, of which 97% had been in the same subgroup at Wave 1.

Although the majority of adolescents remained in the same subgroup over time, the subgroups endorsing past 30-day substance use were the least stable over time, highlighting the instability in their patterns of recent substance use over short time periods. These patterns of transitions do not show a gradual progression from non-use to the use of one substance and then to polysubstance use. Rather, these findings suggest that short-term changes in substance use patterns (i.e., spanning a 3-month time period) may be more erratic than the patterns hypothesized by gateway theory and shown in prior research over longer time periods.

Table 6.

Item Response Probabilities for the Unconditional Latent Transition Model with Longitudinal

Note. $n = 1,810$. Bolded values indicate moderate to high probabilities (i.e., $> .50$).

Table 7

Probability of Wave 2 Subgroup Membership Based on Wave 1 Subgroup Membership from the

Unconditional Latent Transition Analysis

Note. $n = 1810$. Values indicate the probability of Wave 2 subgroup membership (columns) conditional upon Wave 1 subgroup membership (rows). Bolded values in the diagonal indicate the probability of remaining in the same subgroup over time (i.e., stability).
Figure 4.

Percentage of Participants within each Wave 2 Subgroup that were in each of the Wave 1 Subgroups

Note. Values are based on estimates from the unconditional LTA model. $n = 1810$. Each pie chart represents the individuals within their respective most likely subgroup at Wave 2. The percentages indicate how many adolescents had been assigned to each subgroup at Wave 1.

Differential Item Functioning

Prior to finalizing the LTA measurement model, I evaluated measurement invariance for the four-class latent class model using the stepwise method for evaluating DIF recommended by Masyn (2017). Because there are no established methods for testing for DIF within an LTA model, I examined DIF separately at each wave using the latent class parameters from the LTA model that had specified longitudinal measurement invariance (i.e., subgroups constrained over time). Sequential tests for DIF were used to identify indicators that showed evidence of DIF and determine whether the direct effect of the covariate on each specific indicator should be allowed to vary across subgroups (i.e., nonuniform) or be constrained across subgroups (i.e., uniform). More specifically, I examined participants' sex, grade, timing of waves, and intervention phase as sources of DIF. I then incorporated all identified sources of DIF into the LTA model. Please see Appendix B for detailed results for each sequential step examining DIF.

At Wave 1, the final model incorporating all identified sources of DIF included one uniform DIF effect and two nonuniform DIF effects by grade. There was no evidence of DIF associated with sex, time of year, or intervention phase within the combined DIF model at Wave 1. Within all subgroups, youth in eighth grade were less likely to report using *inhalants* in the past 30 days ($OR = 0.36$, 95% CI [0.20, 0.64]) than those in sixth grade. Within the *Polysubstance Use* subgroup, eighth grade students were more likely to report *drug use initiation* than sixth grade students (*OR* = 4.03, 95% CI [1.65, 9.85]). Within the *Initiation* subgroup, seventh and eighth grade students were less likely to report *cigar/cigarette use initiation* compared with sixth grade students (*OR*s = 0.08, 0.07, 95% CI [0.01, 0.82], [0.01, 0.55], respectively).

The final model accounting for DIF at Wave 2 included two uniform and two nonuniform

DIF effects by sex, one uniform and one nonuniform DIF effect by grade and by timing of waves, and three uniform and one non-uniform DIF effect by intervention phase. With respect to sex, within all subgroups, male adolescents were more likely to report drinking beer in the past 30 days than were female adolescents (*OR* = 2.41, 95% CI [1.29, 4.53]). Compared with female adolescents in the same subgroup, male adolescents in the *Initiation* subgroup were more likely to report *drug use initiation* (*OR* = 2.10, 95% CI [1.07, 4.04]) and those in the *Alcohol Use* subgroup were less likely to report *past 30-day inhalant use* (*OR* = 0.0, 95% CI [0.00, 0.002]). Regarding DIF by grade, seventh and eighth grade students within all subgroups were more likely than sixth grade students to report *past 30-day cannabis use* (*OR*s = 4.10, 5.27, 95% CIs [2.09, 8.03], [2.57, 10.81], respectively). Seventh and eighth grade students were also more likely to endorse *been drunk* in the past 30 days in the *Polysubstance Use* subgroup (*OR*s = 9.17, 5.50, 95% CIs [2.48, 33.98], [1.61, 18.79]). With respect to DIF by timing of waves, students were less likely to report *past 30-day illicit drug use* in the spring (i.e., randomized to winter and spring waves) compared with the winter (i.e., randomized to fall and winter waves; $OR = 0.45$, 95% CI [0.21, 0.98]). Students in all subgroups who completed the surveys during a year that their school was in an intervention phase were more likely to report *past 30-day cigar use* (*OR* = 1.83, 95% CI [1.01, 3.30]) and *drug use initiation* (*OR* = 2.13, 95% CI [1.23, 3.65]) than students whose school was not in an intervention phase. All other DIF effects included in the final model were nonsignificant. The resulting latent class models at Wave 1 and Wave 2 that incorporated these identified sources of DIF maintained the same interpretation overall as the unconditional latent class models (see Table 8 for conditional response probabilities).

Table 8.

Item Response Probabilities within Wave 1 and 2 Latent Class Models that Accounted for Differential Item Functioning.

Indicator Variable		Wave 1 $(n = 1778)$				Wave 2 $(n = 1573)$				
		Non-	Initiation	Alcohol	Polysubstance	Non-	Initiation	Alcohol	Polysubstance	
		Use		Use	Use	Use		Use	Use	
		(76%)	(9%)	(9%)	(6%)	(73%)	(14%)	(6%)	(7%)	
Lifetime Initiation	Alcohol	0.04	0.54	0.78	0.88	0.08	0.65	0.87	0.82	
	Drugs	0.00	0.66	0.08	0.67	0.01	0.61	0.17	0.69	
	Smoking	0.01	0.59	0.14	0.66	0.01	0.60	0.20	0.61	
Past 30- Day Use	Liquor	0.00	0.03	0.23	0.79	0.00	0.02	0.45	0.65	
	Beer	0.00	0.03	0.30	0.61	0.01	0.03	0.38	0.53	
	Got drunk	0.00	0.03	0.09	0.55	0.00	0.01	0.13	0.59	
	Wine/wine coolers	0.00	0.00	0.39	0.73	0.01	0.01	0.46	0.63	
	Cannabis	0.00	0.19	0.01	0.59	0.00	0.14	0.07	0.67	
	Inhalants	0.01	0.07	0.07	0.27	0.01	0.02	0.01	0.27	
	Illicit drugs	0.00	0.03	0.02	0.22	0.00	0.03	0.00	0.30	
	Cigars	0.00	0.22	0.02	0.63	0.00	0.19	0.00	0.76	
	Cigarettes	0.00	0.11	0.00	0.45	0.00	0.07	0.00	0.44	

Note. DIF was evaluated in separate models for each wave. Bolded values indicate moderate to high probabilities > .50.

Covariate Relations with Subgroup Membership

Next, I incorporated each DIF effect identified in the Wave 1 or Wave 2 LCA into its respective wave in the LTA model. Within the LTA accounting for DIF, I examined the association between covariates (i.e., sex, grade, intervention phase, timing of waves) and subgroup membership in separate analyses for each covariate. I compared a series of models to identify the optimal way to account for the effects of each covariate (i.e., sex, grade, intervention phase, timing of waves) on subgroup membership or transitions (Muthén, 2021). The baseline model examined associations between the covariate and subgroup membership at Wave 1. The main effect model examined associations between the covariate and subgroup transitions over time (i.e., Wave 1 and Wave 2 subgroup variables regressed on the covariate). This model assumed that the covariate's effect on transition probabilities did not differ for individuals in different Wave 1 subgroups. The interaction model expanded on the main effect model by allowing the effect of the covariate on transition probabilities to vary as a function of Wave 1 subgroup membership (i.e., Wave 2 subgroup regressed on the covariate, conditional upon Wave 1 subgroup membership). Whereas the main effect model constrained the effect of the covariate on transitions to be the same across Wave 1 subgroups, the interaction model allowed these covariate effects to be unconstrained across Wave 1 subgroups. I sequentially examined each of these covariate models and compared them using the scaled log likelihood ratio difference test (Satorra & Bentler, 2010).

Within the final model that best accounted for covariate relations with the transitions over time, individual tests examined whether covariates were related to membership in each subgroup and/or transitions over time. When the there was evidence of significant associations with subgroup membership, I calculated odds ratios and 95% confidence intervals with 10,000

bootstraps to determine the extent to which the odds of membership in each subgroup varied for each dummy-coded covariate. An odds ratio with a confidence interval that did not contain 1.0 indicated that the odds of subgroup membership significantly differed for the covariate relative to its reference group (e.g., seventh versus sixth grade students). When the covariate showed significant associations with subgroup transitions (i.e., in the main effect or interaction models), I examined odds ratios that indicated the extent to which the covariate predicted transitions relative to stability over time. An odds ratio with a 95% confidence interval that did not include 1.0 indicated that the covariate (e.g., male versus female adolescents) impacted the odds of transitioning to a different subgroup relative to staying in the same subgroup over time. The optimal for each covariate was examined to interpret covariate effects and retained to control for covariate effects in the Aim 2 analyses.

Sex Differences

In the baseline model for sex, an omnibus Wald test indicated that sex was significantly associated with subgroup membership at Wave 1 ($\chi^2(3) = 16.58$, $p < .000$). The probability of class membership at Wave 1 for male and female adolescents is presented in Figure 5A. Male adolescents were more likely than female adolescents to be in the *Initiation* subgroup (*OR* = 1.65, 95% CI [1.22, 2.34]). Contrary to hypotheses, male adolescents were less likely to be in the *Polysubstance Use* subgroup ($OR = 0.52, 95\%$ CI [0.32, 0.78]). There were no sex differences in the likelihood of being in the *Alcohol Use* (*OR* = 0.75, 95% CI [0.47, 1.15]) or *Non-Use* subgroups ($OR = 1.05$, 95% CI [0.86, 1.29]). These results did not support hypotheses that male adolescents would engage in more substance use (i.e., *Alcohol Use, Polysubstance Use*) than female adolescents.

Next, I evaluated the main effect and interaction models to determine whether sex was associated with subgroup transitions over time. The main effect model did not fit the data significantly better than the baseline model ($\chi^2(3) = 0.26$, $p = .968$). This indicates that participants' sex was associated with substance use subgroup membership at Wave 1 but did not account for variance in the transition probabilities. The interaction model, which allowed the effects of sex on the transition probabilities to vary across Wave 1 subgroup membership, significantly improved upon the fit of the baseline model (i.e., $\chi^2(12) = 33.65$, $p = .001$). Although this suggests that allowing the effects of sex on subgroup transitions to vary across Wave 1 subgroup membership improved fit of the model to the data, the odds ratios for the effects of sex on transition probabilities were not significant (see Table 9). There were very large standard errors (i.e., $SE = 0.46$ to 14.60) for the effects of sex on the transition probabilities in the interaction model, resulting in large confidence intervals that included 1.00 (see Table 9). This indicates a lack of precision around these estimates due to sparsity in the cells for the transition probabilities. In other words, there may not have been sufficient power to provide sufficient precision to predict the transition probabilities given the small number of individuals following that transition. Although the overall model fit suggests that sex and Wave 1 subgroup interacted to predict subgroup transitions, the sex differences in transition probabilities could not be pinpointed. These analyses provide inconclusive results as to how subgroup transitions might vary across sex. For the Aim 2 analyses, subgroup membership at Wave 1 was regressed on sex (i.e., baseline model) to control for the effects of sex on subgroup membership.

Grade Differences

Grade was significantly associated with Wave 1 class membership (i.e., baseline model; $\chi^2(6) = 35.63, p < .001$). The probability of membership in each subgroup at Wave 1 for students in each grade is displayed in Figure 5B. As expected, students in eighth grade had greater odds than students in sixth and seventh grade of being in the *Polysubstance Use* subgroup (*OR*s = 2.80, 1.77, 95% CI [1.72, 5.21], [1.08, 2.90], respectively). Eighth grade students were also more likely to be in the *Initiation* subgroup than sixth grade students (*OR* = 1.87, 95% CI [1.17, 3.28]). Finally, as hypothesized, eighth graders had lower odds than sixth and seventh graders of being in the *Non-Use* subgroup (*OR*s = 0.51, 0.68, 95% CI [0.38, 0.65], [0.50, 0.90], respectively), as hypothesized. There were no significant differences in the *Alcohol Use* subgroup, or between sixth and seventh grade students in their substance use subgroup membership. These findings suggest that eighth grade students were more likely to report use of multiple substances in addition to alcohol compared with sixth and seventh grade students.

I then evaluated whether the transition probabilities varied as a function of grade. Including grade as a predictor of subgroup transitions in the main effect model did not significantly improve model fit ($\chi^2(6) = 3.14$, $p = .791$). The interaction model, however, fit significantly better than the baseline model ($\chi^2(24) = 398.16$, $p < .001$). This suggests that the interactive effect of grade and Wave 1 subgroup membership impacted the transition probabilities. However, as in the interaction model for sex, none of the odds ratios representing grade differences on transition probabilities were significant (see Table 9). This again appears to reflect sparsity in the cells for certain transition patterns. These analyses suggest that grade impacted subgroup transitions, but provided inconclusive results as to how subgroup transitions vary across grade by Wave 1 subgroup. The baseline model was used to control for the effects of grade on subgroup membership for the Aim 2 analyses.

Differences across Timing of Waves

The timing of waves during the year was not associated with subgroup membership at Wave 1 ($\chi^2(6) = 2.69$, $p = 847$). The model fit was significantly improved by including timing of waves as a predictor of transition probabilities (i.e., main effect model; $\chi^2(12) = 22.21$, $p = .035$). Within the main effect model, an omnibus Wald test indicated that the timing of waves was significantly related to subgroup membership at Wave 2 after accounting for subgroup membership at Wave 1 ($\chi^2(6) = 16.43$, $p = .012$). Differences in the probability of Wave 2 subgroup membership across the seasons of data collection are reported in Figure 5C. According to pairwise comparisons, adolescents were less likely to be in the *Polysubstance Use* subgroup at Wave 2 if their second wave of data was collected during the summer rather than the winter (*OR* $= 0.27, 95\%$ CI [0.08, 0.71]) or spring (*OR* = 0.21, 95% CI [0.06, 0.51]). In other words, early adolescents were less likely to endorse polysubstance use during the summer than during times when school was in session, independent of their substance use 3 months prior. Early adolescents were more likely to be in the *Non-Use* subgroup at Wave 2 if they completed the survey during the summer versus the spring ($OR = 2.46, 95\%$ CI [1.24, 5.99]). This suggests that adolescents were less likely to endorse initiation of substance use during the summer.

The timing of waves on subgroup membership also impacted the likelihood of specific subgroup transitions across waves (see Table 10). Students in the *Non-Use* and *Initiation* subgroups were less likely to transition to the *Polysubstance Use* subgroup (i.e., versus staying in the same subgroup) between the spring to summer assessments compared with the fall to winter assessments (*ORs* = 0.27, 0.25, 95% CI [0.10, 0.71], [0.10, 0.58], respectively). Students were more likely to transition from the *Polysubstance Use* subgroup to the *Initiation* or the *Non-Use* subgroups (i.e., versus staying in the same subgroup) during the spring to summer than they were during the fall to winter (*OR*s = 4.08, 3.76, 95% CI [1.72, 9.66], [1.41, 10.02], respectively). This indicates that students who had endorsed past 30-day substance use at Wave 1 were less likely to endorse past 30-day use at Wave 2 if Wave 2 took place during the summer.

Model fit was further improved by allowing the effects of timing of waves on transition probabilities to vary across Wave 1 subgroup membership (i.e., interaction model; $\chi^2(16)$ = 66.55, $p < .001$). However, the interaction model for the timing of waves also lacked precision around the parameters for the effects of the timing of the waves on the transition probabilities $(SEs = 1.8$ to 60.79) due to sparsity in the cells for certain transition probabilities. Although these results suggest that the effects of the timing of waves on the transition probabilities varied across Wave 1 subgroup membership, there may not have been sufficient power in the data to pinpoint these differences. The main effect model for timing of waves was thus used in the Aim 2 analyses to control for the effects of the timing of waves on transition probabilities.

Intervention Phase Differences

Intervention phase was not significantly related to subgroup membership at Wave 1 (i.e., baseline model; $\chi^2(3) = 5.23$, $p = .156$). Including intervention phase as a predictor of transition probabilities in the main effect ($\chi^2(3) = 0.89$, $p = .828$) and the interaction model ($\chi^2(12) = 5.64$, $p = .933$) did not improve the fit of the baseline model. This suggests that neither subgroup membership nor change in subgroups over time was influenced by whether the intervention was being implemented in the student's school during that year.

Figure 5. Figure 5.

Probability of Membership in each Subgroup at Wave 1 or Wave 2 across Sex, Grade, and Season

Note. Error bars represent 95% confidence intervals for the probability of subgroup membership. Panel C: Probabilities for wave represent probability of class membership at Wave 2 across waves, controlling for subgroup membership at Wave 1.

Table 9.

Odds Ratios and Confidence Intervals for the Effects of Sex, Grade, and Timing of Waves

Wave 1	Wave 2 Subgroup							
Subgroup	Polysubstance Use	Initiation	Alcohol Use	Non-Use				
	Effect of Male sex vs Female sex							
Polysubstance	1.00(1.00, 1.00)	1.54(0.47, 5.03)	3.23(0.62, 16.88)	7.03(0.00, a)				
Use								
Initiation	0.90(0.21, 3.90)	1.00(1.00, 1.00)	0.00(0.00, 0.00)	0.80(0.00, 2133.13)				
Alcohol Use	0.82(0.15, 4.52)	0.02(0.00, a)	1.00(1.00, 1.00)	1.16(0.24, 5.66)				
Non-Use	1.43(0.58, 3.53)	1.63(0.60, 4.42)	0.84(0.25, 2.77)					
	Effect of Grade 7 vs Grade 6							
Polysubstance	1.00(1.00, 1.00)	0.52(0.09, 2.90)	0.24(0.01, 4.68)	0.00(0.00, 0.00)				
Use								
Initiation	0.47(0.04, 5.24)	1.00(1.00, 1.00)	0.00(0.00, 0.00)	0.00(0.00, 0.00)				
Alcohol Use	0.99(0.14, 6.99)	a(a, a)	1.00(1.00, 1.00)	1.61(0.17, 15.63)				
Non-Use	0.74(0.31, 1.76)	1.37(0.58, 3.20)	1.61(0.39, 6.62)	1.00(1.00, 1.00)				
			Effect of Grade 8 vs Grade 6					
Polysubstance	1.00(1.00, 1.00)	0.83(0.17, 3.98)	0.54(0.03, 9.17)	a(a, a)				
Use								
Initiation	1.46(0.28, 7.75)	1.00(1.00, 1.00)	a(a, a)	11.92 (0.04, 3287.71)				
Alcohol Use	0.36(0.02, 5.46)	a(a, a)	1.00(1.00, 1.00)	0.44(0.02, 11.72)				
Non-Use	0.65(0.23, 1.86)	0.61(0.20, 1.91)	1.58(0.36, 6.93)	1.00(1.00, 1.00)				
		Effect of Winter/Spring vs Fall/Winter						
Polysubstance	1.00(1.00, 1.00)	1.97(0.61, 6.38)	0.30(0.01, 14.26)	0.00(0.00, 0.00)				
Use								
Initiation	0.48(0.09, 2.71)	1.00(1.00, 1.00)	0.99(0.08, 12.07)	0.99(0.08, 12.07)				
Alcohol Use	1.71 (0.29,	2.39 (0.03, 201.47)	1.00(1.00, 1.00)	0.78(0.09, 6.72)				
	10.07							
Non-Use	1.21(0.50, 2.95)	1.77(0.82, 3.84)	3.11 (0.51, 19.00)	1.00(1.00, 1.00)				
	Effect of Spring/Summer vs Fall/Winter							
Polysubstance	1.00(1.00, 1.00)	5.47 (0.89, 33.77)	1.32(0.19, 9.12)	3507.10 (0.00, a)				
Use								
Initiation	0.69(0.16, 3.04)	1.00(1.00, 1.00)	0.11(0.00, a)	0.11(0.00, a)				
Alcohol Use	0.00(0.00, 0.00)	6.47 (0.18, 237.54)	1.00(1.00, 1.00)	3.95 (1.06, 14.75)				

Predicting Subgroup Transitions Relative to Subgroup Stability in the Interaction Models

Note. Odds Ratio (95% Confidence Interval). Odds Ratios (OR) represent the odds for each comparison group of transitioning subgroups relative to the odds of remaining in the same subgroup over time (i.e., diagonal). Subheadings indicate results of separate analytic models. Diagonal values have an OR and CI values of 1.00 to indicate that this is the comparison group, or stability in subgroup across waves. ORs with values of 0.00 were fixed at 0.00 by Mplus due to a denominator $= 0.00$.

Non-Use 0.19 (0.03, 1.19) 0.58 (0.18, 1.93) 1.46 (0.16, 13.42) 1.00 (1.00, 1.00)

^a Values were too large to be estimated by Mplus due to empty cells in the joint distribution of the latent class variable and the categorical predictor variable. .

Table 10.

Odds Ratios and Confidence Intervals for the Timing of Waves Predicting Subgroup Transitions

Wave 1 Subgroup	Wave 2 Subgroup						
	Polysubstance Use	Initiation	Alcohol Use	Non-Use			
	Effect of Winter/Spring vs Fall/Winter						
Polysubstance Use	1.00(1.00, 1.00)		$1.56(0.77, 3.15)$ $1.22(0.53, 2.82)$ $0.75(0.35, 1.61)$				
Initiation	0.64(0.32, 1.30)		$1.00 (1.00, 1.00)$ 0.78 $(0.27, 2.30)$ 0.48 $(0.19, 1.27)$				
Alcohol Use	0.82(0.36, 1.90)		$1.28(0.43, 3.76)$ $1.00(1.00, 1.00)$ $0.62(0.29, 1.33)$				
Non-Use	1.33(0.62, 2.85)		$2.07(0.79, 5.40)$ $1.62(0.75, 3.49)$ $1.00(1.00, 1.00)$				
	Effect of Spring/Summer vs Fall/Winter						
Polysubstance Use	1.00(1.00, 1.00)			4.08 (1.72, 9.66) 2.67 (0.86, 8.24) 3.76 (1.41, 10.03)			
Initiation	0.25(0.10, 0.58)		$1.00(1.00, 1.00)$ 0.65 (0.23, 1.86) 0.92 (0.41, 2.06)				
Alcohol Use	0.38(0.12, 1.16)		$1.53(0.54, 4.34)$ $1.00(1.00, 1.00)$ $1.41(0.56, 3.55)$				
Non-Use	0.27(0.10, 0.71)	1.08(0.49, 2.42)	0.71(0.28, 1.79)	1.00(1.00, 1.00)			

relative to Subgroup Stability across Waves in the Main Effect Model

Note. Odds Ratio (95% Confidence Interval). Odds Ratios (OR) represent the odds for each comparison group of transitioning to specific subgroup relative to the odds of remaining in the same subgroup over time (i.e., diagonal). Bolded values are significant based on the 95% confidence interval for the OR. Diagonal values have an OR and CI values of 1.00 to indicate that this is the comparison group, or stability in subgroup across waves.

Subgroup Differences in Externalizing Behaviors

The mean subscale scores for the physical aggression and delinquent behavior variables within each subgroup at each wave are reported in Figure 6. Omnibus Wald tests indicated that there were significant subgroup differences in physical aggression and delinquent behavior at Wave 1 ($\chi^2(3) = 259.68$, 194.15, *ps* < .000, respectively) and Wave 2 ($\chi^2(3) = 221.96$, 159.33, *ps* < .000). The mean subgroup differences (i.e., d-coefficients) adjusted for covariate effects on the externalizing variables were medium to large and generally consistent across waves (see Table 11). Consistent with theories of externalizing behaviors and substance use, early adolescents in the *Polysubstance Use* subgroup reported more frequent engagement in physical aggression and delinquent behavior compared with the *Initiation*, *Alcohol Use*, and *Non-Use* subgroups. These differences were all large (*ds* = 0.86 to 2.41 across comparisons and waves). Although the *Initiation* and *Alcohol Use* subgroups did not differ from each other, both subgroups reported more frequent physical aggression and delinquent behavior than the *Non-Use* subgroup. Whereas differences between the *Initiation* and *Non-Use* subgroups ranged from small to moderate effect sizes (*ds* = 0.36 to 0.67 across waves), comparisons between the *Alcohol Use* and *Non-Use* subgroups resulted in moderate to large effect sizes ($ds = 0.53$ to 0.81).

Figure 6.

Mean Covariate-Adjusted Subscale Scores for Physical Aggression and Delinquent Behavior

Variables across Subgroups at Wave 1 and Wave 2

Note. Physical aggression and delinquent behavior means were adjusted for sex, grade, intervention phase, and timing of waves. Scale scores are averaged on a 4-point scale where $1 =$ never, $2 = 1-2$ times, $3 = 3-5$ times, and $4 = 6$ or more times. Scale subscale scores were log transformed and then rescaled to the same mean and standard deviation as the original subscales. Error bars represent 95% confidence intervals for the mean scores.

Table 11.

Cross-sectional Differences in Covariate-Adjusted Means (d-Coefficients) of Physical

Aggression and Delinquent Behavior across Subgroups at Wave 1 and Wave 2

Note. PU = Polysubstance Use, $I =$ Initiation, $AU =$ Alcohol Use, $NU =$ Non-use. Variables are standardized within wave 1 and wave 2 separately. Means are adjusted for sex, grade, intervention phase, and timing of waves. *P*-values indicating significant differences between specific groups are based on significant tests.

 $*_{p}$ < 0.05, ***p* < 0.01, ****p* < 0.001

Bidirectional Associations between Externalizing and Substance Use Subgroups

Externalizing Behaviors Predicting Subgroup Transitions Over Time

Next, I used cross-lagged regression models to examine the prospective bidirectional associations between each externalizing variable and subgroup membership. I examined separate one-sided models to reduce the complexity of these models (see Figure 2). The first set of models examined the extent to which each externalizing variable predicted transitions in subgroup membership after controlling for covariate effects (see Figure 2a). These analyses were incorporated into the LTA model by regressing the subgroup transition probabilities on the externalizing variable at Wave 1 and controlling for the identified covariate (i.e., sex, grade, timing of waves) effects on subgroup membership. I compared constrained and unconstrained models to determine whether the effects of each externalizing variable on transitions were consistent (i.e., main effect model) or varied (i.e., interaction model) across Wave 1 subgroups. Models were compared using the scaled log likelihood ratio difference test. The externalizing behavior variables were standardized to improve interpretation of the odds ratios, such that they represented the change in the odds of transitioning to a different subgroup relative to remaining in the same subgroup associated with a one standard deviation difference in the externalizing variable. The autoregressive effect of substance use subgroups was accounted for because the transition probability (i.e., regression of Wave 2 subgroups on Wave 1 subgroups) was the dependent variable in this model.

Model fit was significantly better when the effects of delinquent behavior ($\chi^2(8)$ = 144.45, $p < .001$) and physical aggression ($\chi^2(8) = 19.34$, $p = .013$), on the transition probabilities were unconstrained across Wave 1 subgroups (i.e., interaction models). Delinquent behavior and physical aggression significantly predicted a greater likelihood of several subgroup transitions

representing escalation in substance use over time. The odds ratios reported in Table 12 indicate the change in the odds of transitioning to a different subgroup relative to remaining in the same subgroup with each one standard deviation difference in the externalizing variable. Each one standard deviation increase in the frequency of delinquent behavior at Wave 1 was associated with more than two times greater odds of transitioning from the *Non-Use* subgroup to the *Polysubstance Use*, *Initiation*, and *Alcohol Use* (*ORs* = 2.23 to 2.48) subgroups relative to remaining in the *Non-Use* subgroup. Each one standard deviation increase in the frequency of physical aggression at Wave 1 was associated with 1.57 times greater odds of transitioning from the *Non-Use* subgroup to the *Polysubstance Use* subgroup relative to staying in the *Non-Use* subgroup. The externalizing behaviors were not significantly associated with other subgroup transitions.

These results indicate that early adolescents who reported more frequent engagement in physical aggression and delinquent behavior at Wave 1 were more likely to report substance use initiation over the next 3 months. Whereas delinquent behavior increased the likelihood of escalating to all three subgroups reporting substance use, physical aggression only increased the likelihood that youth transitioned to polysubstance use. This is somewhat consistent with theories of causal pathways between externalizing and substance use, which suggest that youth with greater externalizing problems during early adolescence are more likely to initiate substance use. Contrary to hypotheses, however, delinquent behavior and physical aggression did not significantly impact the odds of subgroup transitions that represented using more substances over time (e.g., transition from *Alcohol Use* to *Polysubstance Use*). These results also suggest that different forms of externalizing have different associations with changes in substance use.

Table 12.

Odds Ratios and Confidence Intervals for the Covariate-Adjusted Effects of Delinquent Behavior and Physical Aggression on

Subgroup Transitions Relative to Subgroup Stability across Waves

Note. Adjusted for relations of sex, grade, and waves with subgroup membership and transitions. Externalizing variables were standardized (i.e., z-scores) and covariates were mean centered. Odds Ratios (OR) represent the change in relative odds of transitioning to subgroup relative to the odds of remaining in the same subgroup with each one standard deviation increase in each externalizing variable averaged across sex, grade, intervention, and wave. Bolded values are significant based on the 95% confidence interval for the OR. Diagonal values have an OR and CI values of 1.00 to indicate that this is the comparison group, or stability in subgroup across waves. ORs with values of 0.00 were fixed at 0.00 by Mplus due to a denominator = 0.00.

Subgroup Membership Predicting Longitudinal Changes in Externalizing Behaviors

Next, I examined the extent to which membership in each substance use subgroup at Wave 1 predicted change in the frequency of each externalizing variable, while accounting for the autoregressive and covariate effects on the externalizing variables (see Figure 2b). This was evaluated in models in which each externalizing variable at Wave 2 was regressed on the substance use subgroup variable, the covariates (i.e., sex, grade, intervention phase, timing of waves), and itself at Wave 1. The results from separate models for physical aggression and delinquency are reported in Table 13 and Table 14.

The effects of the covariates on the externalizing variables at Wave 1 and 2 and the autoregressive effects of externalizing variables are reported in Table 13. At Wave 1 none of the covariates were significantly related to early adolescents' frequency of physical aggression. With respect to delinquent behavior, male adolescents reported more frequent delinquent behavior at Wave 1 than female adolescents (β = 0.06, p = .005), and youth in seventh and eighth grade reported less frequent delinquent behavior than those in sixth grade (*ßs* = -0.06, -0.10, *ps* = .015, .002, respectively). This model also indicated the extent to which the covariates predicted changes in the frequency of physical aggression and delinquent behavior across waves (i.e., effects on the externalizing behaviors at Wave 2). The autoregressive effects for both physical aggression and delinquent behavior were positive (β s = 0.46, 0.25, β s < .001), indicating that the Wave 2 frequency was predicted by the Wave 1 frequency for each behavior. When the two waves took place between the spring and summer, this predicted a smaller degree of change in adolescents' frequency of physical aggression and delinquent behavior at Wave 2, beyond their frequency of physical aggression and delinquent behavior at Wave 1 (β s = -0.06, -0.03, p s =

.006, .013, respectively). There were no other significant associations between covariates and changes in the externalizing behaviors.

The covariate-adjusted standardized means for physical aggression and delinquent behavior are reported separately across the Wave 1 substance use subgroups in Table 14. I used an omnibus Wald test to determine whether changes in early adolescents' frequency of physical aggression and delinquent behavior varied as a function of their substance use subgroup at Wave 1. The Wald test indicated that Wave 1 subgroup membership was not significantly related to changes in early adolescents' frequency of physical aggression $(\chi^2(3) = 0.42, p = .935)$ or delinquent behavior across waves $(\chi^2(3) = 6.11, p = .106)$. Consistent with hypotheses and prior research, this indicates that early adolescents' substance use patterns was not associated with longitudinal changes in the frequency of their physical aggression and delinquent behavior.

Table 13.

Standardized Regression Coefficients for the Effects of Wave 1 Subgroup Membership on

	Physical Aggression				Delinquent Behavior			
	ß	SE	<i>p</i> -value			SE	<i>p</i> -value	
	Externalizing Behaviors at Wave 1							
Sex	-0.04	0.02	0.091		$0.06**$	0.02	0.005	
Winter/Spring	-0.02	0.03	0.597		0.02	0.03	0.455	
Spring/Summer	0.00	0.03	0.989		0.02	0.03	0.432	
Grade 7	-0.03	0.03	0.289		$-0.06*$	0.03	0.015	
Grade 8	-0.01	0.03	0.874		$-0.10**$	0.03	0.002	
Intervention Status	-0.04	0.03	0.191		0.01	0.03	0.810	
	Externalizing Behaviors at Wave 2							
Sex	-0.02	0.02	0.291		0.01	0.01	0.555	
Winter/Spring	0.01	0.02	0.764		0.00	0.01	0.849	
Spring/Summer	$-0.06**$	0.02	0.006		$-0.03*$	0.01	0.013	
Grade 7	0.00	0.02	0.980		0.01	0.01	0.647	
Grade 8	-0.03	0.02	0.247		0.01	0.02	0.637	
Intervention Status	0.00	0.02	0.815		0.02	0.01	0.120	
Externalizing Wave 1	$0.46***$	0.04	0.000		$0.25***$	0.03	0.000	

Covariate-Adjusted Changes in Physical Aggression and Delinquent Behavior

Note. SE = standard error. Externalizing refers to either physical aggression or delinquent behavior. Results of separate models for physical aggression and delinquent behavior are indicated by the column headings. Standardized regression parameters were constrained across Wave 1 subgroups.

p* < 0.05, *p* < 0.01, ****p* < 0.001

Table 14.

Covariate-Adjusted Standardized Mean Frequencies of Physical Aggression and Delinquent

Behavior across Wave 1 Subgroups

Note. Wave 2 externalizing variables are adjusted for the autoregressive effects of the externalizing variable at Wave 1. Wave 1 and Wave 2 variables are adjusted for the covariates (i.e., sex, grade, intervention, timing of waves; see Table 13). Positive values at Wave 2 indicate increases over time.

Moderating Effects of Covariates on Bidirectional Associations Between Alcohol Use Subgroups and Externalizing Behaviors

The focus of Aim 2c was to examine whether the longitudinal associations between the externalizing variables and subgroups differed as a function of sex, grade, timing of waves, intervention phase. I first examined the moderating effects of covariates on the associations between the externalizing variables at Wave 1 and transitions in substance use subgroups across waves. Within the LTA model, I followed a path analysis approach to test moderation in separate models for each externalizing variable and dummy-coded covariate (i.e., separate models for sex, grade, timing of waves, and intervention phase by physical aggression and delinquent behavior). The externalizing variables and covariates were grand mean centered before calculating the product term to facilitate interpretation of the simple main effects. Within each model subgroup transitions were predicted by the covariate, the externalizing variable, and their interaction term. This provided a basis for examining the effects of the Wave 1 externalizing variable, the covariate, and their interaction on Wave 2 subgroup, conditional upon Wave 1 subgroup membership. Of the 144 total moderation effects of covariates on transition probabilities that were estimated, only 2 were significant based on the 95% confidence intervals for the odds ratios (see Appendix C). These analyses were limited by the sparseness of the transition probabilities for small subgroups and the joint distribution of the subgroups and predictor variables. The sparseness in these cells led to Mplus fixing estimates for large values and estimating large confidence intervals (e.g., $OR = 60.71$, 95% CI [1.16, 3185.32]). This was especially true for transitions with a small probability (e.g., *Polysubstance Use* to *Non-Use*). These results suggest that due to limited power resulting from small transition probabilities, these data were not sufficient to draw strong conclusions regarding the moderating effects of covariates on the

longitudinal associations between externalizing behaviors and substance use patterns.

In order to examine the moderating effects of the covariates on the associations between substance use subgroups at Wave 1 and changes in each externalizing variable over time (see Figure 2b), I hard-classified individuals into their most-likely class membership. Although this approach is more limited because it does not account for uncertainty in class membership, it provided the most accurate class assignment and successfully estimated the desired moderation model. I estimated four multiple group models separately for each covariate (i.e., separate models for sex, grade, timing of waves, intervention phase). In each multiple group model, the externalizing variable at Wave 2 was regressed on itself (i.e., autoregressive effects), dummycoded variables for class membership at Wave 1, and the other covariates. The associations between most likely class variables and each externalizing variable were allowed to vary across each group defined by the covariate. The effects of all other covariates on the externalizing variables were constrained across groups. For example, in the multiple group models for grade, the effects of subgroup membership on changes in physical aggression were estimated separately for youth in grades 6, 7, and 8, whereas the effects of sex, timing of waves, and intervention phase on physical aggression were constrained across grades. I conducted omnibus Wald tests to determine whether the effect of subgroup membership on change in externalizing variables varied as a function of the covariate that was the focus of that multiple group model.

Omnibus tests did not indicate any significant moderating effects. More specifically, the associations between substance use subgroup at Wave 1 and subsequent changes in delinquent behavior and physical aggression did not vary across sex $(\chi^2(3) = 0.34, 3.27, p = .952, .352,$ respectively). With respect to the moderating effect of grade, sixth grade students did not differ from seventh or eighth grade students on relations between subgroup membership and changes in

physical aggression ($\chi^2(3) = 0.50$, 2.16, *p* = .919, .540) or delinquent behavior ($\chi^2(3) = 5.48$, 6.01, $p = .140, .111$). The results were also consistent across the timing of waves. More specifically, associations did not differ if the first wave was during the fall versus the winter ($\chi^2(3) = 2.35$, 1.05, $p = .504, .788$) or the spring ($\chi^2(3) = 2.28, 1.66, p = .516, .646$). The relations did not differ based on intervention phase ($\chi^2(3) = 0.76$, 3.14, $p = .859$, .370). The prospective associations between substance use subgroup membership and externalizing behaviors were thus consistent across sex, grade, timing of waves, and intervention phase.

Sensitivity Analyses Controlling for Distress Symptoms

I conducted sensitivity analyses to determine the unique associations between externalizing behaviors and change in substance use subgroup membership while accounting for early adolescents' distress symptoms. Exclusion of 361 cases with missing data on the distress symptoms variable resulted in a sample size of 1,447. I first examined the association between distress symptoms at Wave 1 and transitions in subgroup membership over time, controlling for the associations between covariates and subgroup membership (see Model 1, Table 15). Each one standard deviation increase in distress symptoms was associated with greater odds of transitioning from the *Non-Use* subgroup to the *Polysubstance Use* subgroup (*OR* = 1.58) and from the *Initiation* subgroup to the *Polysubstance Use* subgroup (*OR* = 1.72) relative to staying in the same subgroup across waves. Distress symptoms did not significantly impact any other subgroup transitions.

Next, I incorporated Wave 1 distress symptoms into the models examining the effects of Wave 1 externalizing behaviors on change in subgroup membership over time. When distress and physical aggression were entered as simultaneous predictors of subgroup transitions, distress symptoms significantly predicted greater odds of transitioning from the *Non-Use* subgroup to the *Polysubstance Use* subgroup (*OR* = 1.17), but physical aggression did not (see Model 2, Table 15). This suggests that distress symptoms accounted for a greater proportion of *unique* variance in early adolescents' change from no substance use to polysubstance use over time than did physical aggression. In contrast, distress symptoms were no longer significantly related to the transition pattern from *Initiation* to *Polysubstance Use* after accounting for physical aggression, suggesting there was shared variance between physical aggression and distress.

In the model examining the unique effects of delinquent behavior and distress symptoms, only delinquent behavior maintained significant associations with changes in substance use over time (see Model 3, Table 15). More specifically, each one standard deviation increase in delinquent behavior was uniquely associated with more than two times greater odds of transitioning from the *Non-Use* subgroup to the *Polysubstance Use* subgroup (*OR* = 2.15) and the *Alcohol Use* subgroup (*OR* = 2.83) after controlling for distress symptoms. Delinquent behavior was no longer associated with the transition from *Non-Use* to *Initiation* after accounting for distress symptoms. Whereas neither distress symptoms nor delinquent behavior were uniquely related to transitioning to the *Initiation* subgroup*,* delinquent behavior was uniquely related to transitioning to past 30-day substance use (i.e., *Alcohol use*, *Polysubstance Use*).

Only early adolescents' delinquent behavior had a significant impact on change in substance use over time after accounting for adolescents' distress symptoms. The results of the sensitivity analyses indicated that distress symptoms accounted for a greater proportion of variance of change in early adolescents' substance use compared with physical aggression, whereas delinquent behavior accounted for more variance than distress symptoms. These results suggest that the interaction between the internalizing and externalizing pathways to substance use might vary based on the type of externalizing behavior that is being assessed.

Table 15.

Odds Ratios and Confidence Intervals for the Covariate-Adjusted Unique Effects of Externalizing Behaviors and Distress Symptoms

on Subgroup Transitions Relative to Subgroup Stability Across Waves

Note. $n = 1447$. Adjusted for relations of sex, grade, and waves with subgroup membership and transitions. Externalizing and distress variables were standardized (i.e., z-scores) and covariates were mean centered. Odds Ratios (OR) represent the change in the odds of transitioning to a new subgroup relative to remaining in the same subgroup with each one standard deviation increase in each predictor variable. Bolded values are significant based on the 95% confidence interval for the OR. Each subheading represents separate analytic models. Diagonal values have an OR and CI values of 1.00 to indicate that this is the comparison group, or stability in subgroup across waves.

^a Values were too large to be estimated by Mplus due to empty cells in the joint distribution of the latent class variable and the categorical predictor variable

Discussion

Polysubstance use during adolescence is associated with increased risk for a multitude of adverse outcomes. Due to a lack of studies examining patterns of early adolescents' substance use, gaps persist regarding the longitudinal development of polysubstance use during early adolescence and the role of polysubstance use in developmental theories. Several theories posit that externalizing psychopathology is a key mechanism leading to adolescent-onset substance use, but they provide different explanations for the sequencing of these behaviors. More specifically, common cause models indicate that externalizing behaviors and substance use cooccur during adolescence (Jessor, 1987). The externalizing pathway argues that externalizing behaviors lead to substance use onset during adolescence (Zucker, 2006). Finally, bidirectional theories maintain that the behaviors increase and reinforce each other over time. The present study aimed to address gaps in the literature regarding early adolescents' patterns of substance use, changes in substance use over time, and bidirectional associations between substance use patterns and externalizing behaviors.

The focus of this study was on a primarily Black sample of middle school students living in neighborhoods with high rates of community violence and families living at or below the federal poverty threshold. Developmental theories emphasize the influence of adolescents' characteristics, underlying tendencies, and environmental contexts on their behavior. It is thus critical that the current results be conceptualized within this environmental context. Due to a history of residential segregation, youth living in urban settings, in particular Black and Latiné youth, are disproportionately exposed to a broad range of adverse events and stressors in their community, including racism, poverty, food insecurity, and violence (Attar et al., 1994; Hampton-Anderson et al., 2021; Stein et al., 2003; Wade et al., 2014). Exposure to such

community stressors is associated with increased risk for both externalizing and internalizing symptoms (Fowler et al., 2009). Community stressors often experienced by youth in urban settings have been tied to elevated risk for substance use. One study focused on youth ages 14 to 24 years old in an urban community found that having alcohol outlets near one's home was associated with greater risk for polysubstance use, and living in high crime density areas was associated with greater risk for co-occurring alcohol and cannabis use (Goldstick et al., 2016). These contextual stressors may also exacerbate the externalizing pathway to substance use. One prior study found that among youth with higher genetic risk for externalizing symptoms, their likelihood of delinquent behavior was exacerbated by neighborhood stressors such as exposure to community violence (Bares et al., 2020). The early adolescents in the present study likely experienced similar environmental risk factors that may put them at higher risk for the development of externalizing symptoms, internalizing symptoms, and substance use. It is critical that the findings of the current study be interpreted within the context of this high-risk environment.

Patterns of Substance Use and Transitions Over Time (Aim 1)

The first aim of this study was to identify subgroups of early adolescents based on their self-reported history of initiating substance use and their use in the past 30 days. I identified four substance use subgroups at two waves of data 3 months apart. The *Non-Use* subgroup (Wave 1 = 76%, Wave 2 = 73%) had a low probability of any substance use. The *Initiation* (11%, 13%) subgroup had moderate to high probabilities of reporting initiation of alcohol, cigarettes/cigars, or drugs in their lifetime, but not in the past 30 days. The *Alcohol Use* subgroup (7%, 7%) represented youth who endorsed initiation of alcohol use and past 30-day use of at least one type of alcohol. Finally, the *Polysubstance Use* subgroup (6%, 7%) had high probabilities of

endorsing initiation and past 30-day use of three or more substances (i.e., alcohol, cannabis, and cigars). A key finding is that the *Polysubstance Use* subgroup had the highest probability of endorsing inhalant or illicit drug use (e.g., amphetamines, cocaine). This is consistent with prior work indicating that early adolescents who engage in polysubstance use are at increased risk for escalation to more harmful illicit substance use (Conway et al., 2013; Johnson et al., 2020).

The subgroups identified in this study were most similar to those in previous studies of youth in urban communities with primarily Black samples. For example, among middle and high school students (94% Black youth) in Mobile, Alabama, most students reported no substance use (48%), followed by lifetime use of alcohol and cannabis (32%), alcohol only (18%), and polysubstance use (3%; Johnson et al., 2020). The current study's *Initiation* subgroup, which had a high probability of initiation of two or more substances during their lifetime, is most consistent of with the "alcohol and cannabis use initiation subgroup" identified among prior studies of high school students in urban areas (Goldstick et al., 2016; Johnson et al., 2020; Schneider et al., 2020). Prior studies focused on primarily Black samples of youth in urban settings have generally identified a lower prevalence of subgroups characterized by polysubstance use compared with studies of national samples (e.g., Connell et al., 2009; Conway et al., 2013; Lamont et al., 2014). This is also consistent with the finding that 6% to 7% of early adolescents in the present study reported polysubstance use.

The substance use subgroups in this study differed from those identified in past studies in several notable ways. A greater proportion of youth in the current study reported no substance use (i.e., 73% - 76% across waves) than in most prior studies (e.g., 48% - 63%; Conway et al., 2013; Johnson et al., 2020; Schneider et al., 2020). This may be explained by this study's focus on a primarily Black sample of early adolescents. Fewer early adolescents have initiated

substance use compared with middle to late adolescents (Johnston et al., 2021). Even among older adolescents, Black youth are less likely to engage in substance use (Johnston et al., 2018). For example, among high school students in a midwestern state, a greater proportion of Black students reported no past 30-day substance use (i.e., 88%) compared with White students (73%; Banks et al., 2020). A novel aspect of the present study is that it considered both initiation of substance use and past 30-day use, whereas most prior studies that have assessed only initiation (e.g., Johnson et al., 2020; Schneider et al., 2020) or recent use (e.g., Banks et al., 2020; Goldstick et al., 2019). This approach enabled the current study to differentiate between adolescents who reported prior initiation of multiple substances (i.e., *Initiation*) versus those who reported past 30-day polysubstance use. Early adolescents in the *Initiation* subgroup would have been categorized into the *Non-Use* subgroup if only their recent substance use had been considered, but the *Initiation* subgroup was more similar to the *Alcohol Use* subgroup on outcome variables. This suggests that including indicators of both past and current substance use improved categorization of youth based on severity of their substance use and co-occurring behaviors.

Transitions in Patterns of Substance Use

I also examined transitions in subgroups representing different patterns of substance use across two waves. Similar to the results of prior longitudinal studies examining transitions in high school students' substance use patterns (Choi et al., 2018; Mistry et al., 2015), early adolescents in the present study were generally most likely to remain in the same subgroup over time. However, in the present study, youth in the *Polysubstance Use* subgroup were just as likely to remain in the same subgroup as they were to deescalate to no past-month use or the use of fewer substances 3 months later. This finding was unexpected because most prior studies have

found small probabilities (i.e., .00 - .15) that high school students transition out of the recent polysubstance use subgroup over time (Choi et al., 2018; Mistry et al., 2015).

The gateway hypothesis posits that youth typically progress from initiation of legal substances (i.e., alcohol, tobacco) to criminalized substances (e.g., cannabis, cocaine; Kandel & Kandel, 2015). Individuals also typically transition sequentially from no use to initiation of one to two substances (i.e., alcohol and/or tobacco), whereas single- or dual-use subgroups are relatively more likely to escalate to polysubstance use and the use of a greater number of illicit substances (Kandel & Kandel, 2015). This pattern has been supported by prior research. For example, in a primarily African American sample of high school students, Mistry et al. (2015) found that adolescents who reported alcohol and cannabis use at the initial wave were more likely to transition to polysubstance use (probabilities = .30 - .37) than those who reported no use at the initial wave (probabilities $= .09 - .19$). Similarly, Choi et al. (2018) found that high school students were more likely to transition to the polysubstance use subgroup from alcohol and cannabis use (probabilities $= .08, .04$) than from only alcohol use (probabilities $= .00, .01$). The current study's findings, however, did not align with the gateway hypothesis or the results of these prior studies. Early adolescents in the *Non-Use* subgroup were equally likely to transition to the *Initiation, Alcohol Use*, and *Polysubstance Use* subgroups 3 months later. Youth in the *Alcohol Use* subgroup were equally likely to transition to the *Initiation* subgroup (i.e., high probability of initiation of two or more substances with no 30-day use) as they were to transition to the *Polysubstance Use* subgroup (i.e., high probability of past 30-day use of three or more substances). This finding does not support the gateway hypothesis and instead suggests that early adolescents are just as likely to initiate one substance (i.e., *Alcohol Use*) as they are to initiate two or more different substances (i.e., *Initiation* or *Polysubstance Use*) within the next 3 months. Some early adolescents escalated directly to use of cannabis or other drugs from no use. In addition, youth in the *Polysubstance Use* subgroup were as likely to decrease their use as they were to continue polysubstance use. This indicates that a marked portion of early adolescents who had already initiated substance use were not consistently using the same number of substances each month.

As one of the first studies to examine longitudinal changes in substance use patterns within an early adolescent sample, these results suggest that early adolescents' substance use patterns are relatively unstable over short time periods. Whereas most prior studies examined transitions in older adolescents' substance use subgroups over one year or longer (Choi et al., 2018; Merrin et al., 2018; Mistry et al., 2015), the present study examined changes across 3 month intervals. Examining changes over this short time period may have enabled this study to identify inconsistency in substance use patterns that are not seen in studies spanning longer intervals. During this developmental stage when more youth are initiating substance use, early adolescents may be more likely to increase or decrease the number of substances they are using month to month. Results of a previous study of substance use during late adolescence and early adulthood found that substance use patterns became more fixed with age (Mistry et al., 2015). The notion that early adolescents are not consistently engaging in polysubstance use across several months suggests that their substance use patterns are not locked in. Moreover, early adolescents are more likely to engage in impulsive behavior and be influenced by their peers compared with older adolescents (Caudle $&$ Casey, 2014; Steinberg, 2007), potentially explaining why they were just as likely to initiate alcohol use as they were to escalate directly to drug use and polysubstance use. Future research should continue to examine the changes in

substance use patterns during early adolescence in order to draw stronger conclusions about their development during this stage.

Covariate Differences in Subgroup Membership and Transitions

As part of the first study aim, I examined differences in membership in each substance use subgroup and in the probabilities of transitioning subgroups over time as a function of early adolescents' demographic characteristics (i.e., sex, grade), timing of waves, and active/inactive phase of the bullying prevention intervention. First, I evaluated whether each of these covariates were sources of variability in the latent class indicators (i.e., measurement non-invariance), which is typically referred to as differential item functioning (DIF). DIF is present when a covariate has direct effects on the class indicators above and beyond the effects of the covariate on the latent class variable (Masyn, 2017). When DIF effects are omitted from the latent class measurement model, the estimated covariate effects on class membership can be biased (Bettencourt et al., 2021; Masyn, 2017). In other words, accounting for DIF is one way to reduce measurement error in the latent subgroups based on individual characteristics and more accurately assess covariate differences in subgroup membership.

I identified DIF by grade at both waves and DIF by sex at the second wave. Grade and sex were expected to be sources of DIF due to sex and age differences in prevalence of substance use (Johnston et al., 2018). Unexpectedly, I also found evidence of DIF by timing of waves and intervention phase at the second wave. These findings mean that early adolescents' grade, sex, timing of waves, and intervention phase directly impacted the likelihood that they endorsed specific substance use items (e.g., alcohol initiation, past 30-day cannabis use) after accounting for their subgroup membership. These direct effects, however, varied across waves. Although no prior studies could be identified that evaluated DIF within an LTA model, this study provides
preliminary evidence that the degree of measurement non-invariance in latent class indicators can vary across time points. This was true in the present study even though the latent classes were constrained to be the same over time (i.e., longitudinal measurement invariance). Future LTA studies should continue to evaluate DIF in order to accurately identify covariate effects on the subgroups and explore differences in the sources of DIF over time.

With respect to the covariate associations with subgroup membership, there were sex differences in subgroup membership at Wave 1 that were not consistent with my hypotheses. I expected the results of the present study to be similar to those of other primarily Black samples of high school students in urban communities, which have found that female adolescents are less likely to engage in polysubstance use than male adolescents (Banks et al., 2020; Johnson et al., 2020; Schneider et al., 2020). In the present study, however, female early adolescents were more likely to be in the *Polysubstance Use* subgroup and less likely to be in the *Initiation* subgroup compared with male early adolescents. The primary difference between these two subgroups is that the *Polysubstance Use* subgroup had a high probability of using three or more substances in the past 30 days, whereas the *Initiation* subgroup reported prior initiation of multiple substances, but no recent use. This suggests that female and male adolescents were just as likely to have initiated polysubstance use during their lifetime, but female adolescents were more likely to report past 30-day polysubstance use. There were no sex differences in the *Non-Use* or *Alcohol Use* subgroups. These findings are generally consistent with evidence that sex differences in rates of substance use initiation are negligible during early adolescence (Johnston et al., 2018).

Regarding differences in substance use patterns across grades, eighth grade students were less likely to be in the *Non-Use* subgroup, and more likely to be in the *Initiation* and *Polysubstance Use* subgroups, compared with sixth and seventh grade students. Interestingly,

there were no grade differences in the likelihood of being in the *Alcohol Use* subgroup. This indicates that adolescents in different middle school grades were equally likely to have drunk alcohol, whereas eighth graders were more likely to have used additional substances. Although prior studies of substance use subgroups have not compared subgroups across middle school grades, these results are consistent with national data indicating that alcohol use is the most commonly used substance use early adolescence (Johnston et al., 2021) and substance use initiation rates increase across early adolescence (Clemans-Cope et al., 2021; Forman-Hoffman et al., 2017, 2017).

An exploratory analysis examined the extent to which substance use patterns and the probability of particular transitions differed based on the time during the year when adolescents completed the surveys. The two waves of data in the current study were collected during either the (a) fall and winter, (b) winter and spring, or (c) spring and summer. The results indicated that early adolescents were less likely to transition from non-use to past 30-day polysubstance use during the spring to summer wave than they were between the fall and winter or between the winter and spring. There are several potential explanations for this finding. Students participating in the project completed measures at their school during the school year, and at their home or in a community location during the summer. It is possible that early adolescents were more likely to avoid socially undesirable responses (i.e., endorsing substance use) in their home or community than at school. Theory also suggests that early adolescents may be less likely to initiate polysubstance use during the summer because they have less exposure to deviant peer influence when they are not in school (Jessor, 1991; Zucker et al., 2008). Spending more time with peers who use substances (Salvy et al., 2014) and attending a school with more frequent substance use at the school level is associated with greater substance use among early adolescents (Mrug et al.,

2010). When school is in session, early adolescents may have more opportunities to engage in substance use with their peers or feel more pressure to follow perceived social norms. These results provide a basis for future research to examine whether mechanisms of early onset polysubstance use vary across the course of the year.

The results of the covariate analyses should be viewed in light of a limitation. They suggested that early adolescents' sex, grade, and timing of waves impacted their subgroup transitions, but only when these effects were allowed to vary as a function of their subgroup membership at Wave 1 (i.e., interaction models). No effects on the odds of transitioning subgroups emerged from these models, however, potentially due to sparsity in the cells for the transition probabilities. In other words, the small number of individuals in several Wave 1 subgroups and the small transition probabilities led to a large degree of variability in estimates of the effects of covariates on subgroup transitions. This suggests that adolescents' likelihood of changing their substance use patterns over time may have varied based on the interaction between their subgroup at Wave 1 and their sex, grade, and timing of waves. However, there was not sufficient power to provide precise estimates of these interactive effects. There are no current guidelines for the sample size needed to achieve adequate power to predict transition probabilities in LTA. Baldwin (2015) found that power for the LTA is adversely impacted by sparseness in class sizes, small transition probabilities, and transitions from classes with small sizes. These factors appeared to adversely impact the power to estimate the covariate interaction models in this study. Substance use subgroups and transition probabilities often represent a small percentage of the sample, especially in adolescent samples (e.g., Choi et al., 2018). This may make it difficult to precisely estimate the interactive effects of subgroups and predictors in LTA,

even when using larger samples. These issues should be considered in future methodological work to provide recommendations for conducting LTA of substance use subgroups.

Bidirectional Associations between Substance Use Subgroups and Externalizing Behaviors (Aim 2)

The second aim of this study was to examine the extent to which two forms of externalizing behaviors (i.e., aggression, delinquency) were concurrently and prospectively related to substance use subgroups. Based on theories indicating that externalizing behaviors and substance use tend to co-occur during adolescence (Jessor, 1991; Moffitt, 1993), I hypothesized positive cross-sectional associations between externalizing behaviors and substance use patterns. As hypothesized, within each wave, all three subgroups that endorsed substance use reported more frequent externalizing behaviors than the *Non-Use* subgroup. The *Polysubstance Use* subgroup reported more frequent externalizing behaviors than the *Initiation* and *Alcohol Use* subgroups. These findings are consistent with prior research that has found that youth who engage in polysubstance use report more frequent externalizing behaviors than their peers who report no substance use (e.g., Chung et al., 2013) or use of one or two substances (e.g., Johnson et al., 2020). In the current study, the difference between the *Polysubstance Use* and each other subgroup was large, whereas other subgroup differences were small to moderate in size. This large difference represents engaging in about one to two more instances of the five to six specific behaviors assessed by each subscale, or higher frequencies of multiple forms physical aggression (e.g., hit or slapped someone, threatened someone) and delinquent behavior (e.g., theft, vandalism, property damage), in the past 30-days. This difference in frequency of externalizing behaviors between the *Polysubstance Use* and other subgroups underscores the need to distinguish polysubstance use from other patterns of substance use. Early adolescents engaging

in recent polysubstance use are engaging in potentially harmful externalizing behaviors much more frequently than their peers who report concurrent use of only alcohol or prior initiation of multiple substances.

According to the externalizing pathway theory, early adolescents who more frequently engage in externalizing behaviors are more likely to engage in risky substance use at an early age and to increase their use over time (Zucker, 2006). The results of the present study partially supported this hypothesis. Middle school students who reported more frequent aggressive or delinquent behaviors were more likely to escalate from no substance use to initiation within the next 3 months. In particular, they were more likely to escalate to polysubstance use. This is consistent with the findings of prior studies indicating that externalizing symptoms predict initiation of substance use during early adolescence (e.g., King et al., 2004). The present study, however, provides novel information by establishing a prospective association between externalizing behaviors and *polysubstance use* initiation. Contrary to hypotheses, early adolescents' externalizing behaviors did not predict escalation in the number of substances used over time for adolescents who had already initiated use at the first wave. Research examining predictors of increases in substance use is limited because most prior studies have examined changes in one substance at a time (e.g., Lynne-Landsman et al., 2011; Sacco et al., 2015; Turner et al., 2018), or in a composite measure that aggregates multiple substances (e.g., Farrell et al., 2005; Farrell, Goncy, et al., 2018; Mason & Windle, 2002; McAdams et al., 2014). These approaches do not provide a basis for identifying factors related to the progression from initiation of one substance to additional substances.

Only one prior study to my knowledge examined the association between externalizing behaviors and longitudinal changes in substance use subgroups (Chung et al., 2013). They found

104

that high school students' externalizing behaviors did not relate to the probability of transitioning from one substance use subgroup to another. Using a different approach, Roberts et al. (2023) identified dual trajectories of alcohol and cannabis use across five years among a nationally representative sample of adolescents who were ages 12 through 14 at the first wave. Roberts et al. (2023) found that youth with greater externalizing symptoms at the first wave were more likely to follow trajectories with co-occurring substance use during adolescence, and that externalizing was the strongest predictor of concurrent alcohol and cannabis use during early to middle adolescence. Given the relatively small number of studies that have examined the extent to which externalizing behaviors predict progression in co-occurring substance use initiation, no strong conclusions can be made about how early adolescents' externalizing behaviors relate to increases in their substance use. The present study found that externalizing behaviors predicted substance use onset 3 months later, but not increases in the number of substances used after initiation. Future research is needed to better understand how the externalizing pathway relates to the escalation from substance use onset to polysubstance use.

In the present study, the prospective associations between externalizing behaviors and substance use subgroups varied across the two forms of externalizing behavior. Whereas more frequent delinquent behavior predicted a greater likelihood that early adolescents escalated from no substance use to each pattern of substance use, physical aggression only increased the likelihood of transitioning from non-use to the most extreme pattern of substance use (i.e., polysubstance use). Most prior research examining prospective associations between externalizing and substance use has focused on physical aggression (e.g., Herrenkohl et al., 2009), delinquent behaviors (e.g., D'Amico et al., 2008), or a composite variable including both aggressive and non-aggressive delinquency (e.g., Maslowsky et al., 2014; Windle, 1990). One

study that focused on a national sample of high school students found that both violent behaviors and non-violent delinquency predicted cannabis initiation (van den Bree & Pickworth, 2005). No prior study to my knowledge, however, has examined longitudinal associations between physical aggression and delinquent behavior with adolescents' substance use *patterns*. The results of the current study suggest that delinquent behavior might increase risk for any substance use, whereas physical aggression specifically increases risk for the most serious degree of substance use (i.e., polysubstance use). Because the probability of transitioning from the *Non-Use* subgroup to the *Polysubstance Use* subgroup was relatively small (i.e., probability = .03), physical aggression only impacted changes in substance use patterns for a small portion of the sample. Finding different effects of physical aggression and delinquent behaviors may not be surprising as prior research has established that they represent unique factors among adolescents (Farrell et al., 2016). It may be beneficial for future studies to examine how different forms of externalizing relate to adolescents' substance use patterns, rather than relying on broad combined measures of externalizing, to inform understanding of specific behaviors that put adolescents at the highest risk for early onset polysubstance use.

This study also examined the extent to which early adolescents' substance use patterns predicted changes in their frequency of engagement in externalizing behaviors. I found that engaging in a particular pattern of substance use did not differentially predict early adolescents' changes in their externalizing behaviors. This finding is not consistent with the bidirectional associations theory (Moffit, 1993). It is, however, consistent with the findings of most prior studies. Past findings indicate that whereas externalizing behavior predicts increases in substance use during early adolescence, substance use does not predict future externalizing behavior (e.g., Farrell et al., 2005; Miller et al., 2016; Turner et al., 2018). It is possible that the design of the

current study was not well-suited to evaluate bidirectional associations due to the short time period between waves. Prior studies that have found bidirectional associations between delinquent behaviors and substance use have focused on male high school students and examined changes that occurred over longer intervals of time (i.e., 6 months to 1 year apart, D'Amico et al., 2008; Mason & Windle, 2002). It is also notable that in the present study, nearly half of early adolescents who reported past 30-day substance use did not consistently engage in the same pattern of substance use over time (i.e., *Alcohol Use* and *Polysubstance Use* subgroups). Bidirectional associations may emerge later in adolescence as youth begin engaging in substance use more consistently. This was demonstrated by McAdams et al. (2014), who found that delinquency predicted substance use between ages 13 and 14, whereas these behaviors were reciprocally related between ages 14 and 15. In contrast, the findings of the current study are more consistent with those of past studies focused on early adolescent samples (Farrell et al., 2005; Miller et al., 2016; Turner et al., 2018), which indicate that early adolescents' substance use and externalizing behaviors are not bidirectionally related.

Moderating Effects of Covariates on Relations Between Externalizing Behaviors and

Substance Use

The focus of Aim 2c was to evaluate whether the bidirectional associations between early adolescents' substance use patterns and externalizing behaviors differed across grade, sex, timing of waves, and intervention phase. The hypothesis that the associations between substance use patterns and subsequent changes in externalizing behaviors would not vary across covariates was supported. This indicates that early adolescents' substance use patterns did not impact changes in their externalizing, regardless of their individual characteristics or when they were assessed. With regards to the associations between early adolescents' externalizing behaviors and

subgroup transitions, I hypothesized that youth in seventh and eighth grade with high frequencies of externalizing behaviors would be more likely to escalate their substance use over time than youth in sixth grade with high externalizing behaviors. I hypothesized that the associations between externalizing behaviors and subgroup transitions would not differ as a function of the other covariates (i.e., sex, timing of waves, intervention phase). This study did not find sufficient evidence of moderation effects for grade, sex, timing of waves, or intervention phase. These analyses were impacted by the sparseness in the cells for the transition probabilities, limiting the ability of this study to identify any significant moderation effects on the transition probabilities. The extent to which adolescents' individual characteristics (e.g., age, sex) impact their likelihood of following the externalizing pathway to substance use is an important research question. However, LTA may not be the ideal method to evaluate this question, in particular when the subgroups and transition probabilities are small. Using a much larger sample, or variablecentered analytic approaches (e.g., path analysis, trajectory modeling) may be better suited to examine factors that moderate associations between externalizing and changes in substance use.

Sensitivity Analyses Controlling for Distress Symptoms

Finally, I investigated Aim 2d by conducting a sensitivity analysis to determine the extent to which each externalizing behavior predicted transitions in subgroup membership after controlling for distress symptoms. These analyses were designed to account for a developmental pathway to substance use via internalizing psychopathology (Hussong et al., 2011) and to add to the literature on the unique association of internalizing and externalizing symptoms with adolescents' substance use (Hussong et al., 2017). After accounting for distress symptoms, only delinquent behavior predicted escalation from no use to recent alcohol use and recent polysubstance use. In contrast, physical aggression did not uniquely predict subgroup transitions

after accounting for distress symptoms. A review of the literature examining the unique associations between internalizing symptoms and substance use after controlling for externalizing symptoms found that the results of prior studies have varied (Hussong et al., 2017). Some studies have found a unique positive, negative, or non-significant effect of internalizing symptoms. The results of these studies differed across forms of internalizing symptoms (e.g., depression, anxiety) and type of substance use. A generally consistent finding in the literature, however, is that externalizing behaviors maintain a significant positive association with adolescents' substance use even after accounting for internalizing symptoms (Colder et al., 2013; Farmer et al., 2015; Maslowsky et al., 2014). It is thus somewhat surprising that in the current study, physical aggression was not associated with polysubstance use initiation after accounting for distress symptoms. This may be because most prior studies have used broad measures of externalizing that combined physical aggression and delinquent or rule-breaking behaviors. The findings of this sensitivity analysis provide evidence that physical aggression and delinquent behavior show different associations with early adolescents' substance use. Delinquent behavior appears to be a robust predictor of substance use initiation, even when accounting for distress, whereas physical aggression may contribute less to risk for substance use initiation than distress symptoms. This may be in part explained by co-occurrence of physical aggression and distress symptoms, which has been found in primarily Black samples of adolescents in urban communities (Thompson et al., 2023; Webb et al., 2023). To better inform theory, different forms of externalizing and internalizing symptoms should be considered in future studies examining the intersection between these developmental pathways to substance use.

Limitations

The strengths of this study should be viewed in light of several limitations. The sample in

the present study was primarily comprised of Black early adolescents residing in Southeastern, urban communities with a high proportion of individuals living at or below the federal poverty level. The findings may not generalize to youth of other races, settings, or cultural backgrounds. Nonetheless, the narrow focus of this study's sample may help to inform the development of relevant prevention efforts for youth in urban communities who may experience more risk factors for externalizing behaviors and substance use. As with all secondary analysis studies, the current study was limited to the measures included in the original project. The measures of substance use did not incorporate more novel types of substances, such as e-cigarettes or vapes. It is unknown whether participants considered these types of substances when asked about "cigarette" use. Although externalizing psychopathology also includes symptoms indicative of attention-deficit/hyperactivity disorder (Achenbach et al., 2016), including inattentive, hyperactive, or impulsive behaviors, the measure of externalizing behavior used in the present study was more narrowly focused on problematic or risky forms of externalizing (e.g., physical aggression, delinquent behaviors). This study may not capture the full spectrum of externalizing symptomology, but the narrow focus of the subscales used in this study provided an advantage over broad measures of externalizing behaviors due to their specificity. Using these measures enabled me to examine the extent to which the externalizing pathway varied across different forms of externalizing.

The present study aimed to inform developmental theories of adolescent substance use and externalizing, but it should not be considered a complete test of these theories. The study only assessed adolescents' behavior during middle school and thus could not account for events that occurred during early childhood. For example, this study does not distinguish between adolescents who started engaging in externalizing behavior during early childhood (i.e., life

course persistent externalizing) from those who starting engaging in externalizing behavior during middle school (i.e., adolescent limited; Moffitt, 1993; Zucker, 2006). Regardless of their development prior to middle school, these data enabled this study to determine whether individuals engaging in more frequent externalizing behaviors during adolescence were more likely to initiate substance use at an early age, which has important implications for both research and practice. Finally, although the overall sample was large, some of the analyses were limited by the small size of several of the subgroups and the generally small transition probabilities that emerged from the data. Estimates for some predictors of subgroup transitions had large standard errors due to the small number of individuals in that transition. Although one alternative way to address this issue would be to combine small subgroups together, that would not have answered the study's research questions. This limitation does not mean that the results of this study are uninterpretable but is a potential explanation for non-significant predictors of subgroup transitions.

Implications for Theory and Research

The findings of this study have implications for developmental theory. Early adolescents who reported more frequent physical aggression and delinquent behavior concurrently reported more substance use and were more likely to initiate substance use over time. These findings are most consistent with the causal externalizing pathway to substance use (Zucker, 2006). Although externalizing behaviors did not predict increases in substance use for early adolescents who had already initiated use, externalizing behaviors did predict initiation of substance use for those who reported no substance use at the first wave. This finding supports the claim that youth on the externalizing pathway are at elevated risk for initiation of substance use at an early age. Moreover, the current study added to this literature by finding that early adolescents with more

frequent externalizing behaviors were more likely to initiate *polysubstance use* during middle school, which is associated with more adverse long-term outcomes compared with the use of fewer substances (Johnson et al., 2020; Merrin & Leadbeater, 2018; Moss et al., 2014). This is perhaps the first study to establish a longitudinal association between externalizing behaviors and early onset polysubstance use. This suggests that among early adolescents in an urban setting, those engaging in externalizing behaviors are at greater risk of escalating to risky substance use during middle school. Future research should continue to examine the externalizing pathway to early-onset polysubstance use to determine whether these findings are replicated in other samples.

The findings of the current study also suggest that different forms of externalizing behaviors might differentially predict adolescents' substance use. More frequent engagement in delinquent behaviors predicted escalation to all patterns of substance use (i.e., initiation, recent alcohol use, and recent polysubstance use), whereas physical aggression only predicted escalation to polysubstance use. This finding suggests that investigating specific forms of externalizing behavior may be particularly relevant for identifying pathways to substance use. Future research should consider whether the mechanisms that explain the association between externalizing behaviors and substance use also vary based on form of externalizing, and whether these behaviors interact differently with internalizing symptoms.

Implications for Intervention

The findings of this study have several implications for substance use prevention and intervention during early adolescence. In the current sample, 24% to 27% of early adolescents endorsed prior initiation of substance use, and 13% to 14% reported using at least one substance in the past month. Early adolescents' recent substance use patterns were fairly variable over 3month intervals, suggesting that it would be beneficial to intervene during this developmental stage before their pattern of use becomes more consistent. With respect to the timing of delivering these interventions, this study found that early adolescents were more likely to engage in polysubstance use during the school year compared with the summer. This suggests the need for prevention efforts early in the school year or before the start of sixth grade. Implementation of prevention programs in sixth grade have been associated with reduced increases in frequency of substance use and decreased onset of illicit substance use over time (Spoth et al., 2009). Prevention programs prior to or soon after the transition to middle school may help to prevent substance use initiation and escalation over time. Another important consideration for prevention programs is the focus of the content. Among early adolescents who had already initiated substance use, most (71% to 74%) had initiated the use of at least two different substances. Early adolescents in this study were just as likely to initiate polysubstance use as they were to initiate only alcohol use. This indicates that prevention programs should address multiple forms of substance use rather than focusing more narrowly on one substance (e.g., alcohol, tobacco).

This study also found that early adolescents with more frequent externalizing behaviors were at greater risk of initiating substance use shortly afterward. Early adolescents displaying externalizing symptoms might benefit from selective interventions to reduce their risk for substance use initiation. Prior research indicates that selective interventions may be more effective in reducing substance use than traditional education-based universal programs (Conrod, 2016). An example of a selective intervention is PreVenture, a school-based personality-targeted alcohol use prevention program that selects adolescents with high levels of anxiety sensitivity, negative thinking, impulsivity, or sensation seeking and teaches them coping skills based on their primary area of difficulty (Newton et al., 2022). A randomized clinical trial of PreVenture for

high school students found that the intervention was associated with smaller increases in drinking rates over time (Conrod et al., 2013) and reductions in alcohol-related harms into young adulthood (i.e., seven years later; Newton et al., 2022). However, as shown by the findings of this study's sensitivity analyses, both internalizing and externalizing symptoms can increase risk for substance use initiation. Internalizing and externalizing symptoms often co-occur among adolescents and might interact to predict substance use initiation (Scalco et al., 2020). To account for this nuance in adolescents' mental health symptoms, an alternative approach might be interventions that target adolescents with internalizing, externalizing, or co-occurring symptoms in order to personalize the intervention to their specific needs.

Conclusion

Findings from this study provide knowledge that may help to improve theory and inform substance use prevention and intervention efforts for youth living in economically marginalized urban areas. This study focused on a primarily Black sample of middle school students living in urban communities with high rates of crime and individuals living below the federal poverty threshold. Relatively little is known about patterns of substance use during early adolescence and their longitudinal development. Findings of this study identified four distinct subgroups of early adolescents that varied in the number of substances they had initiated and used in the past 30 days. When looking at changes in their patterns of use across 3-month intervals, early adolescents were just as likely to initiate only alcohol use as they were to initiate polysubstance use. Whereas early adolescents who had never used substances were likely to continue non-use 3 months later, adolescents who had initiated substance use did not consistently report using any substances or the same number of substances over time. In order to inform developmental theory, I also examined longitudinal associations between externalizing behaviors and substance use

patterns. Findings were most consistent with the externalizing pathway. Early adolescents with more frequent externalizing behaviors were more likely to initiate substance use 3 months later. Their substance use patterns, however, did not predict changes in the frequency of their externalizing behaviors over time. This study addressed gaps in the literature regarding the role of polysubstance use in the externalizing pathway to early-onset substance use. The findings indicate that early adolescents displaying externalizing behaviors are at greater risk for initiating polysubstance use. This supports the need for selective substance use interventions for early adolescents displaying externalizing symptoms.

References

- Achenbach, T. M., & Edelbrock, C. S. (1984). Psychopathology of childhood. *Annual Review of Psychology*, *35*(1), 227–256. https://doi.org/10.1146/annurev.ps.35.020184.001303
- Achenbach, T. M., Ivanova, M. Y., Rescorla, L. A., Turner, L. V., & Althoff, R. R. (2016). Internalizing/externalizing problems: Review and recommendations for clinical and research applications. *Journal of the American Academy of Child & Adolescent Psychiatry*, *55*(8), 647–656. https://doi.org/10.1016/j.jaac.2016.05.012
- American Psychiatric Association. (1987). *Diagnostic and Statistical Manual of Mental Disorders* (3rd, revised ed.). American Psychiatric Association. https://doi.org/10.1176/appi.books.9780890420188.dsm-iii-r
- Armstrong, T. D., & Costello, E. J. (2002). Community studies on adolescent substance use, abuse, or dependence and psychiatric co-morbidity. *Journal of Consulting and Clinical Psychology*, 1224–1239.
- Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural Equation Modeling: A Multidisciplinary Journal*, *21*(3), 329–341. https://doi.org/10.1080/10705511.2014.915181
- Asparouhov, T., & Muthen, B. (2021). Auxiliary variables in mixture modeling: Using the BCH method in Mplus to estimate a distal outcome model and an arbitrary secondary model. *Mplus Web Notes: No. 21*.
- Asparouhov, T., & Muthen, B. (2013). Computing the Strictly Positive Satorra-Bentler Chi-Square Test in Mplus. *Mplus Web Notes: No. 12*.
- Attar, B., Guerra, N., & Tolan, P. (1994). Neighborhood disadvantage, stressful life events, and adjustment in urban elementary-school children. Special Issue: Impact of poverty on

children, youth, and families. *Journal of Clinical Child and Adolescent Psychology*, *23*, 391–400. https://doi.org/10.1207/s15374424jccp2304_5

- Banfield, J. D., & Raftery, A. E. (1993). Model-based Gaussian and Non-Gaussian clustering. *Biometrics*, *49*(3), 803. https://doi.org/10.2307/2532201
- Banks, D. E., Bello, M. S., Crichlow, Q., Leventhal, A. M., Barnes-Najor, J. V., & Zapolski, T. C. B. (2020). Differential typologies of current substance use among Black and White high-school adolescents: A latent class analysis. *Addictive Behaviors*, *106*. https://doi.org/10.1016/j.addbeh.2020.106356
- Bares, C. B., Chartier, K. G., Karriker-Jaffe, K. J., Aliev, F., Mustanski, B., & Dick, D. (2020). Exploring how family and neighborhood stressors influence genetic risk for adolescent conduct problems and alcohol use. *Journal of Youth and Adolescence*, *49*(7), 1365–1378. https://doi.org/10.1007/s10964-019-01098-9
- Becker, T. D., Arnold, M. K., Ro, V., Martin, L., & Rice, T. R. (2021). Systematic review of electronic cigarette use (vaping) and mental health comorbidity among adolescents and young adults. *Nicotine & Tobacco Research*, *23*(3), 415–425.
	- https://doi.org/10.1093/ntr/ntaa171
- Bettencourt, A. F., Musci, R. J., Masyn, K. E., & Farrell, A. D. (2021). Latent classes of aggression and peer victimization: Measurement invariance and differential item functioning across sex, race-ethnicity, cohort, and study site. *Child Development*, *n/a*(n/a). https://doi.org/10.1111/cdev.13691
- Bolck, A., Croon, M., & Hagenaars, J. (2004). Estimating latent structure models with categorical variables: One-step versus three-step estimators. *Political Analysis*, *12*(1), 3– 27. https://doi.org/10.1093/pan/mph001

Bozdogan, H. (1987). Model selection and Akaike's Information Criterion (AIC): The general theory and its analytical extensions. *Psychometrika*, *52*(3), 345–370. https://doi.org/10.1007/BF02294361

- Bui, K. V. T., Ellickson, P. L., & Bell, R. M. (2000). Cross-lagged relationships among adolescent problem drug use, delinquent behavior, and emotional distress. *Journal of Drug Issues*, *30*(2), 283–303. https://doi.org/10.1177/002204260003000203
- Caudle, K., & Casey, B. J. (2013). Brain development and the risk for substance abuse. In D. S. Charney, J. D. Buxbaum, & E. J. Nestler (Eds.), *Neurobiology of Mental Illness* (pp. 706 - 715). Oxford University Press, Incorporated.
- Chen, C.-Y., Storr, C. L., & Anthony, J. C. (2009). Early-onset drug use and risk for drug dependence problems. *Addictive Behaviors*, *34*(3), 319–322. https://doi.org/10.1016/j.addbeh.2008.10.021
- Choi, H. J., Lu, Y., Schulte, M., & Temple, J. R. (2018). Adolescent substance use: Latent class and transition analysis. *Addictive Behaviors*, *77*, 160–165. https://doi.org/10.1016/j.addbeh.2017.09.022
- Chung, T., Kim, K. H., Hipwell, A. E., & Stepp, S. D. (2013). White and Black adolescent females differ in profiles and longitudinal patterns of alcohol, cigarette, and marijuana use. *Psychology of Addictive Behaviors*, *27*(4), 1110. https://doi.org/10.1037/a0031173
- Cicchetti, D. (2006). Development and psychopathology. In D. Cicchetti & D. Cohen (Eds.), *Developmental Psychopathology, Volume 1: Theory and Method* (Vol. 1, pp 1- 23).
- Cicchetti, D., & Rogosch, F. A. (1996). Equifinality and multifinality in developmental psychopathology. *Development and Psychopathology*, *8*(4), 597–600. https://doi.org/10.1017/S0954579400007318
- Clemans-Cope, L., Lynch, V., Winiski, E., Epstein, M., Taylor, K. J., & Eggleston, A. (2021). Substance use and age of substance use initiation during adolescence: Self-reported patterns by race and ethnicity in the United States, 2015–19. *Urban Institute*.
- Cloninger, C. R. (1987). Neurogenetic adaptive mechanisms in alcoholism. *Science*, *236*(4800), 410–416. http://www.jstor.org/stable/1698998
- Colder, C. R., Scalco, M., Trucco, E. M., Read, J. P., Lengua, L. J., Wieczorek, W. F., & Hawk, L. W. (2013). Prospective associations of internalizing and externalizing problems and their co-occurrence with early adolescent substance use. *Journal of Abnormal Child Psychology*, *41*(4), 667–677. https://doi.org/10.1007/s10802-012-9701-0
- Connell, C. M., Gilreath, T. D., & Hansen, N. B. (2009). A multiprocess latent class analysis of the co-occurrence of substance use and sexual risk behavior among adolescents. *Journal of Studies on Alcohol and Drugs*, *70*(6), 943–951.

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2776124/

- Connor, J. P., Gullo, M. J., White, A., & Kelly, A. B. (2014). Polysubstance use: Diagnostic challenges, patterns of use and health. *Current Opinion in Psychiatry*, *27*(4), 269. https://doi.org/10.1097/YCO.0000000000000069
- Conrod, P. J. (2016). Personality-targeted interventions for substance use and misuse. *Current Addiction Reports*, *3*(4), 426–436. https://doi.org/10.1007/s40429-016-0127-6
- Conrod, P. J., O'Leary-Barrett, M., Newton, N., Topper, L., Castellanos-Ryan, N., Mackie, C., & Girard, A. (2013). Effectiveness of a selective, personality-targeted prevention program for adolescent alcohol use and misuse: A cluster randomized controlled trial. *JAMA Psychiatry*, *70*(3), 334–342. https://doi.org/10.1001/jamapsychiatry.2013.651
- Conway, K. P., Vullo, G. C., Nichter, B., Wang, J., Compton, W. M., Iannotti, R. J., & Simons-Morton, B. (2013). Prevalence and patterns of polysubstance use in a nationally representative sample of 10th graders in the United States. *Journal of Adolescent Health*, *52*(6), 716–723. https://doi.org/10.1016/j.jadohealth.2012.12.006
- Coulter, R. W. S., Ware, D., Fish, J. N., & Plankey, M. W. (2019). Latent classes of polysubstance use among adolescents in the United States: Intersections of sexual identity with sex, age, and race/ethnicity. *LGBT Health*, *6*(3), 116–125. https://doi.org/10.1089/lgbt.2018.0149
- D'Amico, E. J., Edelen, M. O., Miles, J. N. V., & Morral, A. R. (2008). The longitudinal association between substance use and delinquency among high-risk youth. *Drug and Alcohol Dependence*, *93*(1), 85–92. https://doi.org/10.1016/j.drugalcdep.2007.09.006
- Dodge, K. A., Malone, P. S., Lansford, J. E., Miller, S., Pettit, G. S., & Bates, J. E. (2009). A dynamic cascade model of the development of substance-use onset. *Monographs of the Society for Research in Child Development*, *74*(3), vii–119. https://doi.org/10.1111/j.1540-5834.2009.00528.x
- Dunn, C. B., & Farrell, A. D. (2021, June). *Subgroups of early adolescent substance users in an urban setting: An examination of risk and protective factors* [Poster presentation]*.* Annual meeting for the Society for Prevention Research, Virtual conference.
- Dunn, C. B., & Farrell, A. D. (2023, June). *Relations between trajectories of externalizing behaviors and Alcohol use during early adolescence: Differences across sex and setting* [Poster presentation]. Annual meeting for the Research Society on Alcohol, Bellevue, Washington.
- Farmer, R. F., Seeley, J. R., Kosty, D. B., Gau, J. M., Duncan, S. C., Lynskey, M. T., & Lewinsohn, P. M. (2015). Internalizing and externalizing psychopathology as predictors of cannabis use disorder onset during adolescence and early adulthood. *Psychology of Addictive Behaviors*, *29*(3), 541–551. https://doi.org/10.1037/adb0000059
- Farrell, A. D., Goncy, E. A., Sullivan, T. N., & Thompson, E. L. (2018). Victimization, aggression, and other problem behaviors: Trajectories of change within and across middle school grades. *Journal of Research on Adolescence*, *28*(2), 438–455. https://doi.org/10.1111/jora.12346
- Farrell, A. D., Sullivan, T. N., Esposito, L. E., Meyer, A. L., & Valois, R. F. (2005). A latent growth curve analysis of the structure of aggression, drug use, and delinquent behaviors and their interrelations over time in urban and rural adolescents. *Journal of Research on Adolescence*, *15*(2), 179–204. https://doi.org/10.1111/j.1532-7795.2005.00091.x
- Farrell, A. D., Sullivan, T. N., Goncy, E. A., & Le, A.-T. H. (2016). Assessment of adolescents' victimization, aggression, and problem behaviors: Evaluation of the Problem Behavior Frequency Scale. *Psychological Assessment*, *28*(6), 702–714. https://doi.org/10.1037/pas0000225
	-
- Farrell, A. D., Sullivan, T. N., Sutherland, K. S., Corona, R., & Masho, S. (2018). Evaluation of the Olweus Bully Prevention Program in an urban school system in the USA. *Prevention Science*, *19*(6), 833–847. https://doi.org/10.1007/s11121-018-0923-4
- Farrell, A. D., Thompson, E. L., & Mehari, K. R. (2017). Dimensions of peer influences and their relationship to adolescents' aggression, other problem behaviors and prosocial behavior. *Journal of Youth and Adolescence*, *46*(6), 1351–1369. https://doi.org/10.1007/s10964-016-0601-4

Farrell, A. D., Thompson, E. L., Mehari, K. R., Sullivan, T. N., & Goncy, E. A. (2020). Assessment of in-person and cyber aggression and victimization, substance use, and delinquent behavior during early adolescence. *Assessment*, *27*(6), 1213–1229. https://doi.org/10.1177/1073191118792089

- Ford, J. A. (2005). Substance use, the social bond, and delinquency. *Sociological Inquiry*, *75*(1), 109–128. https://doi.org/10.1111/j.1475-682X.2005.00114.x
- Forman-Hoffman, V. L., Edlund, M., Glasheen, C., & Ridenour, T. (2017). Alcohol initiation and progression to use, heavy episodic use, and alcohol use disorder among young adolescents ages 12–14 living in U.S. Households. *Journal of Studies on Alcohol and Drugs*, *78*(6), 853–860. https://doi.org/10.15288/jsad.2017.78.853
- Fowler, P. J., Tompsett, C. J., Braciszewski, J. M., Jacques-Tiura, A. J., & Baltes, B. B. (2009). Community violence: A meta-analysis on the effect of exposure and mental health outcomes of children and adolescents. *Development and Psychopathology*, *21*(1), 227– 259. https://doi.org/10.1017/S0954579409000145
- Gilreath, T. D., Astor, R. A., Estrada, J. N., Johnson, R. M., Benbenishty, R., & Unger, J. B. (2014). Substance use among adolescents in California: A latent class analysis. *Substance Use & Misuse*, *49*(1–2), 116–123. https://doi.org/10.3109/10826084.2013.824468
- Goldstein, P. J. (1985). The drugs/violence nexus: A tripartite conceptual framework. *Journal of Drug Issues*, *15*(4), 493–506. https://doi.org/10.1177/002204268501500406
- Goldstick, J. E., Heinze, J. E., Stoddard, S. A., Cunningham, R. M., & Zimmerman, M. A. (2019). Age-specific associations between violence exposure and past 30-day marijuana and alcohol use. *Journal of Research on Adolescence*, *29*(2), 480–492. https://doi.org/10.1111/jora.12399
- Goldstick, J. E., Stoddard, S. A., Carter, P. M., Zimmerman, M. A., Walton, M. A., & Cunningham, R. M. (2016). Characteristic substance misuse profiles among youth entering an urban emergency department: Neighborhood correlates and behavioral comorbidities. *American Journal of Drug & Alcohol Abuse*, *42*(6), 671–681. https://doi.org/10.1080/00952990.2016.1174707
- Gottfredson, N. C., Rhodes, B. E., & Ennett, S. T. (2019). Demographic moderation of the prediction of adolescent alcohol involvement trajectories. *Prevention Science*, *20*(6), 811–823. https://doi.org/10.1007/s11121-018-0946-x
- Grant, B. F., & Dawson, D. A. (1997). Age at onset of alcohol use and its association with DSM-IV alcohol abuse and dependence: Results from the national longitudinal alcohol epidemiologic survey. *Journal of Substance Abuse*, 103–110.
- Green, K. M., Musci, R. J., Johnson, R. M., Matson, P. A., Reboussin, B. A., & Ialongo, N. S. (2016). Outcomes associated with adolescent marijuana and alcohol use among urban young adults: A prospective study. *Addictive Behaviors*, *53*, 155–160. https://doi.org/10.1016/j.addbeh.2015.10.014
- Griffin, K. W., Bang, H., & Botvin, G. J. (2010). Age of alcohol and marijuana use onset predicts weekly substance use and related psychosocial problems during young adulthood. *Journal of Substance Use*, *15*(3), 174–183. https://doi.org/10.3109/14659890903013109
- Halladay, J., Woock, R., El-Khechen, H., Munn, C., MacKillop, J., Amlung, M., Ogrodnik, M., Favotto, L., Aryal, K., Noori, A., Kiflen, M., & Georgiades, K. (2020). Patterns of substance use among adolescents: A systematic review. *Drug and Alcohol Dependence*, *216*, 108222. https://doi.org/10.1016/j.drugalcdep.2020.108222

Hallquist, M. N., & Wiley, J. F. (2018). MplusAutomation: An R package for facilitating largescale latent variable analyses in Mplus. *Structural Equation Modeling: A Multidisciplinary Journal*, *25*(4), 621–638. https://doi.org/10.1080/10705511.2017.1402334

Hampton-Anderson, J. N., Carter, S., Fani, N., Gillespie, C. F., Henry, T. L., Holmes, E., Lamis, D. A., LoParo, D., Maples-Keller, J. L., Powers, A., Sonu, S., & Kaslow, N. J. (2021). Adverse childhood experiences in African Americans: Framework, practice, and policy. *American Psychologist*, *76*, 314–325. https://doi.org/10.1037/amp0000767

- Heron, J., Maughan, B., Dick, D. M., Kendler, K. S., Lewis, G., Macleod, J., Munafò, M., & Hickman, M. (2013). Conduct problem trajectories and Alcohol use and misuse in mid to late adolescence. *Drug and Alcohol Dependence*, *133*(1), 100–107. https://doi.org/10.1016/j.drugalcdep.2013.05.025
- Herrenkohl, T. I., Catalano, R. F., Hemphill, S. A., & Toumbourou, J. W. (2009). Longitudinal examination of physical and relational aggression as precursors to later problem behaviors in adolescents. *Violence and Victims*, *24*(1), 3–19. https://doi.org/10.1891/0886-6708.24.1.3
- Hingson, R. W., Heeren, T., & Winter, M. R. (2006). Age at drinking onset and alcohol dependence: Age at onset, duration, and severity. *Archives of Pediatrics & Adolescent Medicine*, *160*(7), 739–746. https://doi.org/10.1001/archpedi.160.7.739

Huang, B., White, H. R., Kosterman, R., Catalano, R. F., & Hawkins, J. D. (2001). Developmental associations between alcohol and interpersonal aggression during adolescence. *Journal of Research in Crime and Delinquency*, *38*(1), 64–83. https://doi.org/10.1177/0022427801038001004

- Huang, D. Y. C., Lanza, H. I., Murphy, D. A., & Hser, Y.-I. (2012). Parallel development of risk behaviors in adolescence: Potential pathways to co-occurrence. *International Journal of Behavioral Development*, *36*(4), 247–257. https://doi.org/10.1177/0165025412442870
- Hussong, A. M., Curran, P. J., Moffitt, T. E., Caspi, A., & Carrig, M. M. (2004). Substance abuse hinders desistance in young adults' antisocial behavior. *Development and Psychopathology*, *16*(04). https://doi.org/10.1017/S095457940404012X
- Hussong, A. M., Ennett, S. T., Cox, M. J., & Haroon, M. (2017). A systematic review of the unique prospective association of negative affect symptoms and adolescent substance use controlling for externalizing symptoms. *Psychology of Addictive Behaviors*, *31*(2), 137- 147. https://doi.org/10.1037/adb0000247
- Hussong, A. M., Jones, D. J., Stein, G. L., Baucom, D. H., & Boeding, S. (2011). An internalizing pathway to Alcohol and Substance Use Disorders. *Psychology of Addictive Behaviors*, *25*(3), 390–404. https://doi.org/10.1037/a0024519
- Iacono, W. G., Malone, S. M., & McGue, M. (2008). Behavioral disinhibition and the development of early-onset addiction: Common and specific influences. *Annual Review of Clinical Psychology*, *4*(1), 325–348.

https://doi.org/10.1146/annurev.clinpsy.4.022007.141157

- Jackson, K. M. (2010). Progression through early drinking milestones in an adolescent treatment sample. *Addiction*, *105*(3), 438–449. https://doi.org/10.1111/j.1360-0443.2009.02800.x
- Jessor, R. (1987). Problem-Behavior Theory, psychosocial development, and adolescent problem drinking. *British Journal of Addiction*, *82*(4), 331–342. https://doi.org/10.1111/j.1360- 0443.1987.tb01490.x
- Jessor, R. (1991). Risk behavior in adolescence: A psychosocial framework for understanding and action. *Journal of Adolescent Health*, *12*(8), 597–605. https://doi.org/10.1016/1054- 139X(91)90007-K
- Johnson, E. I., Copp, J. E., Bolland, A. C., & Bolland, J. M. (2020). Substance use profiles among urban adolescents: The role of family-based adversities. *Journal of Child and Family Studies*, *29*(8), 2104–2116. https://doi.org/10.1007/s10826-020-01736-y
- Johnston, L. D., Miech, R. A., O'Malley, P. M., Bachman, J. G., & Schulenberg, J. E. (2018). Demographic subgroup trends among adolescents in the use of various licit and illicit drugs, 1975–2017 (Monitoring the Future Occasional Paper No. 90). Ann Arbor, MI: Institute for Social Research, The University of Michigan. http://www.monitoringthefuture.org/pubs/occpapers/mtfocc90.pdf
- Johnston, L. D., Miech, R. A., O'Malley, P. M., Bachman, J. G., Schulenberg, J. E., & Patrick, M. E. (2021). Monitoring the Future national survey results on drug use 1975-2020: Overview, key findings on adolescent drug use. Ann Arbor: Institute for Social Research, University of Michigan.
- Jun, H.-J., Sacco, P., Bright, C. L., & Camlin, E. A. S. (2015). Relations among internalizing and externalizing symptoms and drinking frequency during adolescence. *Substance Use & Misuse*, *50*(14), 1814–1825. https://doi.org/10.3109/10826084.2015.1058826
- Kakade, M., Duarte, C. S., Liu, X., Fuller, C. J., Drucker, E., Hoven, C. W., Fan, B., & Wu, P. (2012). Adolescent substance use and other illegal behaviors and racial disparities in criminal justice system involvement: Findings from a US national survey. *American Journal of Public Health*, *102*(7), 1307–1310. https://doi.org/10.2105/AJPH.2012.300699
- Kandel, D., & Kandel, E. (2015). The Gateway Hypothesis of substance abuse: Developmental, biological and societal perspectives. *Acta Paediatrica*, *104*(2), 130–137. https://doi.org/10.1111/apa.12851
- Kellam, S., Koretz, D., & Moscicki, E. (1999). Core elements of developmental epidemiologically based prevention research, 27(4), 463-482. *American Journal of Community Psychology*, *27*, 463–482. https://doi.org/10.1023/A:1022129127298
- King, S. M., Iacono, W. G., & McGue, M. (2004). Childhood externalizing and internalizing psychopathology in the prediction of early substance use. *Addiction*, *99*(12), 1548–1559. https://doi.org/10.1111/j.1360-0443.2004.00893.x
- Kogan, S. M., Berkel, C., Chen, Y.-F., Brody, G. H., & Murry, V. M. (2006). Metro status and African-American adolescents' risk for substance use. *Journal of Adolescent Health*, *38*(4), 454–457. https://doi.org/10.1016/j.jadohealth.2005.05.024
- Kulis, S. S., Jager, J., Ayers, S. L., Lateef, H., & Kiehne, E. (2016). Substance use profiles of urban American Indian Adolescents: A latent class analysis. *Substance Use & Misuse*, *51*(9), 1159–1173. https://doi.org/10.3109/10826084.2016.1160125
- Lamont, A., Woodlief, D., & Malone, P. (2014). Predicting high-risk versus higher-risk substance use during late adolescence from early adolescent risk factors using latent class analysis. *Addiction Research & Theory*, *22*(1), 78–89. https://doi.org/10.3109/16066359.2013.772587
- Lillehoj, C. J., Trudeau, L., Spoth, R., & Madon, S. (2005). Externalizing behaviors as predictors of substance initiation trajectories among rural adolescents. *Journal of Adolescent Health*, *37*(6), 493–501. https://doi.org/10.1016/j.jadohealth.2004.09.025
- Lynne-Landsman, S. D., Graber, J. A., Nichols, T. R., & Botvin, G. J. (2011). Trajectories of aggression, delinquency, and substance use across middle school among urban, minority adolescents. *Aggressive Behavior*, *37*(2), 161–176. https://doi.org/10.1002/ab.20382
- Mack, K. A., Jones, C. M., & Ballesteros, M. F. (2017). Illicit drug use, illicit drug use disorders, and drug overdose deaths in metropolitan and nonmetropolitan areas—United States. *American Journal of Transplantation*, *17*(12), 3241–3252. https://doi.org/10.1111/ajt.14555
- Maldonado-Molina, M. M., & Lanza, S. T. (2010). A framework to examine gateway relations in drug use: An application of latent transition analysis. *Journal of Drug Issues*, *40*(4), 901– 924. https://doi.org/10.1177/002204261004000407
- Maslowsky, J., Schulenberg, J. E., & Zucker, R. A. (2014). Influence of conduct problems and depressive symptomatology on adolescent substance use: Developmentally proximal versus distal effects. *Developmental Psychology*, *50*(4), 1179–1189. https://doi.org/10.1037/a0035085
- Mason, W. A., & Windle, M. (2002). Reciprocal relations between adolescent substance use and delinquency: A longitudinal latent variable analysis. *Journal of Abnormal Psychology*, *111*(1), 63–76. https://doi.org/10.1037//0021-843X.111.1.63
- Masyn, K. E. (2013). Latent class analysis and finite mixture modeling. In P. E. Nathan & T. D. Little (Eds.), *The Oxford handbook of quantitative methods* (2nd ed., pp. 551–611). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199934898.013.0025
- Masyn, K. E. (2017). Measurement invariance and differential item functioning in latent class analysis with stepwise multiple indicator multiple cause modeling. *Structural Equation*

Modeling: A Multidisciplinary Journal, *24*(2), 180–197. https://doi.org/10.1080/10705511.2016.1254049

- McAdams, T. A., Salekin, R. T., Marti, C. N., Lester, W. S., & Barker, E. D. (2014). Cooccurrence of antisocial behavior and substance use: Testing for sex differences in the impact of older male friends, low parental knowledge and friends' delinquency. *Journal of Adolescence*, *37*(3), 247–256. https://doi.org/10.1016/j.adolescence.2014.01.001
- Memon, M., Hwa, C., Ramayah, T., Ting, H., Chuah, F., & Cham, T.-H. (2019). Moderation analysis: Issues and guidelines. *Journal of Applied Structural Equation Modeling*, *3*. https://doi.org/10.47263/JASEM.3(1)01
- Merrin, G. J., & Leadbeater, B. (2018). Do classes of polysubstance use in adolescence differentiate growth in substances used in the transition to young adulthood? *Substance Use & Misuse*, *53*(13), 2112–2124. https://doi.org/10.1080/10826084.2018.1455702
- Merrin, G. J., Thompson, K., & Leadbeater, B. J. (2018). Transitions in the use of multiple substances from adolescence to young adulthood. *Drug and Alcohol Dependence*, *189*, 147–153. https://doi.org/10.1016/j.drugalcdep.2018.05.015
- Miller, P. G., Butler, E., Richardson, B., Staiger, P. K., Youssef, G. J., Macdonald, J. A., Sanson, A., Edwards, B., & Olsson, C. A. (2016). Relationships between problematic alcohol consumption and delinquent behaviour from adolescence to young adulthood. *Drug and Alcohol Review*, *35*(3), 317–325. https://doi.org/10.1111/dar.12345

Mistry, R., Heinze, J. E., Cordova, D., Heish, H.-F., Goldstick, J. E., Ayer, S. M., & Zimmerman, M. A. (2015). Transitions in current substance use from adolescence to early-adulthood. *Journal of Youth and Adolescence*, *44*(10), 1871–1883. https://doi.org/10.1007/s10964-015-0309-x

- Mitchell, O., & Caudy, M. S. (2015). Examining racial disparities in drug arrests. *Justice Quarterly*, *32*(2), 288–313. https://doi.org/10.1080/07418825.2012.761721
- Moffitt, T. E. (1993). *Adolescence-Limited and Life-Course-Persistent Antisocial Behavior: A Developmental Taxonomy*. 28.
- Moore, W. (2020, June). *Applied Latent Class Analysis and Finite Mixture Modeling seminar*. Stats Camp, Virtual webinar.
- Moss, H. B., Chen, C. M., & Yi, H. (2014). Early adolescent patterns of alcohol, cigarettes, and marijuana polysubstance use and young adult substance use outcomes in a nationally representative sample. *Drug and Alcohol Dependence*, *136*, 51–62. https://doi.org/10.1016/j.drugalcdep.2013.12.011
- Mrug, S., Gaines, J., Su, W., & Windle, M. (2010). School-level substance use: Effects on early adolescents' alcohol, tobacco, and marijuana use. *Journal of Studies on Alcohol and Drugs*, *71*(4), 488–495. https://doi.org/10.15288/jsad.2010.71.488
- Mustanski, B., Byck, G. R., Dymnicki, A., Sterrett, E., Henry, D., & Bolland, J. (2013). Trajectories of multiple adolescent health risk behaviors in a low-income African American population. *Development and Psychopathology*, *25*(4 0 1), 1155–1169. https://doi.org/10.1017/S0954579413000436
- Muthen, B. (2021, March). *Using Mplus To Do Latent Transition Analysis and Random Intercept Latent Transition Analysis*. Mplus Web Talk.
- Muthen, B. O., & Satorra, A. (1995). Complex sample data in structural equation modeling. *Sociological Methodology*, *25*, 267–316. https://doi.org/10.2307/271070
- Nagin, D. S. (2005). *Group-Based Modeling of Development*. Harvard University Press.
- National Institute on Drug Abuse. (n.d.). *Costs of Substance Abuse*. National Institute on Drug Abuse Archives. Retrieved October 29, 2021, from https://archives.drugabuse.gov/trendsstatistics/costs-substance-abuse
- Newton, N. C., Debenham, J., Slade, T., Smout, A., Grummitt, L., Sunderland, M., Barrett, E. L., Champion, K. E., Chapman, C., Kelly, E., Lawler, S., Castellanos-Ryan, N., Teesson, M., Conrod, P. J., & Stapinski, L. (2022). Effect of selective personality-targeted alcohol use prevention on 7-year alcohol-related outcomes among high-risk adolescents: A secondary analysis of a cluster randomized clinical trial. *JAMA Network Open*, *5*(11), e2242544. https://doi.org/10.1001/jamanetworkopen.2022.42544
- Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396
- Nylund-Gibson, K., Garber, A. C., Carter, D. B., Chan, M., Arch, D. A. N., Simon, O., Whaling, K., Tartt, E., & Lawrie, S. I. (2022). Ten frequently asked questions about latent transition analysis. *Psychological Methods*. https://doi.org/10.1037/met0000486
- Oetting, E. R. (1999). Primary Socialization Theory: Developmental stages, spirituality, government institutions, sensation seeking, and theoretical implications. *Substance Use & Misuse*, *34*(7), 947–982. https://doi.org/10.3109/10826089909039389
- Oetting, E. R., & Donnermeyer, J. F. (1998). Primary socialization theory: The etiology of drug use and deviance. *Substance Use & Misuse*, *33*(4), 995–1026. https://doi.org/10.3109/10826089809056252
- Olweus, D., & Limber, S. P. (2010). Bullying in school: Evaluation and dissemination of the Olweus Bullying Prevention Program. *American Journal of Orthopsychiatry*, *80*(1), 124– 134. https://doi.org/10.1111/j.1939-0025.2010.01015.x
- Parker, R. N., & Auerhahn, K. (1998). Alcohol, drugs, and violence. *Annual Review of Sociology*, *24*, 291–311. https://www.jstor.org/stable/223483
- Patrick, M. E., Kloska, D. D., Terry-McElrath, Y. M., Lee, C. M., O'Malley, P. M., & Johnston, L. D. (2018). Patterns of simultaneous and concurrent alcohol and marijuana use among adolescents. *The American Journal of Drug and Alcohol Abuse*, *44*(4), 441–451. https://doi.org/10.1080/00952990.2017.1402335
- Patrick, M. E., & Schulenberg, J. E. (2014). Prevalence and predictors of adolescent alcohol use and binge drinking in the United States. *Alcohol Research: Current Reviews*, *35*(2), 193– 200. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3908711/
- Pickles, A., & Hill, J. (2006). Developmental Pathways. In D. Cicchetti & D. J. Cohen, *Developmental Psychopathology, Volume 1: Theory and Method* (Vol. 1, pp. 211-243).
- Reid, J. B., & Patterson, G. R. (1989). The development of antisocial behaviour patterns in childhood and adolescence. *European Journal of Personality*, *3*(2), 107–119. https://doi.org/10.1002/per.2410030205
- Richters, J. E., & Martinez, P. (1990). *Checklist of Children's Distress Symptoms: Self-report version*. National Institute of Mental Health.
- Roberts, W., Schick, M. R., Tomko, R. L., McRae-Clark, A. L., Pittmann, B., Gueorgieva, R., & McKee, S. A. (2023). Developmental trajectories of alcohol and cannabis concurrent use in a nationally representative sample of United States youths. *Drug and Alcohol Dependence*, *248*, 109908. https://doi.org/10.1016/j.drugalcdep.2023.109908
- Rose, R. A., Evans, C. B. R., Smokowski, P. R., Howard, M. O., & Stalker, K. L. (2018). Polysubstance use among adolescents in a low income, rural community: Latent classes for middle- and high‐school students. *The Journal of Rural Health*, *34*(3), 227–235. https://doi.org/10.1111/jrh.12268
- Sacco, P., Bright, C. L., Jun, H.-J., & Stapleton, L. M. (2015). Developmental relations between alcohol and aggressive behavior among adolescents: Neighborhood and sociodemographic correlates. *International Journal of Mental Health and Addiction*, *13*(5), 603–617. https://doi.org/10.1007/s11469-015-9546-1
- Salvy, S.-J., Pedersen, E. R., Miles, J. N. V., Tucker, J. S., & D'Amico, E. J. (2014). Proximal and distal social influence on alcohol consumption and marijuana use among middle school adolescents. *Drug and Alcohol Dependence*, *144*, 93–101. https://doi.org/10.1016/j.drugalcdep.2014.08.012
- Satorra, A., & Bentler, P. M. (2010). Ensuring positiveness of the scaled difference chi-square test statistic. *Psychometrika*, *75*(2), 243–248. https://doi.org/10.1007/s11336-009-9135-y
- Scalco, M. D., Colder, C. R., Read, J. P., Lengua, L. J., Wieczorek, W. F., & Hawk, L. W. (2020). Testing alternative cascades from internalizing and externalizing symptoms to adolescent alcohol use and alcohol use disorder through co-occurring symptoms and peer delinquency. *Development and Psychopathology*. https://doi.org/10.1017/S0954579419001512

Schneider, K. E., Brighthaupt, S.-C., Winiker, A. K., Johnson, R. M., Musci, R. J., & Linton, S. L. (2020). Characterizing profiles of polysubstance use among high school students in Baltimore, Maryland: A latent class analysis. *Drug and Alcohol Dependence*, *211*, 108019. https://doi.org/10.1016/j.drugalcdep.2020.108019

- Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, *6*(2), 461– 464. https://doi.org/10.1214/aos/1176344136
- Shin, S. (2012). A longitudinal examination of the relationships between childhood maltreatment and patterns of adolescent substance use among high-risk adolescents. *The American Journal on Addictions*, *21*(5), 453–461. https://doi.org/10.1111/j.1521- 0391.2012.00255.x
- Shin, S. H., Hong, H. G., & Hazen, A. L. (2010). Childhood sexual abuse and adolescent substance use: A latent class analysis. *Drug and Alcohol Dependence*, *109*(1), 226–235. https://doi.org/10.1016/j.drugalcdep.2010.01.013
- Skara, S., Pokhrel, P., Weiner, M. D., Sun, P., Dent, C. W., & Sussman, S. (2008). Physical and relational aggression as predictors of drug use: Gender differences among high school students. *Addictive Behaviors*, *33*(12), 1507–1515. https://doi.org/10.1016/j.addbeh.2008.05.014
- Spear, L. P. (2000). The adolescent brain and age-related behavioral manifestations. *Neuroscience & Biobehavioral Reviews*, *24*(4), 417–463. https://doi.org/10.1016/S0149- 7634(00)00014-2
- Stein, B. D., Jaycox, L. H., Kataoka, S., Rhodes, H. J., & Vestal, K. D. (2003). Prevalence of child and adolescent exposure to community violence. *Clinical Child and Family Psychology Review*, *6*(4), 247–264.

https://doi.org/10.1023/B:CCFP.0000006292.61072.d2

Steinberg, L. (2007). Risk taking in adolescence: New perspectives from brain and behavioral science. *Current Directions in Psychological Science*, *16*(2), 55–59.

- Su, J., Supple, A. J., & Kuo, S. I.-C. (2018). The role of individual and contextual factors in differentiating substance use profiles among adolescents. *Substance Use & Misuse*, *53*(5), 734–743. https://doi.org/10.1080/10826084.2017.1363237
- Sullivan, T. N., Farrell, A. D., Sutherland, K. S., Behrhorst, K. L., Garthe, R. C., & Greene, A. (2021). Evaluation of the Olweus Bullying Prevention Program in us urban middle schools using a multiple baseline experimental design. *Prevention Science*, *22*(8), 1134– 1146. https://doi.org/10.1007/s11121-021-01244-5
- Thompson, E. L., O'Connor, K. E., & Farrell, A. D. (2023). Childhood adversity and cooccurring post-traumatic stress and externalizing symptoms among a predominantly lowincome, African American sample of early adolescents. *Development and Psychopathology*, *35*(1), 383–395. https://doi.org/10.1017/S0954579421001383
- Tomczyk, S., Isensee, B., & Hanewinkel, R. (2016). Latent classes of polysubstance use among adolescents—A systematic review. *Drug and Alcohol Dependence*, *160*, 12–29. https://doi.org/10.1016/j.drugalcdep.2015.11.035
- Turner, R., Daneback, K., & Skårner, A. (2018). Assessing reciprocal association between drunkenness, drug use, and delinquency during adolescence: Separating within- and between-person effects. *Drug and Alcohol Dependence*, *191*, 286–293. https://doi.org/10.1016/j.drugalcdep.2018.06.035
- van den Bree, M. B., & Pickworth, W. B. (2005). Risk factors predicting changes in marijuana involvement in teenagers. *Arch Gen Psychiatry*, *62*, 311-319.
- van Lier, P. A. C., Vitaro, F., Barker, E. D., Koot, H. M., & Tremblay, R. E. (2009). developmental links between trajectories of physical violence, vandalism, theft, and
alcohol-drug use from childhood to adolescence. *Journal of Abnormal Child Psychology*, *37*(4), 481. https://doi.org/10.1007/s10802-008-9289-6

- Wade, R., Jr, Shea, J. A., Rubin, D., & Wood, J. (2014). Adverse childhood experiences of lowincome urban youth. *Pediatrics*, *134*(1), e13–e20. https://doi.org/10.1542/peds.2013- 2475
- Webb, L., Musci, R., & Mendelson, T. (2023). Co-occurring mental health symptoms in urban adolescents: Comorbidity profiles and correlates. *Journal of Clinical Child & Adolescent Psychology*, *52*(2), 171–183. https://doi.org/10.1080/15374416.2021.1901228
- Windle, M. (1990). A longitudinal study of antisocial behaviors in early adolescence as predictors of late adolescent substance use: Gender and ethnic group differences. *Journal of Abnormal Psychology*. https://doi.org/10.1037/0021-843X.99.1.86
- Zapolski, T. C. B., Pedersen, S. L., McCarthy, D. M., & Smith, G. T. (2014). Less drinking, yet more problems: Understanding African American drinking and related problems. *Psychological Bulletin*, *140*, 188–223. https://doi.org/10.1037/a0032113
- Zucker, R. A. (2006). Alcohol use and the Alcohol use disorders: A developmentalbiopsychosocial systems formulation covering the life course. In D. Cicchetti $\&$ D. J. Cohen (Eds.), *Developmental psychopathology: Risk, disorder, and adaptation* (Vol. 3, 2nd ed, pp. 620–656). John Wiley & Sons, Inc.
- Zucker, R. A., Donovan, J. E., Masten, A. S., Mattson, M. E., & Moss, H. B. (2008). Early developmental processes and the continuity of risk for underage drinking and problem drinking. *Pediatrics*, *121*(Suppl4), S252–S272. https://doi.org/10.1542/peds.2007-2243B

Zych, I., Rodríguez-Ruiz, J., Marín-López, I., & Llorent, V. J. (2020). Longitudinal stability and change in adolescent substance use: A latent transition analysis. *Children and Youth Services Review*, *112*. https://doi.org/10.1016/j.childyouth.2020.104933

Appendix A

Supplemental Latent Class Enumeration

Supplemental analyses were conducted to determine how best to address responses from youth who responded inconsistently across waves on items assessing substance use initiation. The analyses reported in the results section were consistent with prior longitudinal research that has used an approach where endorsement of initiation items is carried forward. In other words, if an individual endorsed initiation of substance use in their lifetime, their response is carried forward to subsequent waves even if they reported no initiation at a subsequent wave. The supplemental analyses reported here conducted latent class enumeration for Wave 2 models where individuals who responded "yes" at Wave 1 to any lifetime substance use item and then responded "no" at Wave 2 were *not* recoded.

As in the results reported in the main body of my dissertation, the four-class model was identified as optimal based on having the best fit as indicated by the minimum values for the BIC and CAIC (see Table A1). Although the AWE supported the three-class model, I weighed the optimal model suggested by the BIC more strongly because the BIC more consistently identifies the optimal number of classes compared with other fit indices (Nylund et al., 2007). The LMR-LRT indicated that adding the fifth class did not significantly improve upon the four-class model. Average posterior probability values ranging from .87 to .97, and odds of correct classification values between 9 and 260, suggested that the classes were well-separated and the model had high accuracy in class assignment. All model class assignment proportions based on most likely class membership values fell within a 95% confidence interval for the model estimated proportions, supporting classification accuracy.

When comparing the results of the approach described here to the one reported in the main body of my dissertation, the subgroup patterns and response probabilities were generally the same across the four subgroups (see Table A2). This suggests that recoding the inconsistent responses did not change the class structure. Examining crosstabs of each individual's most likely class assignment indicated that over 95% of individuals remained in the same subgroup regardless of whether or not the three initiation items were recoded. Recoding the items primarily resulted in individuals staying in the *Initiation* subgroup over time versus moving into the *Non-Use* subgroup. Recoding inconsistent responses as has been established in prior longitudinal studies did not produce a meaningful difference in the subgroups, so I elected recode the responses so that endorsement of the initiation items was carried forward for the Wave 2 LCA (see main Results).

								Adj			
						RI		LMR $p-$	BLRT	BF	
K	LL	npar	BIC	CAIC	AWE	$(K, K+1)$	LRTS	value	p -value	$(K, K+1)$	$\text{cmP}(K)$
1-class	-4567.036	12	9222.40	9234.40	9346.73	na	na	na	na	$\boldsymbol{0}$	$\overline{0}$
2-class	-3420.469	25	7024.96	7049.96	7283.97	na	2293.13	0.000	< .001	$\overline{0}$	$\overline{0}$
3-class	-3278.512	38	6836.73	6874.73	7230.44	0.12	289.91	0.000	< .001	$\overline{0}$	$\overline{0}$
4-class	-3199.378	51	6774.15	6825.15	7302.55	0.07	158.27	0.001	< .001	>100	$\mathbf{1}$
5-class	-3170.191	64	6811.47	6875.47	7474.56	0.03	58.37	0.148	< .001	>100	$\overline{0}$
6-class	-3140.285	77	6847.35	6924.35	7645.12	0.03	60.55	0.151	< .001	>100	$\overline{0}$
7-class	-3116.351	90	6895.17	6985.17	7827.64	0.02	54.97	0.279	< .001	na	$\overline{0}$

Table A1. *Fit Indices for the Latent Class Models at Wave 2 where Initiation Items were not Recoded*

Note. n = 1778 at Wave 1, 1573 at Wave 2. *K* number of latent classes, *LL* maximum likelihood value obtained for each model, *Npar* number of free parameters in the model. *LR χ*2 likelihood ration chi-square goodness of fit statistic with degrees of freedom and *p*-value, *BIC* Bayesian information criterion, *CAIC* consistent Akaike's information criterion, *AWE* average weight of evidence criterion, *RI* relative improvement, *LRTS* likelihood ratio test statistic comparing row model with *K* classes to the model with *K + 1* classes, *Adj. LMR p* adjusted Lo–Mendell–Rubin p-value for the LRTS, *BLRT p* parametric bootstrapped p-value for the LRTS, *BF* approximate Bayes factor comparing model with k classes to model with K + 1 classes, *cmP(K)* approximate correct model probability for the row model with k classes compared with all other models in the table.

Values in bold for the BIC, CAIC, and AWE indicate the model with the minimum value. Values in bold for the BF indicates the model with the smallest number of classes that is favored over a model with an additional class. Values in bold for the cmP(K) indicates values above 0.10.

Table A2

Item Response Probabilities for the Supplementary Analyses of the Unconditional Latent Class

		Non-use (77.7%)	Initiation (9.8%)	Alcohol Use (6.3%)	Polysubstance Use (6.1%)
Lifetime	Alcohol	0.05	0.56	0.83	0.73
Initiation	Drugs	0.00	0.63	0.15	0.57
	Cigarettes/Cigars	0.01	0.59	0.10	0.58
Past 30-	Liquor	0.00	0.03	0.44	0.66
Day Use	Beer	0.01	0.04	0.40	0.54
	Got drunk	0.00	0.01	0.15	0.63
	Wine/wine coolers	0.01	0.00	0.48	0.66
	Cannabis	0.00	0.22	0.08	0.68
	Inhalants	0.01	0.02	0.02	0.27
	Illicit drugs	0.00	0.05	0.00	0.30
	Cigars	0.00	0.27	0.02	0.76
	Cigarettes	0.00	0.11	0.00	0.45

Model at Wave 2 where Initiation Items were not Recoded

Note. Bolded values indicate moderate to high probabilities (i.e., $> .50$).

Appendix B

Aim 1c: Tests of Differential Item Functioning (DIF)

Individual Sources of DIF

The process for evaluating DIF for each indicator followed the recommended sequential approach (Masyn, 2017), such that any significant sources of DIF identified in each step were carried forward into each subsequent step. I compared all models using the scaled log likelihood ratio difference test (Satorra & Bentler, 2010). If the scaled log likelihood ratio difference test resulted in a negative log likelihood value, I used the strictly positive log likelihood test (Asparouhov & Muthen, 2013). See Table B1 for a summary of stepwise DIF models. The following steps were followed separately for each covariate (i.e., sex, grade, timing of waves, intervention phase):

Step 1: An omnibus test compared the fit of an All Nonuniform DIF Model (M1.1) specifying nonuniform DIF for all indicators (i.e., direct effect of the covariate on all indicators in all subgroups) to a model specifying No DIF (M1.0). The No DIF model regressed subgroup membership on the covariate but did not include any direct effects of covariates on indicators.

Step 2: If the All Nonuniform DIF Model significantly improved upon the fit of the No DIF Model, I conducted follow-up tests to identify specific indicators for which there was evidence of nonuniform DIF (i.e., direct covariate effects on an indicator that vary across subgroups). Models specifying no DIF for a given indicator (M2.0.x) were compared with models specifying nonuniform DIF for that indicator (M2.1.x).

Step 3: All indicators that showed evidence of nonuniform DIF in Step 2 were incorporated into a Select Nonuniform DIF Model (M3.0), which was compared with the No DIF and All Nonuniform DIF Models. The Select Nonuniform DIF model was retained if it fit the data significantly better than the No DIF Model and no worse than the All Nonuniform DIF Model. If the All Nonuniform DIF Model fit the data significantly better than the Select Nonuniform DIF model according to the log likelihood ratio test, but the Select Nonuniform DIF had a smaller BIC, the more parsimonious Select Nonuniform DIF model was retained.

Step 4: Next, I evaluated whether the nonuniform DIF effects identified in Step 2 could be constrained to uniform DIF (i.e., constrained to be equal across subgroups). For each indicator that showed evidence of DIF, I estimated a model in which DIF was constrained to uniform (M4.x). If the Select Nonuniform DIF Model (M3.0) did not fit significantly better than the model with DIF constrained to uniform, then uniform DIF was supported. **Step 5:** Finally, all sources of uniform and nonuniform DIF identified in Steps 2 through 4 were incorporated into the Select Nonuniform and Uniform DIF Model (Model 5.0). This model was compared with the Select Nonuniform DIF Model (Model 3.0) to verify that including uniform DIF constraints did not significantly decrease model fit.

Combined DIF

After identifying the individual sources of DIF for each covariate (i.e., sex, grade, intervention phase, timing of waves), I followed a similar sequential process described by Bettencourt et al. (2021) to combine the sources of DIF into the same model while maintaining the most parsimonious model. This process involved the follow sequential steps (see Table B1):

Step 6: I examined whether incorporating all sources of DIF effects on each indicator that were identified in Steps 1 through 5 (Combined Identified DIF Model; M6.1) improved upon the fit of the No DIF Model (M6.0). In the Combined No DIF Model,

class membership was regressed on all covariates, with no direct effects of covariates on indicators.

Step 7: This step informed whether it was necessary to include all sources of DIF in the combined model. I examined whether the Combined Identified DIF Model fit the data better than models where individual sources of DIF were excluded (e.g., DIF by sex on all indicators was excluded; M7.x). If the Combined Identified DIF Model fit the data significantly better than the model that excluded an individual source of DIF, this supported retaining that source of DIF in subsequent steps. If Step 7 indicated that multiple sources of DIF could be excluded from the combined model (e.g., sex and intervention phase), I evaluated whether the Combined Identified DIF model fit better than a model excluding multiple sources of DIF.

Step 8: I evaluated whether individual DIF effects on specific indicators (e.g., direct effects of grade on 30-day cannabis use) could be excluded from the model (M8.x). If the optimal model from Step 7 fit the data significantly better than the model that excluded a specific DIF effect, this indicated that the specific effect should be retained.

Step 9: All DIF effects for comparisons that were not significant in Step 8 were considered in Step 9. I examined whether combinations of these effects could be removed without significant detriment to model fit (M9.x). This resulted in a more parsimonious final DIF model with uniform and nonuniform sources of DIF by each covariate at each wave.

Step 10: Finally, I interpreted the substantive effects of accounting for DIF on subgroup interpretation. The item response probabilities and class sizes for the final, most parsimonious model incorporating all supported DIF effects (M10.0) was compared with

the No DIF model (M6.0) to determine whether accounting for DIF substantially altered model interpretation. If the subgroups were not interpreted differently after accounting for DIF, then DIF effects were retained for all subsequent analyses.

Description of each Step and Model Estimated for Stepwise Tests of Differential Item Functioning (DIF)

Description of each Step and Model Estimated for Stepwise Tests of Differential Item Functioning (DIF)

Note. Nonuniform DIF indicates direct covariate effects on an indicator that vary across subgroups. Uniform DIF indicates direct covariate effects on an indicator that are constrained across subgroups. X indicates a new model for each specific indicator. Number of x models is number of indicators being evaluated for DIF.

Wave 1 DIF

Sex

The initial omnibus test indicated that including DIF by sex (M1.1) improved model fit compared with the No DIF model (M1.0; see Table B2). Follow-up tests in Step 2 provided evidence of nonuniform DIF by sex for six items: *drug use initiation, 30-day liquor, 30-day wine/wine coolers, 30-day cannabis, 30-day cigars, 30-day cigarettes.* However, the Select Nonuniform DIF Model (M3.0), which included these six sources of nonuniform DIF, did not significantly improve upon the No DIF Model (M1.0). I examined a second version of the Select Nonuniform DIF Model (Model 3.1) that incorporated the nonuniform effect of DIF by sex for the *30-day beer* item, which had yielded a negative loglikelihood ratio test value even when using the strictly positive loglikelihood test. Because this alternative model did not fit significantly better than the Select Nonuniform DIF (M3.0) or No DIF Models, I did not retain DIF effects on the *30-day beer* item in the DIF by sex model.

When a model in Step 3 did not improve upon the No DIF Model, Masyn (2017) recommended looking for additional items with *p-*values that neared significance in Step 2 (i.e., $.05 < p < .10$) and examining whether accounting for DIF effects on these indicators improved model fit. No other direct effects in Step 2 neared significance according to this guideline. Although the Select Nonuniform DIF Model (M3.0) did not fit significantly better than the No DIF model (M1.0), the BIC value was smaller than that for All Nonuniform DIF and there were no other obvious direct effects identified in the data. I therefore retained the Select Nonuniform DIF Model (3.0) and proceeded to Step 4. Results of Step 4 indicated that all direct effects of sex on indicators could be constrained to be uniform across classes, with the exception of the effects on 30-day *wine/wine cooler use*. The Select Nonuniform DIF Model (M3.0) model did not fit the data significantly better than the Select Uniform and Nonuniform DIF (M5.0). This supported the Select Uniform and Nonuniform DIF Model (M5.0). The final model for DIF by sex at Wave 1 thus had five effects of uniform DIF (*drug use initiation, 30-day liquor, 30-day cannabis, 30 day cigars, 30-day cigarettes)*, and one effect of nonuniform DIF (30-day *wine/wine cooler use*).

Grade

The initial omnibus test supported DIF by grade (see Table B3). Follow-up tests in Step 2 provided evidence of DIF by grade for seven items: *drug use initiation, cigar/cigarette use initiation, 30-day beer, 30-day cannabis, 30-day inhalants, 30-day cigars,* and *30-day cigarettes.* The Select Nonuniform DIF model (M3.0) that included these seven effects of nonuniform DIF significantly improved upon the No DIF model (M1.0), and its fit was not further improved upon by the All Nonuniform DIF Model (M1.1). Results of Step 4 indicated that DIF effects on four indicators could be constrained to be uniform across classes (*30-day beer, 30-day cannabis, 30 day inhalants, 30-day cigars*), whereas the other three indicators showed evidence of nonuniform DIF (*drug use initiation, cigar/cigarette use initiation, 30-day cigarettes)*. The Select Nonuniform DIF Mode (M3.0), however, fit the data significantly better than the model incorporating uniform and nonuniform DIF effects (M5.0). Following procedures recommended by Masyn (2017), I inspected the model comparisons in Step 4 for other comparisons that neared significance (i.e., $.05 < p < .10$) and evaluated an alternative Select Uniform and Nonuniform DIF Model (M5.1) that expanded upon M5.0 by allowing nonuniform DIF for one additional item (*30-day cigars*). The alternative model did not improve upon the fit of M5.0. Given the significant improvement in fit from the No DIF (M1.0) to the Select Nonuniform & Uniform DIF Model (M5.0), and no other indicators showing clear evidence of nonuniform DIF, I retained M5.0. The final model for Wave 1 DIF by grade had uniform DIF effects on four indicators (*30-* *day beer, 30-day cannabis, 30-day inhalants, 30-day cigars*) and nonuniform DIF effects on three indicators (*drug use initiation, cigar/cigarette use initiation, 30-day cigarettes*).

Timing of waves

The initial omnibus test supported DIF by timing of waves (see Table B4). Results of Step 2 indicated DIF for five items: *30-day liquor, 30-day beer, 30-day been drunk, 30-day wine/wine coolers,* and *30-day inhalants.* The Select Nonuniform DIF model (M3.0) significantly improved upon the fit of the No DIF model (M1.0), and its fit was not further improved by the All Nonuniform DIF model (M1.1). Model comparisons in Step 4 indicated that all the nonuniform DIF effects could be constrained to be uniform across classes, with the exception of *30-day been drunk*. However, the Select Nonuniform DIF Model (M3.) fit the data significantly better than The Select Uniform and Nonuniform DIF Model (M5.0), which constrained several effects to be uniform across classes. Inspecting the model comparisons in Step 4 suggested that the direct effect of grade on the *30-day wine/wine coolers* item could be examined as nonuniform because the comparison neared significance (Masyn, 2017). However, allowing this item to be nonuniform (M5.1) did not improve model fit. The Select Uniform and Nonuniform DIF Model (M5.0) achieved a better BIC than the All Nonuniform DIF Model (M1.1) and was more parsimonious than the Select Nonuniform DIF Model (M3.0), so I retained M5.0 as the final model for DIF by timing of waves at Wave 1.

Intervention Phase

The omnibus test supported DIF by intervention phase (see Table B5). Follow up tests indicated that *30-day wine/wine coolers, 30-day cannabis,* and *30-day cigars* showed evidence of DIF by intervention phase. The Select Nonuniform DIF Model (M3.0), which incorporated nonuniform DIF effects on these three indicators, did significantly improve upon the fit of the No

DIF Model (M1.0). No other indicators showed potential evidence of DIF in Step 2. The Select Nonuniform DIF Model (M3.0) achieved a better BIC than the All Nonuniform DIF Model (M1.1). M3.0 was retained for subsequent stepwise tests. The results of Step 4 indicated that the three DIF effects could be constrained to be uniform across classes without detriment to model fit. The final model with uniform DIF effects on three indicators (M5.0) improved upon the fit of the No DIF Model (M1.0). The fit of the Select Nonuniform DIF Model (M3.0) was not significantly better than the Select Uniform and Nonuniform DIF Model (M5.0). The final model for DIF by intervention phase (M5.0) thus included uniform DIF for items *30-day wine/wine coolers, 30-day cannabis,* and *30-day cigars.*

Combined DIF

Steps 6 through 10 involved additional comparisons to find the most parsimonious model that combined the individual sources of DIF that were identified in Steps 1 through 5 (see Table B6). The model incorporating all DIF effects that were identified in separate analyses for each covariate (i.e., Combined Identified DIF Model; M6.1) fit significantly better than the model that only regressed class membership on the covariates (Combined No DIF; M6.0). In Step 7, the Combined Identified DIF Model (M6.1) did not fit significantly better than individual models that excluded the identified DIF effects by sex (M7.1), intervention phase (M7.2), and timing of waves (M7.3). The All Nonuniform DIF Model (M6.1) also did not fit significantly better than a model that excluded all effects of DIF by sex, intervention phase, *and* timing of waves (M7.5). This indicated that including these three sources of DIF (i.e., sex, intervention phase, timing of waves) did not significantly improve model fit. Only DIF by grade were included in Steps 8 through 10. Results from Steps 8 and 9 indicated that the direct effects of grade on four items (i.e., *30-day beer, 30-day cannabis, 30-day cigars*, *30-day cigarettes*) could be excluded from

the combined model without adversely impacting model fit*.* The final combined model accounting for DIF at Wave 1 (M10.0) included DIF by grade for three items, with one uniform direct effect of grade (*30-day inhalants*) and two nonuniform direct effects of grade (*drug use initiation, cigar/cigarette use initiation*).

Within the final model accounting for DIF at Wave 1 (M10.0), I evaluated the extent to which accounting for DIF impacted the interpretation of the latent class model. The final class counts and proportions for the estimated model changed by about 2% after accounting for DIF. Examination of the response probabilities before (see Table 6) and after accounting for DIF (see Table 8) indicated that accounting for DIF by grade did not substantially alter the interpretation of the subgroups at Wave 1. These direct effects of grade on three indicators were thus retained in subsequent Aim 1 and Aim 2 analyses to account for measurement invariance in the latent subgroups.

Model Comparisons for Stepwise Differential Item Functioning (DIF) Testing for Sex within the Wave 1 Four-Class Model

Note. DIF = differential item functioning, LL = maximum log likelihood, Npar = number of free parameters in the model, SCF = scaling factor, df = degrees of freedom, CF = correction factor, LRTS = likelihood ratio test statistic, = multiple indicator multiple cause model. P-values for significant comparisons and rows for the final model are bolded.

a = strictly positive LL difference test was used for comparison

Model Comparisons for Stepwise Differential Item Functioning (DIF) Testing for Grade within the Wave 1 Four-Class Model

Note. DIF = differential item functioning, LL = maximum log likelihood, Npar = number of free parameters in the model, SCF = scaling factor, df = degrees of freedom, CF = correction factor, LRTS = likelihood ratio test statistic, = multiple indicator multiple cause model. P-values for significant comparisons and rows for the final model are bolded.

a = strictly positive LL difference test was used for comparison

Model Comparisons for Stepwise Differential Item Functioning (DIF) Testing for Timing of Waves within the Wave 1 Four-Class Model

Note. DIF = differential item functioning, LL = maximum log likelihood, Npar = number of free parameters in the model, SCF = scaling factor, df = degrees of freedom, CF = correction factor, LRTS = likelihood ratio test statistic, = multiple indicator multiple cause model. P-values for significant comparisons and rows for the final model are bolded.

a = strictly positive LL difference test was used for comparison

Model Comparisons for Stepwise Differential Item Functioning (DIF) Testing for Intervention phase within the Wave 1 Four-Class Model

Note. DIF = differential item functioning, LL = maximum log likelihood, Npar = number of free parameters in the model, SCF = scaling factor, df = degrees of freedom, CF = correction factor, LRTS = likelihood ratio test statistic, = multiple indicator multiple cause model. P-values for significant comparisons and rows for the final model are bolded.

a = strictly positive LL difference test was used for comparison

Model Comparisons for Stepwise Differential Item Functioning (DIF) Testing for Combined Model with Sex, Grade, Timing of Waves, and Intervention phase

within the Wave 1 Four-Class Model

Note. DIF = differential item functioning, LL = maximum log likelihood, Npar = number of free parameters in the model, SCF = scaling factor, df = degrees of freedom, CF = correction factor, LRTS = likelihood ratio test statistic, = multiple indicator multiple cause model. P-values for significant comparisons and rows for the final model are bolded.

Wave 2 DIF

Sex

The initial omnibus test supported DIF by sex (see Table B7). Follow-up tests in Step 2 provided evidence of DIF by sex for six items: *drug use initiation, 30-day liquor, 30-day beer, 30-day been drunk, 30-day wine/wine coolers, 30-day inhalants,* and *30-day cigarettes.* The model included these six effects (Select Nonuniform DIF Model; M3.0) significantly improved upon the fit of the No DIF Model (M1.0), and its fit was not further improved upon by the All Nonuniform DIF Model (M1.1). This supported the Select Nonuniform DIF Model (M3.0). Results of Step 4 indicated that the direct effects of sex on four indicators could be constrained to be uniform across classes (*30-day liquor, 30-day beer, 30-day been drunk, 30-day cigarettes)*. The Select Nonuniform DIF Model (M3.0) did not fit significantly better than the model that constrained these four DIF effects to uniform (i.e., Select Nonuniform and Uniform DIF; M5.0). The final model (M5.0) thus included four uniform (*30-day liquor, 30-day beer, 30-day been drunk, 30-day cigarettes)* and three nonuniform (*drug use initiation, 30-day wine/wine coolers, 30-day inhalants*) DIF effects by sex at Wave 2.

Grade

The initial omnibus test supported DIF by grade (see Table B8). Follow-up tests in Step 2 identified significant direct effects of grade on four indicators: *30-day been drunk, 30-day wine/wine coolers, 30-day cannabis,* and *30-day cigarettes.* The model with nonuniform effects of grade on these four indicators (i.e., Select Nonuniform DIF; M3.0) significantly improved upon the fit of the No DIF Model (M1.0). The All Nonuniform DIF Model (M1.1) did not fit the data better than the Select Nonuniform DIF Model (M3.0), supporting the Select Nonuniform DIF Model. Results of Step 4 indicated that two DIF effects could be constrained to be uniform

across classes (*30-day cannabis, 30-day cigarettes)*. The Select Nonuniform DIF Model (M3.0) did not have significantly better fit than the Select Uniform and Nonuniform DIF (M5.0), which further supported constraining the two effects to be uniform. The final model for DIF by grade (M5.0) thus included uniform DIF for *30-day cannabis* and *30-day cigarettes* items and nonuniform DIF for *30-day been drunk* and *30-day wine/wine coolers* items.

Timing of waves

The initial omnibus test supported DIF by the timing of waves (see Table B9). Step 2 showed evidence of five sources of DIF: *alcohol use initiation, 30-day liquor, 30-day been drunk, 30-day illicit drugs,* and *30-day cigarettes.* The All Nonuniform DIF Model (M1.1), however, fit the data significantly better than the Select Nonuniform DIF Model (M3.0). Examination of the results of Step 2 indicated that the direct effects of the timing of waves on *alcohol use initiation* neared significance. The All Nonuniform DIF Model did not fit significantly better than the alternate Select Nonuniform DIF Model (M3.1), which incorporated direct effects on the *alcohol use initiation* item. These five sources of uniform DIF (M3.1) were retained for subsequent models. Results of Step 4 indicated that three sources of DIF could be constrained to be uniform across classes without adversely impacting model fit (*alcohol use initiation, 30-day liquor, 30-day illicit drugs*). The final Select Uniform and Nonuniform DIF Model (M5.0) improved upon the fit of the No DIF Model (M1.0), and model fit was not further improved by the Select Nonuniform DIF Model (M3.0). The final model for DIF by timing of waves (M5.0) thus included uniform DIF for three items (*alcohol use initiation, 30-day liquor, 30-day illicit drugs*) and nonuniform DIF for two items (*30-day been drunk, 30-day cigarettes)*.

Intervention phase

The omnibus test supported DIF by intervention phase (see Table B10). Follow up tests supported direct effects of intervention phase on six items: *cigar/cigarette use initiation, drug use initiation, 30-day wine/wine coolers, 30-day cannabis, 30-day cigars,* and *30-day cigarettes*. The Select Nonuniform DIF Model (M3.0) incorporating nonuniform DIF effects on these six items fit significantly better than the No DIF Model (M1.0). The All Nonuniform DIF Model (M1.1) did not have significantly better model fit than the Select Nonuniform DIF Model (M3.0), so the Select Nonuniform DIF Model (M3.0) was retained for subsequent steps. Results of the model comparisons in Step 4 supported constraining DIF effects on all but one indicator (i.e., *30-day cannabis*) to be uniform across classes. The Select Nonuniform DIF Model model did not fit significantly better than The Select Nonuniform and Uniform DIF Model (M5.0), which improved upon the fit of the No DIF Model (M1.0). The final model for DIF by intervention phase (M5.0) thus included uniform DIF for five items (*cigar/cigarette use initiation, drug use initiation, 30-day wine/wine coolers, 30-day cigars, 30-day cigarettes)* and nonuniform DIF for one item (*30-day cannabis*).

Combined DIF

In Steps 6 through 10, I combined the DIF effects that were supported by separate tests for each covariate in Steps 1 through 5 into one model (M6.1; see Table B11). The Combined Identified DIF Model (M6.1) yielded significantly better fit to the data than the model that only regressed class membership on the covariates (i.e., No DIF; M6.0). In Step 2, the All Nonuniform DIF Model (M1.1) fit significantly better than models that removed the DIF effects for each covariate (i.e., M7.1 through M7.4). Results from Steps 3 and 4 indicated that the All Nonuniform DIF Model (M1.1) did not fit significantly better than models that excluded several DIF effects on specific indicators. More specifically, DIF by sex for three items (*30-day liquor,*

30-day been drunk, 30-day wine/wine coolers), DIF by grade for two items (*30-day wine/wine coolers, 30-day cigarettes)*, DIF by timing of waves for three items (*30-day liquor, cigarettes*, *alcohol use initiation*), and DIF by intervention phase for two items (*30-day wine/wine coolers, cigar/cigarette use initiation*) were excluded from the model. The final model accounting for combined DIF at Wave 2 (M10.0) included DIF by sex for four items (*30-day beer 30-day cigarettes* uniform; *drug use initiation* and *30-day inhalants* nonuniform), DIF by grade for two items (*30-day cannabis* uniform; *30-day been drunk* nonuniform), DIF by intervention phase for four items (*drug use initiation, 30-day cigars,* and *30-day cigarettes* uniform; *30-day cannabis* nonuniform), and DIF by waves for two items (*30-day illicit drugs* uniform; *30-day been drunk* nonuniform).

Finally, I evaluated the impact of accounting for DIF in the final model (M10.0) on the interpretation of the subgroups at Wave 2. The final class counts and proportions for the estimated model shifted less than 2% after accounting for DIF. Examination of the response probabilities before (see Table 6) and after accounting for DIF (see Table 8) indicated that accounting for DIF did not substantially alter the subgroup interpretation at Wave 2. These sources of DIF at Wave 2 were thus retained in subsequent analytic models in Aims 1 and 2 to account for measurement invariance in the subgroups.

Model Comparisons for Stepwise Differential Item Functioning (DIF) Testing for Sex within the Wave 2 Four-Class Model

Model	model comparisons for siepwise Differential neur Functioning (DH) Festing for sex within the wave 2 Four-Class model Description	BIC	LL		Npar SCF	Comparison	cf	LRTS	$\mathrm{d}\mathrm{f}$	\boldsymbol{p}
	Step 1: Comparison of models with and without DIF									
M1.0	No DIF	7392.03	-3497.29	54	1.08					
M1.1	All Nonuniform DIF	7682.24	-3465.75	102	0.97	M1.0 vs M1.1	0.85	74.52	48	0.008
		Step 2: Testing for nonuniform DIF one item at a time								
M2.0.1	Alcohol use initiation: No DIF		-1730.33	10	1.00	M2.0.1 vs. M2.1.1	1.00	2.75	$\overline{4}$	0.600
M2.1.1	Alcohol use initiation: Nonuniform DIF		-1728.96	14	1.00					
M2.0.2	Cigar/cigarette use initiation: No DIF		-1531.18	10	1.00	M2.0.2 vs. M2.1.2	0.50	2.67	$\overline{4}$	0.615
M2.1.2	Cigar/cigarette use initiation: Nonuniform DIF		-1530.51	14	0.86					
M2.0.3	Drug use initiation: No DIF		-1525.62	10	1.00	M2.0.3 vs. M2.1.3	0.49	11.10	$\overline{4}$	0.026
M2.1.3	Drug use initiation: Nonuniform DIF		-1522.87	14	0.86					
M2.0.4	30-day liquor use: No DIF		-1392.01	10	1.00	M2.0.4 vs. M2.1.4 a	0.08	103.94	$\overline{4}$	0.000
M2.1.4	30-day liquor use: Nonuniform DIF		-1392.01	14	0.72					
M2.0.5	30-day beer use: No DIF		-1439.85	10	1.01	M2.0.5 vs. M2.1.5	0.47	23.48	$\overline{4}$	0.000
M2.1.5	30-day beer use: Nonuniform DIF		-1434.28	14	0.86					
M2.0.6	30-day been drunk: No DIF		-1355.35	10	1.00	M2.0.6 vs. M2.1.6 ^a	0.19	61.38	$\overline{4}$	0.000
M2.1.6	30-day been drunk: Nonuniform DIF		-1355.35	14	0.73					
M2.0.7	30-day wine/wine cooler use: No DIF		-1399.79	10	1.00	M2.0.7 vs. M2.1.7 ^a	0.11	155.21	$\overline{4}$	0.000
M2.1.7	30-day wine/wine cooler use: Nonuniform DIF		-1399.79	14	0.72					
M2.0.8	30-day cannabis use: No DIF		-1408.41	10	1.00	M2.0.8 vs. M2.1.8	0.50	1.97	$\overline{4}$	0.741
M2.1.8	30-day cannabis use: Nonuniform DIF		-1407.92	14	0.86					
M2.0.9	30-day inhalant use: No DIF		-1365.97	10	1.00	M2.0.9vs. M2.1.9	0.74	13.35	$\overline{4}$	0.010
M2.1.9	30-day inhalant use: Nonuniform DIF		-1361.01	14	0.93					
M2.0.10	30-day illicit drug use: No DIF		-1319.06	10	1.00	M2.0.10 vs. M2.1.10	0.10	5.80	4	0.215
M2.1.10	30-day illicit drug use: Nonuniform DIF		-1318.78	14	0.74					
M2.0.11	30-day cigar use: No DIF		-1389.73	10	1.00	M2.0.11 vs. M2.1.11 ^a	-0.06	-50.69	$\overline{4}$	
M2.1.11	30-day cigar use: Nonuniform DIF		-1389.73	14	0.71					
M2.0.12	30-day cigarette use: No DIF		-1357.31	10	1.00	M2.0.12 vs. M2.1.12 ^a	0.21	48.11	4	0.000
M2.1.12	30-day cigarette use: Nonuniform DIF		-1357.31	14	0.73					
	Step 3: Comparison of models with nonuniform DIF to models with and without uniform DIF for selected items									
M3.0	Nonuniform: Drug use initiation; 30-day liquor,	7551.81	-3474.14	82	0.97	M1.0 vs M3.0	0.75	62.12	28	0.000
	beer, been drunk, wine/wine cooler, inhalant, &					M1.1 vs M3.0	0.99	16.98	20	0.654
	cigarette use									
	Step 4: Testing models for uniform DIF for selected items									
M4.1	All nonuniform except Drug use initiation		-3507.37	79	1.20	M3.0 vs. M4.1 ^a	0.42	473.98	\mathfrak{Z}	0.000
M4.2	All nonuniform except 30-day liquor use		-3474.69	79	0.98	M3.0 vs. M4.2	0.57	1.93	3	0.586
M4.3	All nonuniform except 30-day beer use		-3475.12	79	1.11	M3.0 vs. M4.3 ^a	10.41	0.57	3	0.904
M4.4	All nonuniform except 30-day been drunk		-3477.31	79	1.12	M3.0 vs. M4.4 a	6.44	2.95	3	0.400

Note. DIF = differential item functioning, LL = maximum log likelihood, Npar = number of free parameters in the model, SCF = scaling factor, df = degrees of freedom, CF = correction factor, LRTS = likelihood ratio test statistic, = multiple indicator multiple cause model. P-values for significant comparisons and rows for the final model are bolded.

a = strictly positive LL difference test was used for comparison

Model Comparisons for Stepwise Differential Item Functioning (DIF) Testing for Grade within the Wave 2 Four-Class Model

Model	model comparisons for siepwise Differential hem I anchorang (DII) Testing for Grade winni me wave 2 I oar Class model Description	BIC	LL	Npar SCF		Comparison	cf	LRTS	df	\boldsymbol{p}
Step 1: Comparison of models with and without DIF										
M1.0	No DIF	7425.08	-3502.76	57	1.07					
M1.1	All Nonuniform DIF	8019.20	-3446.50	153	0.84	M1.0 vs M1.1	0.70	161.27	96	0.000
Step 2: Testing for nonuniform DIF one item at a time										
M2.0.1	Alcohol use initiation: No DIF		-1728.75	13	1.00	M2.0.1 vs. M2.1.1	1.00	4.71	8	0.788
M2.1.1	Alcohol use initiation: Nonuniform DIF		-1726.40	21	1.00					
M2.0.2	Cigar/cigarette use initiation: No DIF		-1532.03	13	1.00	M2.0.2 vs. M2.1.2	0.75	5.39	8	0.716
M2.1.2	Cigar/cigarette use initiation: Nonuniform DIF		-1530.02	21	0.90					
M2.0.3	Drug use initiation: No DIF		-1524.63	-13	1.00	M2.0.3 vs. M2.1.3	0.62	11.87	8	0.157
M2.1.3	Drug use initiation: Nonuniform DIF		-1520.95	21	0.86					
M2.0.4	30-day liquor use: No DIF		-1393.54	-13	1.00	M2.0.4 vs. M2.1.4	0.25	6.81	8	0.557
M2.1.4	30-day liquor use: Nonuniform DIF		-1392.69	21	0.71					
M2.0.5	30-day beer use: No DIF		-1439.68	13	1.00	M2.0.5 vs. M2.1.5	0.49	11.72	8	0.164
M2.1.5	30-day beer use: Nonuniform DIF		-1436.79	21	0.81					
M2.0.6	30-day been drunk: No DIF		-1355.86	-13	1.00	M2.0.6 vs. M2.1.6	0.37	42.46	8	0.000
M2.1.6	30-day been drunk: Nonuniform DIF		-1348.02	21	0.76					
M2.0.7	30-day wine/wine cooler use: No DIF		-1401.11	13	1.00	M2.0.7 vs. M2.1.7	0.25	26.66	8	0.001
M2.1.7	30-day wine/wine cooler use: Nonuniform DIF		-1397.80	21	0.71					
M2.0.8	30-day cannabis use: No DIF		-1408.15	13	1.01	M2.0.8 vs. M2.1.8	0.61	30.23	8	0.000
M2.1.8	30-day cannabis use: Nonuniform DIF		-1398.88	21	0.86					
M2.0.9	30-day inhalant use: No DIF		-1366.24	-13	1.00	M2.0.9vs. M2.1.9	0.75	5.26	8	0.730
M2.1.9	30-day inhalant use: Nonuniform DIF		-1364.28	21	0.90					
M2.0.10	30-day illicit drug use: No DIF		-1319.21	13	1.00	M2.0.10 vs. M2.1.10	0.25	14.63	8	0.067
M2.1.10	30-day illicit drug use: Nonuniform DIF		-1317.38	21	0.71					
M2.0.11	30-day cigar use: No DIF		-1389.77	-13	1.00	M2.0.11 vs. M2.1.11	0.25	4.95	8	0.763
M2.1.11	30-day cigar use: Nonuniform DIF		-1389.15	21	0.71					
M2.0.12	30-day cigarette use: No DIF		-1357.88	13	1.00	M2.0.12 vs. M2.1.12 0.25		26.86	8	0.001
M2.1.12	30-day cigarette use: Nonuniform DIF		-1354.55	21	0.71					
	Step 3: Comparison of models with nonuniform DIF to models with and without uniform DIF for selected items									
M3.0	Nonuniform: 30-day beer, wine/wine cooler,	7607.00	-3475.95 89		0.91	M1.0 vs M3.0	0.63	85.66	32	0.000
	cannabis, & cigarette use					M1.1 vs M3.0	0.73	80.28	64	0.082
	Step 4: Testing models for uniform DIF for selected items									
M4.1	All nonuniform except 30-day been drunk		-3481.54	83	0.94	M3.0 vs. M4.1	0.47	23.64	6	0.001
M4.2	All nonuniform except 30-day wine/wine cooler use		-3479.69	83	0.96	M3.0 vs. M4.2	0.20	38.19	6	0.000
M4.3	All nonuniform except 30-day cannabis use		-3477.03	83	0.91	M3.0 vs. M4.3	0.94	2.30	6	0.890
M4.4	All nonuniform except 30-day cigarette use		-3476.69	83	0.93	M3.0 vs. M4.4	0.56	2.63	6	0.853
Step 5: Comparing models with uniform and nonuniform DIF to model with nonuniform DIF only										

Note. DIF = differential item functioning, LL = maximum log likelihood, Npar = number of free parameters in the model, SCF = scaling factor, df = degrees of freedom, CF = correction factor, LRTS = likelihood ratio test statistic, = multiple indicator multiple cause model. P-values for significant comparisons and rows for the final model are bolded.

a = strictly positive LL difference test was used for comparison

Model Comparisons for Stepwise Differential Item Functioning (DIF) Testing for Timing of Waves within the Wave 2 Four-Class Model

Model	μ , and μ is a set of μ is the computation of the computational μ . The computation will be a set of μ Description	BIC	LL	Npar	SCF	Comparison	cf	LRTS	df	\boldsymbol{p}	
Step 1: Comparison of models with and without DIF											
M1.0	No DIF	7420.39	-3500.41	57	1.06						
M1.1	All Nonuniform DIF	8021.09	-3447.45	153	0.88	M1.0 vs M1.1	0.77	137.35	96	0.004	
	Step 2: Testing for nonuniform DIF one item at a time										
M2.0.1	Alcohol use initiation: No DIF		-1725.88	13	1.00	M2.0.1 vs. M2.1.1	0.99	13.75	$8\,$	0.088	
M2.1.1	Alcohol use initiation: Nonuniform DIF		-1719.04	21	1.00						
M2.0.2	Drug use initiation: No DIF		-1526.59	13	1.00	M2.0.2 vs. M2.1.2	0.62	3.10	8	0.928	
M2.1.2	Drug use initiation: Nonuniform DIF		-1525.63	21	0.86						
M2.0.3	Cigar/cigarette use initiation: No DIF		-1521.66	13	1.00	M2.0.3 vs. M2.1.3	0.62	13.74	$8\,$	0.089	
M2.1.3	Cigar/cigarette use initiation: Nonuniform DIF		-1517.38	21	0.86						
M2.0.4	30-day liquor use: No DIF		-1390.06	13	1.00	M2.0.4 vs. M2.1.4	0.25	21.98	8	0.005	
M2.1.4	30-day liquor use: Nonuniform DIF		-1387.33	21	0.71						
M2.0.5	30-day beer use: No DIF		-1435.67	13	1.00	M2.0.5 vs. M2.1.5	0.75	8.87	8	0.353	
M2.1.5	30-day beer use: Nonuniform DIF		-1432.37	21	0.90						
M2.0.6	30-day been drunk: No DIF		-1351.19	13	1.00	M2.0.6 vs. M2.1.6	0.25	16.11	8	0.041	
M2.1.6	30-day been drunk: Nonuniform DIF		-1349.20	21	0.71						
M2.0.7	30-day wine/wine cooler use: No DIF		-1396.36	13	1.00	M2.0.7 vs. M2.1.7	0.37	11.58	8	0.171	
M2.1.7	30-day wine/wine cooler use: Nonuniform DIF		-1394.20	21	0.76						
M2.0.8	30-day cannabis use: No DIF		-1404.08	13	1.00	M2.0.8 vs. M2.1.8	0.49	8.67	$\,8\,$	0.371	
M2.1.8	30-day cannabis use: Nonuniform DIF		-1401.95	21	0.81						
M2.0.9	30-day inhalant use: No DIF		-1361.76	13	1.00	M2.0.9vs. M2.1.9	0.87	11.32	$\,8\,$	0.184	
M2.1.9	30-day inhalant use: Nonuniform DIF		-1356.82	21	0.95						
M2.0.10	30-day illicit drug use: No DIF		-1314.72	13	1.00	M2.0.10 vs. M2.1.10	0.25	17.38	$8\,$	0.026	
M2.1.10	30-day illicit drug use: Nonuniform DIF		-1312.56	21	0.71						
M2.0.11	30-day cigar use: No DIF		-1385.39	13	1.00	M2.0.11 vs. M2.1.11	0.25	8.73	$\,8\,$	0.366	
M2.1.11	30-day cigar use: Nonuniform DIF		-1384.30	21	0.71						
M2.0.12	30-day cigarette use: No DIF		-1353.53	13	1.00	M2.0.12 vs. M2.1.12	0.25	19.23	8	0.014	
M2.1.12	30-day cigarette use: Nonuniform DIF		-1351.13	21	0.71						
	Step 3: Comparison of models with nonuniform DIF to models with and without uniform DIF for selected items										
M3.0	Nonuniform: 30-day liquor, been drunk, illicit	7632.94	-3488.92	89	0.81	M1.0 vs M3.0	0.37	62.57	32	0.001	
	drug, & cigarette use					M1.1 vs M3.0	0.97	85.23	64	0.039	
M3.1	Nonuniform: 30-day liquor, been drunk, illicit	7672.06	-3479.04	97	0.85	M1.0 vs M3.1	0.53	79.96	40	0.000	
	drug, cigarette, & alcohol use initiation					M1.1 vs M3.1	0.94	67.19	56	0.145	
			Step 4: Testing models for uniform DIF for selected items								
M4.1	All nonuniform except Alcohol use initiation		-3485.92	91	0.82	M3.0 vs. M4.1	1.23	11.21	6	0.082	
M4.2	All nonuniform except 30-day liquor use		-3481.37	91	0.86	M3.0 vs. M4.2	0.59	7.97	6	0.241	
M4.3	All nonuniform except 30-day been drunk		-3480.83	91	0.89	M3.0 vs. M4.3	0.11	33.12	6	0.000	

Note. DIF = differential item functioning, LL = maximum log likelihood, Npar = number of free parameters in the model, SCF = scaling factor, df = degrees of freedom, CF = correction factor, LRTS = likelihood ratio test statistic, = multiple indicator multiple cause model. P-values for significant comparisons and rows for the final model are bolded.

a = strictly positive LL difference test was used for comparison
Table B10

Model Comparisons for Stepwise Differential Item Functioning (DIF) Testing for Intervention phase within the Wave 2 Four-Class Model

Model	nower comparisons for siep was Differential neur Fanchoning (DIF) Festing for Intervention phase within the wave 21 out cluss model Description	BIC	LL			Npar SCF Comparison	cf	LRTS	df	\boldsymbol{p}		
Step 1: Comparison of models with and without DIF												
M1.0	No DIF	7410.26	-3506.39	54	1.05							
M1.1	All Nonuniform DIF	7706.59	-3477.90	102	0.91	M1.0 vs M1.1	0.75	76.48	48	0.006		
Step 2: Testing for nonuniform DIF one item at a time												
M2.0.1	Alcohol use initiation: No DIF		-1732.26	10	1.00	M2.0.1 vs. M2.1.1	0.74	4.09	$\overline{4}$	0.394		
M2.1.1	Alcohol use initiation: Nonuniform DIF		-1730.75	14	0.93							
M2.0.2	Drug use initiation: No DIF		-1532.59	10	1.00	M2.0.2 vs. M2.1.2	0.49	14.82	$\overline{4}$	0.005		
M2.1.2	Drug use initiation: Nonuniform DIF		-1528.95	14	0.86							
M2.0.3	Cigar/cigarette use initiation: No DIF		-1530.06	10	1.01	M2.0.3 vs. M2.1.3	0.49	16.94	4	0.002		
M2.1.3	Cigar/cigarette use initiation: Nonuniform DIF		-1525.94	14	0.86							
M2.0.4	30-day liquor use: No DIF		-1395.54	10	1.00	M2.0.4 vs. M2.1.4 ^a	-0.07	-68.82	$\overline{4}$			
M2.1.4	30-day liquor use: Nonuniform DIF		-1395.54	14	0.71							
M2.0.5	30-day beer use: No DIF		-1441.92	10	1.00	M2.0.5 vs. M2.1.5	0.74	5.93	4	0.205		
M2.1.5	30-day beer use: Nonuniform DIF		-1439.72	14	0.93							
M2.0.6	30-day been drunk: No DIF		-1358.48	10	1.00	M2.0.6 vs. M2.1.6 ^a	-0.02	-1057.45	$\overline{4}$			
M2.1.6	30-day been drunk: Nonuniform DIF		-1358.48	14	0.71							
M2.0.7	30-day wine/wine cooler use: No DIF		-1402.97	10	1.00	M2.0.7 vs. M2.1.7 a	0.09	113.09	$\overline{4}$	0.000		
M2.1.7	30-day wine/wine cooler use: Nonuniform DIF		-1402.97	14	0.72							
M2.0.8	30-day cannabis use: No DIF		-1410.39	10	1.01	M2.0.8 vs. M2.1.8	0.22	26.10	$\overline{4}$	0.000		
M2.1.8	30-day cannabis use: Nonuniform DIF		-1407.56	14	0.79							
M2.0.9	30-day inhalant use: No DIF		-1368.48	10	1.01	M2.0.9vs. M2.1.9	0.49	7.34	4	0.119		
M2.1.9	30-day inhalant use: Nonuniform DIF		-1366.69	14	0.86							
M2.0.10	30-day illicit drug use: No DIF		-1321.60	10	1.00	M2.0.10 vs. M2.1.10 ^a	-0.20	-45.51	$\overline{4}$			
M2.1.10	30-day illicit drug use: Nonuniform DIF		-1321.60	14	0.70							
M2.0.11	30-day cigar use: No DIF		-1392.04	10	1.00	M2.0.11 vs. M2.1.11 ^a	0.28	32.87	4	0.000		
M2.1.11	30-day cigar use: Nonuniform DIF		-1392.04	14	0.74							
M2.0.12	30-day cigarette use: No DIF		-1360.32	10	1.00	M2.0.12 vs. M2.1.12	0.00	280.00	4	0.000		
M2.1.12	30-day cigarette use: Nonuniform DIF		-1360.31	14	0.71							
	Step 3: Comparison of models with nonuniform DIF to models with and without uniform DIF for selected items											
M3.0	Nonuniform: cigarette/cigar & drug initiation; 30-	7555.08	-3490.47	78	0.89	M1.0 vs M3.0	0.53	60.63	24	0.000		
	day wine/wine cooler, cannabis, cigar, & cigarette					M1.1 vs M3.0	0.97	26.06	24	0.350		
Step 4: Testing models for uniform DIF for selected items												
M4.1	All nonuniform except Cigar/cigarette use initiation		-3492.13	75	0.93	M3.0 vs. M4.1 a	2.84	3.51	3	0.320		
M4.2	All nonuniform except Drug use initiation		-3491.60	75	0.89	M3.0 vs. M4.2	0.81	2.79	\mathfrak{Z}	0.426		
M4.3	All nonuniform except 30-day wine/wine cooler use		-3491.45	75	0.90	M3.0 vs. M4.3	$0.60\,$	3.26	\mathfrak{Z}	0.353		
M4.4	All nonuniform except 30-day cannabis use		-3493.27	75	0.91	M3.0 vs. M4.4	0.39	14.16	3	0.003		
M4.5	All nonuniform except 30-day cigar use		-3491.37	75	0.89	M3.0 vs. M4.5	0.77	2.34	3	0.504		

Note. DIF = differential item functioning, $LL =$ maximum log likelihood, Npar = number of free parameters in the model, $SCF =$ scaling factor, df = degrees of freedom, CF = correction factor, LRTS = likelihood ratio test statistic, = multiple indicator multiple cause model. P-values for significant comparisons and rows for the final model are bolded.

a = strictly positive LL difference test was used for comparison

Table B11

Model Comparisons for Stepwise Differential Item Functioning (DIF) Testing for Combined Model with Sex, Grade, Timing of Waves, and Intervention phase within the Wave 2 Four-Class Model

Model	Description	BIC	LL	Npar	SCF	Comparison	cf	LRTS	$\mathrm{d}\mathrm{f}$	p		
Step 1: Comparison of models with and without identified DIF												
M6.0	No DIF, just c on sex, grade, timing of waves, intervention	7461.50	-3476.83	69	1.04							
M6.1	All DIF from sex, grade, timing of waves, intervention	7818.53	-3408.78	136	0.85	M6.0 vs M6.1	0.66	207.63	67	0.000		
Step 2: Comparing models to determine whether accounting for all four sources of DIF is necessary												
M7.1	DIF for sex@0	7884.85	-3500.82	120	0.79	M7.1 vs. M6.1	1.31	141.05	16	0.000		
M7.2	DIF for intervention phase $@0$	7912.53	-3488.90	127	0.76	M7.2 vs. M6.1	2.18	73.43	9	0.000		
M7.3	DIF for grade $@0$	7728.24	-3437.23	116	0.86	M7.3 vs. M6.1	0.80	70.78	20	0.000		
M7.4	DIF for timing of waves $@0$	7818.14	-3489.54	114	0.86	M7.4 vs. M1.2	0.81	199.84	22	0.000		
Step 3: Evaluating whether any individual sources of DIF can be removed from model												
M8.0.1	Excluded: 30-day liquor use for sex		-3409.53	135	0.84	M6.1 vs M8.0.1	2.49	0.61	1	0.436		
M8.0.2	Excluded: 30-day beer use for sex		-3413.27	135	0.84	M6.1 vs M8.0.2	2.42	3.72	$\mathbf{1}$	0.054		
M8.0.3	Excluded: 30-day been drunk for sex		-3410.06	135	0.83	M6.1 vs M8.0.3	3.97	0.64	$\,1\,$	0.422		
M8.0.4	Excluded: 30-day cigarette use for sex		-3412.31	135	0.85	M6.1 vs M8.0.4	0.96	7.36	$\,1\,$	0.007		
M8.0.5	Excluded: Drug use initiation for sex		-3415.21	132	0.82	M6.1 vs M8.0.5	1.79	7.20	4	0.126		
M8.0.6	Excluded: 30-day wine/wine cooler use for sex		-3411.87	132	0.83	M6.1 vs M8.0.6	1.69	3.66	4	0.453		
M8.0.7	Excluded: 30-day inhalant use for sex		-3418.93	132	0.82	M6.1 vs M8.0.7	1.86	10.92	4	0.028		
M8.1.1	Excluded: 30-day cannabis use for grade		-3418.09	134	0.82	M6.1 vs M8.1.1	2.87	6.49	\overline{c}	0.039		
M8.1.2	Excluded: 30-day cigarette use for grade		-3411.30	134	0.84	M6.1 vs M8.1.2	2.05	2.46	$\overline{2}$	0.292		
M8.1.3	Excluded: 30-day been drunk for grade		-3422.23	128	0.89	M6.1 vs M8.1.3	0.28	95.00	8	0.000		
M8.1.4	Excluded: 30-day wine/wine cooler use for grade		-3413.09	128	0.83	M6.1 vs M8.1.4	1.22	7.10	8	0.526		
M8.2.1	Excluded: Alcohol use initiation for timing of waves		-3411.22	134	0.84	M6.1 vs M8.2.1	1.61	3.04	\overline{c}	0.219		
M8.2.2	Excluded: 30-day liquor use for timing of waves		-3410.98	134	0.81	M6.1 vs M8.2.2	3.59	1.23	\overline{c}	0.541		
M8.2.3	Excluded: 30-day illicit drug use for timing of waves		-3410.16	134	0.62	M6.1 vs M8.2.3	16.61	0.17	$\overline{2}$	0.920		
M8.2.4	Excluded: 30-day been drunk for timing of waves		-3415.31	128	0.89	M6.1 vs M8.2.4	0.27	48.00	8	0.000		
M8.2.5	Excluded: 30-day cigarette use for timing of waves		-3410.76	128	0.83	M6.1 vs M8.2.5	1.17	3.39	8	0.907		
M8.3.1	Excluded: Cigar/cigarette use initiation for intervention phase		-3409.30	135	0.84	M6.1 vs M8.3.1	3.17	0.33	$\mathbf{1}$	0.565		
M8.3.2	Excluded: Drug use initiation for intervention phase		-3412.34	135	0.82	M6.1 vs M8.3.2	5.54	1.29	$\mathbf{1}$	0.257		
M8.3.3	Excluded: 30-day wine/wine cooler use for intervention		-3412.36	135	0.83	M6.1 vs M8.3.3	3.88	1.85	1	0.174		
	phase											
M8.3.4	Excluded: 30-day cigar use for intervention phase		-3412.96	135	0.82	M6.1 vs M8.3.4	4.66	1.80	1	0.180		
M8.3.5	Excluded: 30-day cigarette use for intervention phase		-3411.73	135	0.86	M6.1 vs M8.3.5	0.35	16.74	$\,1$	0.000		
M8.3.6	Excluded: 30-day cannabis use for intervention phase		-3430.79	132	0.84	M6.1 vs M8.3.6	1.29	34.09	$\overline{4}$	0.000		
Step 4: Comparing models with and without additional sources of DIF for all four covariates												
M9.1	Excluded: 30-day liquor use for sex & timing of waves		-3415.86	133	0.81	M6.1 vs M9.1	2.59	5.47	3	0.140		
M9.2	Excluded: 30-day wine/wine cooler use for sex $\&$		-3411.96	131	0.84	M6.1 vs M9.2	1.20	5.32	5	0.378		
	intervention phase											

of freedom, CF = correction factor, LRTS = likelihood ratio test statistic, = multiple indicator multiple cause model. P-values for significant comparisons and rows for the final model are bolded.

Appendix C

Table C1.

Odds Ratios and Confidence Intervals for the Interactive Effects of Each Covariate by Covariate-Adjusted Delinquent Behavior on

Subgroup Transitions

Note. 95% Confidence Intervals. Poly Use = Polysubstance Use, Alc Use = Alcohol Use. Separate models examined moderating effects of dummy-coded variables for sex, grade, timing of waves, and intervention phase. Bolded values indicate significant effects based on the 95% CI.

^a Values were too large to be estimated by Mplus due to empty cells in the joint distribution of the latent class variable and the categorical predictor variable

Table C2.

Odds Ratios and Confidence Intervals for the Interactive Effects of Each Covariate by Covariate-Adjusted Physical Aggression on

Subgroup Transitions

Note. 95% Confidence Intervals. Poly Use = Polysubstance Use, Alc Use = Alcohol Use. Separate models examined moderating effects of dummy-coded variables for sex, grade, timing of waves, and intervention phase. Bolded values indicate significant effects based on the 95% CI.

^a Values were too large to be estimated by Mplus due to empty cells in the joint distribution of the latent class variable and the categorical predictor variable.

Vita

Courtney Bernice Dunn was born on January 30, 1997, in Wooster, Ohio. She received her Bachelor of the Arts degrees in Psychology and Criminology from Cleveland State University in 2019. She began her graduate study in the Clinical Psychology program at Virginia Commonwealth University in 2019. She received her Master of Science degree in Psychology from Virginia Commonwealth University, Richmond, Virginia in 2021. Courtney will complete her predoctoral clinical psychology internship at Cincinnati Children's Hospital Medical Center, Acute Care Track, during the 2024-2025 academic year.