DIFFERENTIAL EFFECTS IN EXPOSURE TO ACEs AND PROBLEMATIC DRINKING: AN EXAMINATION OF PROTECTIVE FACTORS

By

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ABSTRACT

DIFFERENTIAL EFFECTS IN EXPOSURE TO ACEs AND PROBLEMATIC DRINKING:
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Exposure to Adverse Childhood Experiences (ACEs) has been associated with numerous negative developmental outcomes across the lifespan, including problematic drinking. However, not all individuals exposed to ACEs go on to drink problematically. This difference in the effect of exposure to ACEs on drinking use is an example of heterogeneity and is called a differential effect. Relatively little research has examined what factors predict resilience to the harmful effects of ACEs. Most existing research has examined either a single protective factor or examined the total number of protective factors in a cumulative scale. No study has yet to specifically examine differential effects in the context of ACEs and alcohol use.

The aim of this study was to examine differential effects in exposure to ACEs and alcohol use to empirically identify a resilient group of individuals. Two research questions drove this study 1) How can heterogeneity in the association between ACEs and alcohol use be characterized? and 2) What factors predict group membership? Using data from the National Longitudinal Study of Adolescent to Adult Health (Add health), two complimentary analytic tools were used to achieve these aims: Regression Mixture Modeling (RMM) and Structural Equation Model Trees (SEM trees).

Results from the RMM found evidence of two groups: a resilient group consisting of 72.6% percent of the sample and a harmful effects group consisting of 27.4% percent of the sample. Two factors were positively associated with belonging to the resilient group, school bonding and self-control. One factor, having a mentor, was associated with a lower likelihood of

being in the resilient group. Results from the SEM-tree divided the data into three groups based on two variables: self-esteem and having a mentor. In this analysis, higher self-esteem and having a mentor during adolescence were both associated with problematic drinking.

Findings from this study provide empirical evidence of a resilient group of individuals for whom there is not an association between exposure to ACEs and alcohol use. Despite testing multiple theoretically based protective factors, only school bonding and problem solving were associated with resilience. This suggests future research should consider additional alternative protective factors. The results suggest therapists and clinicians working with youths exposed to ACEs should work to foster increased levels of school bonding during adolescence and should assess levels of self-control and focus on helping youths develop greater self-control.

Dedicated to Hilary.
Your life inspires me to invest everything I can
into everything I do
and everyone I meet.

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CHAPTER 1: AN INTRODUCTION TO ADVERSE CHILDHOOD EXPERIENCES, ALCOHOL USE AND RESILIENCE

Introduction

A large body of research documents a strong association between exposure to adverse childhood experiences (ACEs) and problematic drinking across the lifespan (Crouch et al., 2018; Dube et al., 2006; Hughes et al., 2017; Lee & Chen, 2017; Xiao et al., 2008). However, not all adolescents exposed to ACEs develop alcohol problems. Understanding this differential effect, and how the effect of a risk factor varies across individuals, is a key step to understanding why some adolescents exposed to ACEs develop alcohol problems while others do not.

Although research on resiliency has been extensively studied for decades, efforts to understand what factors promote resiliency after exposure to ACEs is nascent (Mclaughlin, 2016). Examining ACEs in isolation without also considering positive, or advantageous experiences is limited and may create an incomplete or inaccurate assessment of risk (McEwen & Gregerson, 2019). Identifying what factors are associated with resilient functioning can help determine which adolescents are most at risk for developing alcohol problems and help identify targets for prevention and interventions.

Alcohol Use During Adolescence

Alcohol is the most commonly abused substance in adolescents and adults alike (Marshall, 2014), and has many long-term consequences. Almost 10% of all deaths are alcohol related in adolescents and young adults (Redfield et al., 2017). Alcohol use in adolescence is associated with other risky behaviors including tobacco use, illicit substance use, and risky sexual behaviors (Marshall, 2014). Adolescents who begin drinking before age 15 are between 2-4 times more likely to develop alcohol dependence in their lives (Dawson, Goldstein, Patricia Chou, June Ruan, & Grant, 2008). The adolescent brain is also more vulnerable to the effects of alcohol (Marshall 2014), which can lead to lasting changes in the brain (Welch, Carson, & Lawrie, 2013), pointing to the importance of prioritizing prevention of alcohol abuse during adolescence.

While rates of alcohol use among adolescents have declined, they remain high (Redfield et al., 2017). In the United States, almost 80% of older adolescents had consumed alcohol in their lifetimes, and 15.1% met criteria for alcohol use disorder (Swendesen et al. 2012). Problematic drinking during adolescence often persists disrupting the ability to navigate developmental tasks as adolescents enter adulthood (Marshall 2014).

Adverse Childhood Experiences and Alcohol use

In the past two decades there has been an increased scientific interest in the lasting harmful effects of adverse experiences in childhood and adolescence (Kelly-Irving & Delpierre, 2019; Steptoe et al., 2019). ACEs refer to a set of interrelated stressful or traumatic experiences during childhood or adolescence typically consisting of exposure to abuse, neglect, or household dysfunction (Felitti et al., 1998). Prevalence estimates of childhood adversity range from a low of approximately 57% (Bomysoad & Francis, 2020) to over 90% in a sample of at-risk children and matched controls (Flaherty et al., 2013). Cumulative exposure to ACEs elevates the risk for concurrent and future mental illnesses across a broad range of disorders (McLaughlin, 2016), with childhood adversity directly accounting for the onset of approximately one third of any psychiatric disorder, and over a quarter of all substance use disorders during adolescence and early adulthood (Green et al., 2010).

There is a dose-response relationship between exposure to different types of ACEs and risk for alcohol or substance use. Exposure to one ACE during adolescence increases the risk of having a substance use problem during adolescence by five times, and exposure to four ACEs increase in the odds of substance use disorder by 15 times (Bomysoad & Francis 2020). Adolescents exposed to ACEs are approximately twice as likely to initiate alcohol use before the age of 14 (Chatterjee et al., 2018). Higher likelihood of substance use for exposure to ACEs has been observed in pre adolescents aged 9-11 (Garrido et al., 2018). In addition to risk for alcohol or substance use disorder, exposure to ACEs also increases the risk of drinking to intoxication and binge-drinking in the past 30 days (Afifi et al., 2020; Shin, Edwards, & Heeren, 2008). Additionally, both exposure to multiple forms of childhood maltreatment, and the frequency of childhood maltreatment are associated with greater increases in binge-drinking during adolescence with a higher peak in binge-drinking that occurs at an older age. This indicates binge-drinking persists for a greater duration into early adulthood for adolescents exposed to childhood maltreatment, which may disrupt successfully completing developmental tasks (Shin, Miller, & Teicher, 2013).

Although exposure to ACEs is associated with an increased risk of alcohol abuse, there is an increasing recognition that not all adolescents develop alcohol use problems (McLaughlin 2017). Efforts to investigate what factors predict positive adaptation despite exposure to ACEs often adopt a resiliency perspective (Crouch et al., 2019). Recent reviews of the ACEs literature have noted a large gap in empirical research on why some individuals are resilient to the potentially harmful effects of ACEs, and what factors can promote resilience (McEwen & Gregerson, 2019; Steptoe et al., 2019). Only a handful of studies have examined resilience to the potentially harmful effects of ACEs (McLaughlin 2017) and even fewer studies have specifically examined resilience to alcohol use (Brown & Shillington 2017).

Resilience

There are multiple definitions of resiliency (Luthar et al., 2006; Southwick et al., 2014) and debate on whether resiliency should be operationalized as an outcome, a trait or a process (Masten, 2007). A commonly accepted definition of resilience is "positive adaptation during or following exposure to adversities that have the potential to harm development" (Masten 2007 p. 923). The concept of resilience has been applied to individuals, families, economies, organizations and other systems (Masten, 2018a). Resilience research recognizes that individuals are embedded in multiple levels of systems (Bronfenbrenner 1979), and that resilience is shaped not only by internal attributes but also through interactions across multiple levels such as the family, neighborhood, or culture (Masten & Barnes, 2018; Masten, 2018).

To accommodate these multi-level influences, research on resilience has adopted an integrative multidisciplinary perspective that incorporates developmental systems theory (Masten, 2018a). According to this perspective, individuals develop through diverse interactions across multiple levels from the genetic, to social and cultural (Masten, 2018). Various adaptive systems such as the immune system or stress-regulation systems develop within a person and are simultaneously shaped by the external contexts across larger systems including families, schools, communities, and other sociocultural or ecological systems. These multilevel systems shape development through dynamic interactions which give rise to diverse pathways potentially leading either to resilience or poor adaptation (Masten, 2018a). Accordingly, efforts to catalog what factors promote resilience to the harmful effects of ACEs have identified factors across multiple levels.

Promotive and Protective Factors

Researchers have investigated which factors promote resiliency despite exposure to risk, or adversity for nearly five decades (Masten & Barnes 2018). Factors that increase the likelihood of resilience are termed protective factors (Masten, 2001) These factors compensate, or mitigate, the risk associated with exposure to high adversity. Conversely, promotive factors are factors that positively influence development or positive outcomes regardless of exposure to risk (Masten 2018b). A factor could be both promotive or protective if it both facilitates positive development and mitigates the harmful effects of exposure to adversity. For example, skillful parenting is both a promotive factor because it positively influences development across all children, and a protective factor because it can mitigate harmful consequences from exposure to different risk factors (Masten 2018b).

Despite research on diverse types of risk ranging from exposure to natural disasters, poverty, or maltreatment, findings on what factors promote resilience are consistent across numerous studies (Masten & Brown 2018). This consistency led to the creation of a “shortlist” of protective factors. Masten and Barnes (2018) argue the “shortlist” consists of examples of fundamentally adaptive systems that are vital for healthy development such as self-regulatory systems, belief systems, or the attachment-system The shortlist involves factors across multiple levels from internal factors including self-regulation, problem-solving skills, and a sense of self-efficacy, parenting and family factors such as family belonging, sensitive caregiving, family routines and rituals, and community level factors such as school belonging and neighborhood context.

ACEs and Resilience

Research investigating resiliency after exposure to ACEs has predominantly examined either individual factors in isolation (Bethell, Newacheck, Hawes, & Halfon, 2014; Brown & Shillington, 2017), or used a scale that catalogs whether an individual had experienced different protective factors during their childhood (Narayan et al., 2018b). This format results in scales that are analogous to the ACEs scale. Just as the ACEs scale consists of a summed list of different types of childhood adversity, these protective experience scales catalog multiple positive childhood experiences and create a summed score of the total number of protective experiences an individual reports experiencing during childhood.

Positive Childhood Experiences

There is little empirical research on what factors promote resilience after exposure to ACEs (Mclaughlin 2017). Several studies have examined the effect of an isolated protective factor in with positive findings. For example, the effects of exposure to multiple ACEs on poor health and mental distress was moderated by reports an adult making them feel safe and protected growing up, or an adult who tried hard to meet their basic needs (Crouch et al., 2019). Similarly, individuals who reported having adult support available some or most of the time in childhood did not have an increased risk for heavy drinking even if they had been exposed to multiple ACEs (Bellis et al., 2017). Brown and Shillington (2017) found having a supportive relationship with parents and other adult figures moderated the association between ACEs and substance use in adolescence. Bethell, Newacheck, Haes and Halfon (2014) measured the individuals' ability to stay calm when under stress as a resilience asset, and found it predicted higher school engagement and better health outcomes.

Other research articles that examine the effect of the cumulative number of positive childhood experiences (PCEs) have inconsistent findings. For example, PCEs demonstrated protective effects for post-traumatic stress symptoms, but not depression or stress in a study of low-income pregnant women (Narayan et al., 2018b). A similar study that measured four PCEs found only two factors (warm maternal relationship and being told "you're great" frequently) predicted lower depression symptoms. However, when considering the effects of both PCEs and ACEs simultaneously, none of the four PCEs remained significant (Chung et al., 2007). Conversely, when Crandall et al. (2020) examined the effect of ACEs and PCEs simultaneously, the effect of ACEs was no longer significant for any of the health indicators, and PCEs predicted lower risk for substance abuse and other factors. A third study examined the effects of ACEs, and PCEs on adult poor mental health and relational health. Bethell et al. (2019) examined 7 PCEs and found a similar dose response relationship between the cumulative number of ACEs and PCEs: after controlling for exposure to ACEs, adults who reported multiple PCEs were 72% less likely to report poor mental health compared to individuals with no PCEs.

Person-Centered Approaches to Resilience

In addition to the previously described research that employs a variable-centered analyses, Masten (2001) noted resilience research has also incorporated person-centered analyses. Variable and person-centered analyses have strengths and weaknesses depending on the research aims (Masten 2001). Variable focused analyses often use statistical moderation to determine if the effect of a risk is dampened when considering the presence of a third protective factor. This is accomplished by using multiplicative interaction terms and is appropriate when there is strong theoretical justification for examining the effect of single or small number of moderators (Van Horn et al., 2015). However, variable centered analyses are less efficient when there are a larger number of moderators due to lower power, increased risk for multicollinearity and difficulties interpreting complex higher-order interactions.

In contrast, person-centered analyses seek to identify similar groups of individuals who may be resilient, despite exposure to risk factors, such as ACEs. While person-centered analyses have been studied with other risks, very few articles have employed a person-centered analysis approach when considering ACEs. Person-centered analyses focus on “naturally occurring configurations” of variables and can be used to identify resilient groups of individuals or individuals at the greatest risk and in need of intervention (Masten 2001 p. 229). In addition to empirically identifying a resilient group of individuals, some person-centered analyses such as regression mixture-models can also be used determine which factors are associated with belonging to the resilient group (Van Horn et al., 2009).

Only a few studies have used person-centered analyses to examine the effect of ACEs and PCEs simultaneously. Lui et al. (2019) examined co-occurring profiles of ACEs and protective factors using a cross-sectional latent transition analysis. In this model two latent profiles were estimated, one for exposure to ACEs, and one for exposure to protective factors. The profile of protective factors was regressed on the profile of ACEs to estimate a co-occurring profile of ACEs and protective factors. These profiles were used to predict the number of health conditions the adolescent reported experiencing. The results demonstrated that while ACEs are linked with worse health outcomes, adolescents who also experience moderate to high levels of protective factors fare better than those who have lower levels of protective factors. A similar study on military families used latent profile analysis (LPA) to identify family profiles (Oshri et al., 2015). The authors examined mean differences in the number of adverse childhood experiences reported in each profile and examined how profile membership predicted several indices of physical, mental, and family health. The highest number of ACEs were found in the unbalanced and rigidly balanced profiles, with the unbalanced profile demonstrating the worst outcomes in all domains.

Limitations of Current Research

While there is a robust association between exposure to ACEs and numerous health and psychological problems across the lifespan, including alcohol use, far less is known about what factors promote resilience. The existing studies are predominantly cross-sectional, and rely on either retrospective reports of ACEs and PCEs, or use parents to provide information on exposure to ACEs (e.g., Bethell et al. 2014).

Further, most studies on resilience in ACEs have examined broader outcomes such as general mental health difficulties (Bethell et al., 2019) or physical health outcomes such as BMI (Crandall et al., 2020). Only one study reviewed (Brown & Shillington 2017) specifically focused on alcohol related outcomes. However, the Brown and Shillington study (2017) also only examined one protective factor, experiences of parental/adult support. Given that alcohol is the most commonly abused substance in adolescence and adulthood, alcohol problems often develop during adolescence (Marshall, 2014), and are strongly associated with ACEs (Hughes et al. 2017), more research is needed to examine what factors promote resilience to alcohol problems in individuals exposed to ACEs. However, the studies that used a cumulative index of PCEs may provide only limited information to therapists or other practitioners and are of limited value to help develop future interventions. Knowledge that multiple protective experiences mitigate the effects of ACEs is not specific enough to guide a therapist working with an adolescent or family with high levels of ACEs or help develop interventions.

Examining both ACEs and PCEs either simultaneously in a regression or using a hierarchical analysis does not actually identify groups of adolescents who are resilient, or predict which adolescents are resilient. It only demonstrates whether exposure to ACEs is still significantly associated with a health or other developmental outcome when accounting for the association between the number of PCEs and the outcome. One study (Bethel et al. 2019) stratified the number of ACEs and PCEs into groups which demonstrated a dose-response relationship between increased number of PCEs and fewer mental health difficulties even for individuals who reported high levels of ACEs. However, this also does not inform which positive experiences, or what combination of positive experiences may result in the best outcomes or mitigate the risk from ACEs.

A regression model that includes both ACEs and PCEs demonstrates the total number of PCEs associated with decreased risk of a health outcome, even after accounting for the risk of ACEs. This modeling strategy does not identify individuals who are resilient, however. It assumes the effect of all PCEs are equivalent to each other, and presumes the effects of multiple PCES are additive, and that they increase linearly. This ignores the possibility of potentially more complex interactions between the different types of PCEs. However, examining multiple interactions, and higher-order or complex interactions are difficult to interpret and may be statistically problematic when using a regression-based framework. The limitations and improbable assumptions of using a cumulative scale, and the inherent difficulties of interpreting complex statistical interactions point to the need of future research to employ more sophisticated analyses that can better inform what PCEs, and what combination of PCEs may promote resiliency.

Future Directions for Research

An alternative approach to examining resilience and protective factors is to use person-centered and other types of analyses to identify groups of adolescents who are resilient, despite exposure to ACEs. The observation that similar environmental factors may have different effects on some individuals is called multifinality (Cicchetti & Rogosch, 2002). Research that examines multifinality seeks to understand differential effects: how the association between a predictor variable (e.g., ACEs) and an outcome variable (e.g., alcohol use) may vary across individuals (Van Horn et al., 2015). This variation in the association between two variables is an example of heterogeneity. Efforts to understand heterogeneous effects move research beyond simple statistical associations to determining what factors influence the associations. This can help to understand how different psychosocial variables influence developmental outcomes, such as alcohol use (Lerner, 2006).

However, despite the potential benefits of using person-centered analyses to understand heterogeneous effects, only a few studies on ACEs have done so (e.g., Lew & Xian, 2019; Liu et al., 2019; Oshri et al., 2015) and none have done so in examining alcohol use. Research that can identify resilient groups of adolescents, can be used to then determine what factors predict resilience. This can help better understand which adolescents may be at most risk of developing an alcohol use problem, as well as potential targets for intervention. Further, given that protective factors likely exhibit non-linear patterns of association, including potentially complex interactions that cannot be easily modeled with regression-based analyses, research that employs sophisticated tools used in exploratory data mining can help to better understand how protective factors intersect to influence the association between ACEs and alcohol use.

The current Study

Differential Effects of Exposure to ACEs, Alcohol Use and Identification of Protective Factors

The aim of this study is to empirically identify a resilient group of adolescents and determine what factors predict belonging to the resilient group. Two separate but complimentary analyses will be used to identify and characterize this differential effect: regression mixture modeling (RMM) (Lamont, Vermunt, & Horn, 2016) and Structural Equation Model Trees (SEM trees) (Brandmaier et al., 2016). These analyses empirically identify groups of individuals who are similar on parameter of interests (e.g., the association between exposure to ACEs and alcohol use). These analyses can then be used to determine what factors predict belonging to the different groups.

Although both methods are data driven approaches, two research questions guided the study 1) How can heterogeneity in the association between ACEs and alcohol use be characterized? Research question one refers to the question of the number of groups identified using the RMM and SEM Tree. It is hypothesized there will be at least two different groups. There will be a "harmful effects" group characterized by a significant association between exposure to ACEs and alcohol use and a "resilient" group characterized by a non-significant association between exposure to ACEs and alcohol use. 2) What factors predict group membership to? To answer research question two, different factors identified from research that are associated with lower alcohol use will be tested to determine if they predict belonging to the resilient group. Research question two hypothesizes that the protective factors identified from previous research will be associated with belonging to the resilient group.

CHAPTER 2: LITERATURE REVIEW OF ACEs, ALCOHOL USE AND RESILIENCE IN ADOLESCENTS

To provide support for the study, research questions and hypotheses, in this chapter I will review and critique research on ACEs, alcohol use and resilience. I will first briefly describe research that identifies adolescence as a relevant developmental time-period for the development of alcohol use problems and summarize commonly researched predictors of alcohol use. Then I will review and summarize relevant research on the association between ACEs and alcohol use. I will then review conceptual and empirical research on resilience. I will argue that adopting a relational developmental systems theory perspective provides a useful explanatory framework for understanding the complex associations between exposure to ACEs, protective factors, and the development of resiliency. Lastly, I will describe how relational developmental systems theory informs the study of both hypotheses and choice of research methods.

Adolescence and Alcohol Use

Adolescence is the developmental period between childhood and adulthood. Although adolescence begins around the onset of puberty, there is no biological or universally agreed upon social transition that marks the end of adolescence and the start of adulthood (Sawyer et al., 2018). Adolescence is characterized by rapid biological changes across multiple physiological systems, including important structural and functional changes in the developing brain (Casey, 2015). In addition to these profound biological changes, adolescence is marked by important transitions across multiple social roles (Christie & Viner, 2005). Many developmental tasks occur during adolescence such as identity formation (Marcia 1980), successfully developing peer and romantic relationships, and achieving a greater degree of independence and autonomy (Steinberg & Morris, 2000).

Adolescence is also characterized by heightened sensation-seeking and increased risk taking (Casey, 2015; Steinberg & Morris 2000). The adolescent brain is primed to be more responsive to stimulating and rewarding experiences. Adolescents are influenced by their peers (Leung, Toumbourou, & Hemphill, 2014), and are vulnerable to the physiological effects of alcohol and other substances due to their maturing brains (Clark et al., 2008). These profound biological and social changes all contribute to the increased risk of alcohol use and misuse that occurs during adolescence. Adolescence is thus a developmentally sensitive period and critical time to intervene before the long-term health consequences of different risky behaviors such as drinking have materialized. Understanding how various risk factors for alcohol use problems intersect is vital for intervention and prevention efforts.

The Importance of a Developmental Framework for Understanding Alcohol Abuse

Alcohol use disorder (AUD) is a developmental disorder that can best be studied with a lifespan perspective (Cicchetti & Rogosch, 2002).This perspective is useful to study the complex interplay between risk and protective factors that contribute to the likelihood of an individual developing alcohol use problems. Numerous risk factors for alcohol use have been identified and studied across multiple levels ranging from genetic, biological, personality, familial, peer, and larger social contexts (Cicchetti & Handley, 2019).

Exposure to ACEs is a well-studied path associated with problematic alcohol use (Anda et al., 2002; Dube et al., 2001; Felitti et al., 1998; Shin, McDonald, & Conley, 2018). Additionally, the onset of almost one third of all psychiatric disorders, and over a quarter of all substance use disorders in adolescence can be directly attributed to exposure to childhood adversity (Green et al., 2010). As such, better understanding the association between ACEs and alcohol use, and what factors reduce the likelihood of problematic drinking represents an important line of research to help address problematic drinking that often begins during adolescence.

ACEs and Alcohol Use

A meta-analysis of the harmful effects of exposure to multiple ACEs such as alcohol use, found individuals who have experienced four or more different ACEs are twice as likely to report current heavy drinking, and nearly six times as likely to report problematic drinking during their lifetimes (Hughes et al., 2017). This effect may be even higher in adolescence; Bomysoad and Francis (2020) found exposure to one ACE in adolescence was associated with a five times greater risk of having a substance use problem, and exposure to four ACEs was associated with a more than 15 times higher risk of having a substance use problem compared to someone who has no exposure to ACEs. 15 times higher. While a substantial body of research documents the association between ACEs and alcohol use, there is wide variability in the definition of alcohol problems, how ACEs are measured, and the age range studied. Definitions of alcohol problems have included earlier age of alcohol initiation (Chatterjee et al., 2018), lifetime diagnosis of alcohol use disorder (AUD) (Dube et al., 2001), past year diagnosis of AUD (LeTendre & Reed, 2017), current (past month) binge drinking (Loudermilk et al., 2018), and current heavy drinking (Lee & Chen, 2017). The effect of individual ACEs, as well as categories of ACEs (e.g., abuse vs household dysfunction) have also been studied, with mixed results. The effect of exposure to ACEs and alcohol use has been examined in pre-adolescents as young as age 9-11 (Garrido et al., 2018), college-aged individuals (Loudermilk et al., 2018), as well as middle-age and older adults (Leung, Britton, & Bell, 2016) .

ACEs and Alcohol Use Problems

Exposure to multiple ACEs is related to earlier initiation of alcohol use, and greater chances of ever using alcohol (Dube et al., 2001). Individuals who experience four or more ACEs are 6 times more likely to self-report being an alcoholic (Hughes et al. 2017) and 50% times more likely to currently meet criteria for Alcohol use Disorder (AUD) diagnosis (LeTendre & Reed, 2017). This increased likelihood remains even after adjusting for family history of alcohol problems, early initiation of alcohol use, lifetime heavy binge drinking, and demographic variables (Pilowsky et al., 2009).

In addition to increased lifetime risk of diagnosis of AUD, large representative samples of adults document the long-term effects of ACEs on current problematic drinking. Exposure to multiple ACEs is associated with 50% increased risk of binge drinking (Loudermilk et al., 2018) and 80% increased risk of heavy drinking (Crouch et al., 2018) in the past 30 days. However, examining individual ACEs in isolation has led to mixed results. While several studies have found significant independent associations across the majority of individual adversities (Crouch et al., 2018; Lee & Chen, 2017), other studies have not (Fang & McNeil, 2017). This difference may be because Fang and McNeil (2017) included current depression as a covariate, when research suggests it may be a mediator (Jung et al., 2020). Likewise, Loudermilk et al. (2018) examined categories of ACEs (i.e., child-abuse or household dysfunction) and found only child-abuse (having experienced physical, emotional, or sexual abuse) significantly predicted higher binge and heavy drinking. In contrast, Lee and Chen (2017) found both child abuse and household dysfunction significantly predicted binge-drinking.

These findings demonstrate that a cumulative exposure to multiple types of childhood adversity has a stronger association with problematic drinking than exposure to either an individual adversity, or the broad category of ACEs. This body of research focused on the effects of ACEs on adult drinking, rather than adolescence. Nonetheless, these studies document that the long-term effects of exposure to ACEs can last well into adulthood. However, as alcohol use typically begins during adolescence, examining the link between ACEs and adolescent alcohol is an important step to then identify protective factors that may prevent future drinking problems.

Adolescence and ACEs

Estimates for the prevalence of ACEs measured during adolescence are similar or higher than estimates using retrospective adult reports. Estimates range from a low of approximately 57% (Bomysoad & Francis, 2020) to over 90% (Flaherty et al., 2013) in an at-risk sample. This large discrepancy may result from different definitions of ACEs, the use of different informants, and differences in risk-levels in the sample. Bomysoad and Francis (2020) used a nationally representative sample relying on a parent report of their child's exposure to ACEs but did not include items related to maltreatment (e.g., abuse or neglect). Flaherty et al. (2013) used data from a sample of at-risk youth followed longitudinally that relied on social service records of allegations of abuse or neglect as well as parent self-report from validated questionnaires measuring depression, substance use and exposure to interparental violence. Socially desirable responding may have reduced the prevalence estimate in Bomysoad and Francs (2020), as parents may not fully disclose their own mental health or substance use problems, however the use of an at-risk sample in (Flaherty et al. 2013) may have increased the prevalence estimate.

Despite differences in the number of youths exposed to ACEs, a similar dose-response relationship exists for exposure to ACEs and risk for alcohol or substance use (Bomysoad & Francis 2020). Exposure to ACEs is associated with multiple alcohol use problems in adolescence including drinking at an earlier age, (Chatterjee et al., 2018) drinking to intoxication and binge-drinking in the past 30 days (Afifi et al., 2020; Shin, Edwards, & Heeren, 2008). Further, both exposure to multiple forms of childhood maltreatment, and the frequency of childhood maltreatment is associated with greater increases in binge-drinking during adolescence with a higher peak in binge-drinking at a later age, indicating binge-drinking persists for a greater duration into early adulthood for adolescents exposed to childhood maltreatment (Shin, Miller, & Teicher, 2013).

Despite the robust and well-documented association between ACEs and various drinking problems from adolescence into adulthood, research on ACEs and alcohol use has been critiqued on methodological grounds and conceptual grounds (Kelly-Irving & Delpierre, 2019; Lacey & Minnis, 2019). In the next section I will review commonly cited critiques of ACEs research, provide my own critiques, and identify future areas of research for ACEs.

Critique of ACEs Research

Since the original ACE study was published over twenty years ago (Felitti et al., 1998), numerous studies have since documented the harmful effects of ACEs, with an exponential increase in the number of publications in the past decade (Kelly-Irving & Delpierre, 2019). Although strong associations between the number of ACEs and many negative outcomes such as problematic drinking are consistently found, there are several noteworthy criticisms of research on ACEs. Two recently published critical reviews of ACEs literature (Kelly-Irving & Delpierre, 2019; Lacey & Minnis, 2019) critiqued existing research on ACEs on several ground such as 1) ambiguities in the definition of adversity; 2) inconsistencies in what items are included in measures of ACEs; 3) insufficient research identifying mechanisms linking exposure to ACEs to different health outcomes; and 4) lack of research examining resiliency and ACEs.

Definition of Adversity and Expanded ACEs

The original ACE study consisted of seven items (psychological, physical, or sexual abuse, witnessing interparental violence, living with a household member who has a mental illness or substance abuse problem, or a parent who was incarcerated) (Felitti et al., 1998). Subsequent studies published by the same research team later included parental separation and exposure to criminal behavior (Anda et al., 1999), as well as emotional and physical neglect (Dong et al., 2003) resulting in a list of 10 items. This list of ACEs reflects three broad categories: abuse, neglect, and exposure to household instability.

Lacey and Minnis (2019) note that the original ACE study did not include any explicit theoretical reason for what items were included or excluded. McLauglin (2016) wrote adversity is a “construct in search of a definition” (p. 363). Several authors have argued that research on ACEs is hindered by not having an explicit operational definition, or criteria for whether an experience should be included as an ACE or not. McLaughlin (2016) provides an operational definition of adversity as “exposure during childhood or adolescence to environmental circumstances that are likely to require significant psychological, social, or neurobiological adaptation by an average child and that represent a deviation from the expectable environment” (p. 363). Based on this definition, McLaughlin notes that not all childhood stressors may be counted as ACEs and gives the example of the death of an elderly grandparent. While stressful, the death of a grandparent during childhood or adolescence is a normative experience and typically does not require significant adaptation (McLaughlin 2016).

These differences in what items to include, and how to define adversity have problematic implications as several large nationally representative routine surveys now include a measure of ACEs. For example, starting in 2010 The CDCs Behavioral Risk Factor Surveillance System

(BRFSS), and in 2011 the National Survey of Children's Health (NSCH) began to routinely measure ACEs (CDC 2010). The BRFSS scale measure consists of 10 items closely resembling the original ACE scale collected by self-report from adults. In contrast, the NSCH scale consists of adult reports of a chosen youth, and does not contain items involving physical, sexual, or emotional abuse, but includes items measuring financial hardship, community violence, and racial/ethnic discrimination. These wide discrepancies in what items are included limits the ability to make comparisons across studies and confound interpretations of conflicting results. Difference in what items are included as "ACEs" may impede research on understanding what developmental processes ACEs disrupt and identifying protective processes as certain ACEs may differentially affect developmental processes (Mclaughlin & Lambert, 2017).

Implications of Definitions for Prevention and Intervention

The choice of what items are included in measures of ACEs has direct implications for prevention and intervention efforts. Although preventing and combating ACEs requires a multi-pronged approach, differences in what ACEs are measured could affect what level (e.g., family, community, or policy) to focus intervention efforts. For example, in social epidemiology there was a debate on whether health inequities are the consequence of material deprivation and poverty (Lynch et al., 2000), or of psychosocial factors (Marmot & Wilkinson 2001). Studies that include SES, economic disadvantage, or material neglect as ACEs may confound these different pathways (Kelly-Irving 2019). Hartas (2019) argues whether the deleterious effects of ACEs are primarily driven by experiences of abuse or neglect, or from material deprivation (e.g., poverty, food insecurity, instable housing, exposure to environmental toxins) has implications for whether interventions should primarily target parents and families, or policies aimed at reducing the effects of poverty and decreasing income inequality.

In response to health iniquities that are brought on from exposure to ACEs, British public policy has emphasized parenting and family level interventions to combat the harmful effects of ACEs (Hartas 2019). Hartas (2019) contends the emphasis on families, and not the ecological context in which they are embedded, has been at the expense of other more macro policy interventions aimed at reducing structural inequalities. However, framing the issue as a dichotomous either-or debate simplifies the complex ways in which both material deprivation and psychosocial stressors simultaneously contribute to health outcomes and inequities. For example, children in poverty are more likely be exposed to ACEs (McKelvey et al., 2018). Likewise, the effects of poverty are associated with increased parental stress, higher levels of harsh and punitive parenting and less responsive parenting (Evans & Kim 2013). ACEs and the broader environment and ecology are interrelated and associated with numerous negative health outcomes. As such, future research aimed at identifying protective processes should examine factors across multiple ecological levels.

The next section will examine potential biological and developmental pathways that explain the association between ACEs and alcohol use. Identifying how ACEs disrupt development and lead to problematic drinking can be used to help identify protective factors and processes.

ACEs and Allostatic Load

The emergence of research on ACEs coincided with early research on allostasis (Hays-Grudo et al., 2021). Research on allostasis provides a plausible biological pathway to explain the harmful long-lasting negative effects of ACEs (Hays-Grudo et al., 2021). Research on toxic-stress and allostasis documents how prolonged exposure to stressful environments impairs the development of multiple biological and psychological systems. Diverse evidence from multiple sources in both human and animal studies demonstrate how stressful experiences are biologically embedded through physiological changes at the neurological, immunological and genetic levels (Hays-Grudo et al., 2021).

Danese and McEwen (2012) review research that describes how stressful experiences (e.g., ACEs) activate multiple stress-response systems that lead to beneficial short-term adaptations that maximize survival. However, prolonged and repeated exposure to stressful experiences results in long-term neurobiological adaptations, that while beneficial for immediate survival, are nonetheless detrimental to long-term health and well-being. The cumulative wear and tear of the body that occurs from repeated activation of stress response systems is called allostatic load (Danese & McEwen 2012). These long-term changes in brain structure and function, as well as in immunological and metabolic functioning demonstrate how stressful experiences "get under the skin" resulting in the biological embedding of stress (Hays-Grudo et al., 2021).

The effects of ACEs extend beyond the stress-response. Evidence documents the detrimental effects of exposure to ACEs on brain development. Children who have been exposed to ACEs exhibit both structural and functional changes in brain development (McLaughlin et al., 2019). Specifically, maltreated children exhibit changes in multiple neurological systems such as changes in the hippocampus which affects learning and memory; smaller volume of the prefrontal cortex, which impairs executive functioning and decision making, and changes in the amygdala resulting in a heightened threat response, diminished responses to reward and greater susceptibility to negative emotionality.

Exposure to ACEs results in neurobiological adaptations across several physiological systems that lead to impairment across multiple developmental systems. Hays-Grudo et al (2021) describe several of these developmental systems including attachment and various social, emotional, and cognitive systems. These changes then can lead to impairments in executive functioning such as problems with working memory, inhibitory functioning, and emotion regulation, which in turn may increase the likelihood of experiencing a mental illness or substance abuse problem.

The list of developmental systems listed by Hays-Grudo et al. (2021) parallels the list of fundamental adaptive systems described by Masten (2004). Masten (2001) argues exposure to adversity may not result in long term maladaptation unless these fundamental adaptive systems are compromised. Some of the adaptive systems may be located within the individual such as executive functioning, while other may exist in their context such as effective caregiving. Masten (2004) provides a list of possible adaptive regulatory systems including executive function, emotion regulation, attachment, relationships with pro-social peers and interactions with prosocial community organizations. Factors that promote or enhance developmental systems that are disrupted by ACEs, such as the adaptive systems listed by Masten may also be prime candidates for identifying factors that promote resilience to ACEs.

Resilience

There are increasing calls for research on ACEs to begin focusing on identifying protective factors that buffer from the harmful effects of ACEs (Lacey & Minnis, 2019; Mclaughlin, 2016; Steptoe et al., 2019). While the harmful effects of exposure to ACEs are well documented, not all individuals who are exposed to ACEs experience detrimental effects (Hays-Grudo et al., 2021; McLaughlin, 2016). A focus on identifying protective factors can help explain the diversity of outcomes in individuals exposed to ACEs during childhood. Although research on resilience and ACEs is nascent, resilience to other types of adversities ranging from exposure to war, natural disasters, poverty, and maltreatment has been studied for several decades (Luthar et al., 2000; Masten, 2018a). The conceptual, theoretical, and empirical research from resilience can be fruitfully applied to research on ACEs to guide and inform the process of identifying protective factors and uncovering the developmental mechanisms through which ACEs confer heightened risk for numerous outcomes, including alcohol use.

Research on resilience has its origins in clinical scientists seeking to understand the connection between adversity and mental health to help elucidate the origins of mental health problems (Masten 2018). Early research focused on understanding the variation in adaptation in "at risk" youths and uncovering what factors or processes explained why some individuals experienced positive adaptation despite exposure to risk.

Resilience involves two necessary components: 1) positive adaptation 2) exposure to significant adversity (Luthar, Cicchetti & Becker 2000). However, resiliency researchers have differed in their definition of adversity, positive adaptation, and resilience. Measures of adversity have included single stressful life experiences such as a natural disaster as well as aggregates of multiple negative events (e.g., ACEs) (Southwick et al., 2014). Likewise, the definition of positive adaptation has varied from a lack of symptoms (e.g., symptoms of depression), average or excellent performance in a single domain, success across multiple domains, or competence in meeting developmental tasks (Luthar et al. 2000; Masten 2018a). However, measuring resilience is complicated by the fact that resilient functioning in an individual can vary both across domains as well as across time (Masten, 2018a). That is, an individual could be resilient with respect to one outcome (e.g., school performance), while not resilient in others. Likewise, an individual could also be resilient at one time point, but not at another.

The diversity of definitions and findings have led to criticism about lack of conceptual clarity on resilience (Luthar et al. 2000). While the earliest writing on resilience identified it as a personality trait within an individual (Masten 2018b), subsequent conceptualizations of resilience broadened the focus beyond the individual. This shifted the focus from defining resilience as either an attribute, outcome, or a process to understanding the more complex and systemic nature of resilience (Masten 2018). The shift in focusing on resilience from a static trait to a dynamic and systemic concept occurred in concert with the ascendance in developmental science of using integrative metatheoretical frameworks, such as relational developmental systems (Lerner, 2006; Masten, 2007; Overton, 2013).

Relational Developmental Systems

The relational developmental systems (RDS) paradigm is a multi-level and integrative framework that incorporates ideas and concepts from several other theories such as Bronfenbrenner's ecological systems theory (Bronfenbrenner 1979), developmental systems theory (Lerner 2006), and developmental psychopathology (Cicchetti & Rogosch, 2002). RDS rejects dichotomies (e.g., nature vs nurture) and instead seeks to integrate analyses and findings across multiple levels from the biological to the societal. It focuses on the relations between parts to their whole and individuals to their context by examining mutually influential (bidirectional) relations between individuals and their contexts (Lerner, 2006; Overton, 2015). The complexity of these relations leads to an emphasis on examining the diversity of developmental outcomes and acknowledging the capacity for positive adaptation at any developmental point.

Using this framework, resilience is seen as a dynamic attribute of the developmental system, which cannot exist solely as an attribute of either the person or their context (Lerner 2006). Focusing on resilience in this way acknowledges that individuals are embedded in intersecting and interacting ecological levels (Bronfenbrenner 1979), and that changes in one level can influence another level. Organisms, including the human organism, are seen as a living system who are composed of various biological and psychological systems and also embedded within different systems (e.g., family, school, community) (Masten 2018). Resilience, then, is "the capacity of a system to adapt successfully to disturbances that threaten the viability, function or development of the system." (p. 101).

Thus, perturbations in a system at one level can interactively influence resilience at other levels. Resilience therefore arises from the complex interplay across many different processes and systems. The resilience of an individual at any given time will depend on the level of strain and resources available across these different systems (Masten, 2018a). The dynamic nature of resiliency implies the need to focus on identifying and examining pathways of risk and resilience.

Resilience and ACEs

Research examining what factors promote resilience to ACEs is in its infancy (McLaughlin 2016). To date, only a small number of studies have empirically examined why some individuals exposed to ACEs develop problems and others do not. Existing studies have primarily examined either a factor in isolation (Easterlin et al., 2019) or created a composite index of items (Bethell, Jones, Gombojav, Linkenbach, & Sege, 2019; Crandall et al., 2020; Crandall et al., 2019; Narayan, Rivera, Bernstein, Harris, & Lieberman, 2018a).

Identifying Factors that Promote Resilience

Several scales analogous in their structure and format to the ACE index exist, such as the benevolent childhood experiences scale (Narayan et al., 2018a), the positive experiences in childhood (Bethell et al., 2019), Family Resilience and Connection Index (Bethell, Gombojav, &

Whitaker, 2019), the protective and compensatory experiences (PACEs) scale **(**Hays-Grudo & Morrison 2020**)** and counter-ACEs (Crandall et al., 2020). While the ACEs scale is a cumulative risk factor scale (i.e., total number of different ACEs), these scales are designed to be analogous to the ACE index by cataloging the total number of protective factors an individual has experienced. The items are summed to create a cumulative "protective factors" index.

There is considerable overlap in the composition of these scales, as well as to the short-list of resilience factors developed by Masten (Masten, 2004, 2018b; Masten & Barnes, 2018). Each of the scales measure some or all of the following domains: internal resources (e.g., self-esteem, meaning making), parental/family factors (e.g., caregiver support), community factors (e.g., sense of school belonging, residing in a safe neighborhood). Although the Protective and Compensatory Experiences (PACEs) scale was developed by examining literature related to what factors commonly promote resilience (Hays-Grudo et al., 2021), not all items included in the scales may be associated with reduced alcohol use. For example, although both the PACEs and Benevolent Childhood Experiences (BCEs) scale identify supportive-peer relations as a resilience factor (Hays-Grudo et al., 2021; Narayan et al., 2018), some research has found supportive peers may be a risk factor for alcohol use (Hodder et al., 2018)**.** Likewise, while the PACEs scale lists involvement in team-sports as a protective factor against ACEs, involvement in team sports has been linked to increased alcohol usage (Hoffmann, 2006).

Despite their limitations, existing scales such as the PACEs scale (Hays Grudo & Morris 2020) offer a useful starting point for examining resiliency to ACEs in the context of alcohol use. Although no comprehensive list of protective factors exist, previous research and theoretical models on the development of alcohol problems such as the social development model (SDM) (Cleveland et al., 2012) can be used to identify potential protective factors. Based on examining items commonly associated with promoting resilience in general (Masten 2018) and toward alcohol use specifically (Cleveland et al., 2012; Hodder et al., 2018; Syvertsen et al., 2010), I identified several candidate factors that may be associated with resilient functioning across the various ecological levels: individual (self-control and self-esteem) family (parental bond, parental monitoring) and school/community (school bond, low peer involvement in substances and a supportive relationship with a non-parental adult mentor).

Ecological Protective Factors for Alcohol Use

Research examining risk and protective factors for alcohol use has frequently used a developmental and ecological perspective that examines how multiple factors across a broad range of levels interact to influence the development of alcohol problems (Ennett et al., 2008; Lee et al., 2014). For example, the social developmental model (SDM) and related communities that care (CTC) framework have identified both risk and protective factors related to familial, school, peer, and community institutions (Cleveland et al., 2012). I will briefly review research on factors associated with reduced alcohol use across multiple ecological factors and discuss how they relate to research on ACEs and resilience.

Individual Factors

Self-regulation is a commonly studied individual factor related to alcohol use. An individual who exhibits characteristics high in self-regulation uses self-monitoring to guide and plan their behavior to reach their goals (Patock-Peckham et al., 2001). Self-regulation is a multidimensional construct which encompasses both the ability to inhibit automatic responses (e.g., impulsivity) and to engage in effortful planned behavior (Chassin et al., 2013; Nigg, 2016).

A high level of self-regulation is associated with positive outcomes across numerous developmental domains (Robson et al., 2020). Specifically, adolescents who show high self-regulation use less drugs and alcohol (Chassin et al., 2013; Li et al., 2019; Robson et al., 2020). Similarly, adolescents capable of competent planning and problem solving are less likely to abuse substances (Syvertsen et al., 2009). Conversely, adolescents who are impulsive or have difficulties with attentional control are more likely to use alcohol (Chassin et al., 2013).

Additionally, both self-regulation and executive functioning more broadly are posited to be affected by exposure to ACEs (Hayes-Grudo 2021, McLaughlin 2017). This disruption in the development of effective self and emotion regulation may influence the later development of substance using problems (Felitti 1998). Shin et al. (2012) examined this association in adolescents and found that exposure to childhood maltreatment was associated with increased levels of inattentiveness, and that inattentiveness mediated the effects of maltreatment on binge drinking. In a review of research on resilient functioning in maltreated youth, Cicchetti (2013) noted individual factors such as self-control are commonly associated with resilience. Individuals exposed to an unpredictable or chaotic environment may develop higher levels of self-control as an adaptive coping mechanism as an effort to protect against being the target of future maltreatment (Cicchetti 2013). The previously cited research provides evidence that high self-control is associated with a lower risk of alcohol abuse as well as higher resilient functioning in the context of childhood maltreatment.

Self-esteem is defined as a positive evaluation of the self-including judging the self as worthy (Scheier et al., 2016). Self-esteem is positively associated with resiliency in maltreated children (Cichetti, 2013) and is also listed as a protective factor in several indices of positive childhood experiences (Hays-Grudo & Morris 2020; Narayan et al., 2018). However, research on the association between self-esteem and alcohol use is not consistent: some research has found lower self-esteem is associated with increased drinking (Bartsch et al., 2017), other research has found no association (Luhtanen & Crocker, 2005), and some has found a positive association between self-esteem and alcohol use (DeSimone et al., 1994). Multiple factors may explain these discrepant findings include the age of the sample (early adolescent vs college students) and the timing of measurement. DeSimone et al. (1994) examined the cross-sectional association of alcohol use and self-esteem, while Luhtanen and Crocker (2005) measured self-esteem at a single point to predict alcohol one year later. Alcohol use and self-esteem are both dynamic and change over the course of adolescence, which may have affected these findings.

Scheier et al. (2016) simultaneously modeled the trajectories of self-esteem and alcohol use using a latent growth curve and found that declines in self-esteem were associated with increased alcohol use which provided evidence for the protective role of self-esteem in the development of an alcohol use disorder (Scheier et al., 2016). The protective effects of self-esteem for alcohol use appear to be stronger in younger adolescents and vary across gender (Bartsch et al., 2017). Since previous research has found that higher levels of self-esteem is associated with resilient functioning in maltreated youth (Cicchetti 2013) and because self-esteem is commonly included in measures of protective factor to ACEs (Hays-Grudo & Morris 2020; Narayan et al., 2018), examining whether self-esteem is protective against the harmful effects of ACEs is warranted even though it there is inconsistent research supporting the protective role of self-esteem related to alcohol use problems.

Family Factors

Parental monitoring, a high-quality parent-child relationship, and parental involvement in the adolescent's life are three aspects of parenting that have the strongest evidence for their preventive effect on adolescent alcohol use (Jorm et al., 2010; Ryan et al., 2011; Yap et al., 2017).There is strong empirical support for the protective link between parental monitoring and alcohol use (Lac & Crano, 2009; Smetana, 2008). Parental monitoring involves a parent's knowledge of their child's activities and whereabouts (Stattin & Kerr, 2000). Parental knowledge can derive from adolescent disclosure or from a parent's active efforts to solicit information. Some evidence indicates adolescent disclosure is the primary source of parental knowledge (Kerr et al., 2010), but other researchers indicate parental solicitation can be important in riskier contexts (Laird et al., 2010), however, there is no clear consensus on whether parental knowledge primarily derives from active solicitation or adolescent disclosure (Yap et al., 2017).

Many factors influence an adolescent's choice to disclose information to their parents, such as their perception of the parent's right to know information, and belief in the legitimacy of parental authority (Rote & Smetana, 2017; Smetana & Daddis, 2002). Nonetheless, parental monitoring exists within the broader parent-child relationship and is related to family closeness and parent-child communication (Mynttinen, Pietilä, Kangasniemi, & Pietil, 2017). In riskier contexts, adolescents may perceive efforts to monitor their activities or whereabouts as an expression of care (Bendezú et al., 2018). Interviews from adolescents with high exposure to ACEs showed a similar finding: adolescents who experienced multiple ACEs reported a lack of household rules was interpreted as evidence of parental apathy or that their parents did not care (Rothman et al., 2010). Although parental monitoring is often seen as a type of behavioral control, parental can also be seen as a type of positive parental involvement.

A strong-parent child relationship characterized by clear and open communication that involves adolescents and parents spending time together has been consistently found to protect against adolescent drinking (Ryan et al., 2011; Yap et al., 2017). A warm relationship in which adolescents perceive their parents as loving, responsive to their needs, involved in their lives, and caring can facilitate parental knowledge through adolescent disclosure, and has been prospectively linked to lower levels of binge drinking (Donaldson et al., 2016). Youth who perceive their relationship with their parent is poor, and who have uninvolved parents are more likely to initiate alcohol use and binge drink (Rusby, Light, Crowley, & Westling, 2018) . Likewise, parental warmth is associated with higher levels of parental monitoring (Lowe & Dotterer, 2013), and lower discrepancies between parent and adolescent reports of monitoring (Ksinan & Vazsonyi, 2016).

Although there is robust empirical evidence and theoretical justification for including parent and family related variables as protective factors, examining these variables in the context of ACEs presents challenges. The dimensions of ACEs typically measured include exposure to household dysfunction and different types of abuse (physical, sexual, or emotional) and neglect (emotional or physical) (Felitti et al., 1998). This complicates viewing parenting or family variables as protective from ACEs, since parents are often the direct or indirect source of the ACE. For example, the most common perpetrator of maltreatment (e.g., physical or emotional abuse) is a biological parent (United States Department of Health and Human Services, 2020). For indirect exposure, categories of household dysfunction include parental substance use, or parental mental illness (e.g., depression) both of which can lead to impaired parenting (Lovejoy et al., 2000; Neger & Prinz, 2015), or another form of ACE, such as neglect. Likewise, two ACEs involve parental absence: parental incarceration and divorce.

However, there are still many instances in which a parent can be protective from exposure to ACEs. Although a biological parent is the most common perpetrator of childhood maltreatment, both biological parents (i.e. mothers and fathers) are involved in only 20% of reported cases of childhood victimization (United States Department of Health and Human Services, 2020), and dual alcohol abuse in both parents occurs rarely (Anda et al., 2002). The negative effects of parental absence (e.g., incarceration) may also be dampened by a strong parental relationship with the non-incarcerated parent. Likewise, although the prevalence of neglect (either material or supervisory) is higher in low SES families (United States Department of Health and Human Services, 2020), supportive parenting can buffer some of the adverse effects of financial insecurity (Pettit et al., 1997). Collectively, this suggests the harmful effects of exposure to an ACE when one parent is the source of the adversity could be mitigated by a strong relationship with the other parent (Wilkinson et al., 2019), if they are present.

School Factors

Multiple studies have found that higher levels of school-connection have a protective effect on alcohol use (Cleveland et al., 2012; Guo et al., 2001; Hawkins et al., 1997). According to the social development model (SDM) prosocial bonds towards institutions such as school inhibit deviant behavior such as alcohol use, as adolescents have a “higher stake in conforming” to social norms (Guo et al., 2001). Research from the monitoring-the-future (MTF) study found that adolescents who report higher levels of school bonding engage in alcohol use less frequently (Dever et al., 2012). In a nationally representative study of Australian adolescents, participants who reported high levels of school support (e.g., the presence of a caring adult), were less likely to report ever-using alcohol, drinking in the past thirty days, or binge drinking (Hodder et al. 2018). Additionally, both the PACEs (Hays-Grudo & Morris 2020) and BCES (Narayan et al., 2018) scales include items related to positive experiences with a caring teacher or higher levels of school bonding as protective factors for ACEs. Nurius et al., (2020) found school engagement was a protective factor against depression and suicidality for adolescents exposed to violent victimization.

The association between relationships with peers and adolescent alcohol use is complicated. Peer influence increases during adolescence as adolescents spend more time interacting with peers and the developing strong peer relationships becomes an important developmental task (Steinberg & Morris 2000). Although peer influence is often perceived as a risk factor for substance use, Syversten et al. (2010) argue affiliation with friends who avoid substance use may encourage pro-social behaviors including abstaining from alcohol or substance use. Maxwell (2002) found that peers can both influence initiating and abstaining from alcohol and tobacco use and argued that peers serve as a protective factor against adolescent risky behavior.

While both the PACEs (Hays-Grudo & Morris 2020) and BCEs (Narayan et al., 2018) identify having a best friend or having a good friend as protective factors, previous research on peer support and alcohol use during adolescence is more ambiguous. For example, Hodder et al. (2018) found that higher levels of supportive peer-relationships were associated with an increased risk of alcohol use, which indicates close peer relationships may not be a protective factor in the context of alcohol use. Because peers are a powerful socializing agent during adolescence, if an adolescent's peers use alcohol, they may be more likely to use alcohol as well (Steinberg & Morris 2000). In the context of alcohol use, supportive peer relationships may not be as relevant as the kinds of peers (e.g., deviant affiliating vs pro-social) that an adolescent socializes with. Hodder et al., (2018) provides evidence for this finding that relationships with peers who engage in pro-social activities was a protective factor for alcohol use.

Mentor

Research supports that an on-going relationship with a non-familial adult (i.e., a mentor) may reduce the risk of adolescent alcohol use and other high-risk behaviors such as illicit drug use. Research has examined both the role of natural mentors as well as interventions that involve providing a mentor to at-risk adolescents. Both lines of research broadly support the role that adult mentors may have in reducing alcohol use. In a high-risk sample Zimmerman et al., (2002) found that individuals with a natural mentor were less likely to consume marijuana or be involved in delinquent activities. Similarly, Beier et al. (2000) found that adolescents with a mentor were less likely to engage in several high-risk behaviors. Research on using adult mentors as an intervention have found some evidence that mentorship reduced alcohol use (Thomas et al., 2013).

ACEs Resilience and Relational Developmental Theory

Lerner (2007) argues adopting a relational developmental systems framework has implications for what research methods are used. For example, both person-centered analyses, and longitudinal analyses can better capture the complex intersection of risk and protective factors that lead to positive adaptation. Overton (2015) also notes that theory and concepts drive the kinds of research questions that are asked or are seen as useful to ask. The predominant paradigm for understanding ACEs came from epidemiological and preventative medicine. These theoretical paradigms have implications for the kinds of analyses that are typically used such as an emphasis on identifying the main effects of ACEs. Adopting a RDS approach shifts the focus from quantifying the harm associated with exposure to ACEs to examining what developmental processes ACEs disrupt, and what factors or processes may protect against the harmful effects of ACEs.

The dynamic, reciprocal, and mutually reinforcing associations among both exposure to ACEs and protective factors requires an analytic strategy that could identify multiple additive, interactive, or non-linear associations among the variables. Although the use of a cumulative protective experiences index is simple, it presumes equal weighting for each item, and ignores the possibility of either non-linear or interactive effects (Evans et al., 2013). Recent research on ACEs found these assumptions are invalid when examining the association between ACEs and later mental illnesses as there are multiple synergistic effects that occur depending on the specific pairing of ACEs (Briggs et al., 2021).

Given the many potential associations between the ten different indicators of ACEs and multiple indicators of protective experiences, as well as insufficient theoretical evidence to guide how different processes may affect exposure to ACEs or interact with one another, analytic methods that are data driven may be more appropriate. In recent years, social scientists have begun to employ data mining and machine learning techniques that can better capture the complexity of associations often found in the social sciences (Jacobucci et al., 2017).

Analytic strategies from machine learning have been synthesized with more traditional approaches used in social sciences research. As an example, decision trees have been integrated into a SEM framework called SEM trees (Brandmaier et al., 2016). SEM trees create homogenous groups of individuals who are maximally similar to one another with respect to the parameters of SEM specified. The construction of the tree is based on partitioning the data along every possible value of a set of covariates. SEM trees allow researchers to identify similar groups of individuals and explore complex nonlinear associations and interactions among the set of covariates.

Data-driven classification strategies more commonly used in the social sciences may also be appropriate. For example, a variety of mixture models can be flexibly employed to identify homogeneous groups of individuals who are similar in their association between a predictor and outcome variables (regression mixture modeling), similar in their means and variances (latent class analysis) or similar in their trajectories of change (growth mixture modeling) (Van Horn et al., 2009). Depending on the goals of the analysis and the research questions specified, either machine learning algorithms (e.g., regression trees) or mixture modeling may be appropriate analytic choices.

Future Directions for Research

To date, the majority of studies examining ACEs and resilience have either used a single protective factor (Brown & Shillington, 2017) or an index of protective factors (e.g. Narayan et al., 2018). Hierarchical regression and structural equation modeling have been used to examine resilience to ACEs (Crandall et al., 2020; Crandall et al., 2019). While these studies provide preliminary evidence for whether factors are promotive (main effect) or protective (interaction term), or can compensate for exposure to ACEs (hierarchical regression), they are not able to capture the complexity of how protective processes may affect exposure to ACEs or specifically identify groups of resilient individuals.

Although research on resilience has long employed person-centered analyses that identify groups of similar individuals (Masten, 2001) only a small number of studies have applied this analytic strategy in the context of ACEs and resilience (e.g., Lui et al., 2019) and none in the context of alcohol use specifically. Research on resilience seeks, in part, to understand the phenomenon of differential effects: why the same environmental influence (ACEs) affects people differently (Van Horn et al., 2016). Person-centered analyses are well-suited for answering this question as they can empirically identify resilient groups of individuals, and then determine which factors predict group membership (Van Horn et al., 2016). Thus, future research can move the science of resilience to ACEs forward in two ways 1) directly examining differential effects to empirically identify a resilient group of individuals, and 2) examining multiple factors simultaneously that may be associated with resilient functioning.

Current Study

This study sought to examine differential effects in the association between exposure to ACEs and alcohol use. The study examined both how the effect of exposure to ACEs varies across individuals and identified what factors explain that variation. Thus, the goal of the study was to identify a resilient group of individuals and determine what factors promote resilience in individuals exposed to ACEs. The next chapter will detail the methods used to answer this question.

CHAPTER 3: METHODS

Sample

The public use version of the National Longitudinal Study of Adolescent to Adult Health (Add Health) dataset was used to answer the research questions for this study (Harris et al., 2009). Add Health is a multidisciplinary study initiated to understand how the social contexts in which adolescents live influence their growth and development across social, behavioral, and biological domains (Resnick, 1997). The Add Health study consists of a longitudinal, nationally representative sample of adolescents who began the study when they were in grades 7-12 during the 1994-1995 academic year (Chen & Harris 2020). Eighty high schools were selected proportional to enrollment size and were stratified based on urbanization, census region, and racial composition, resulting in a total sample of over 90,000 students who completed an in-school questionnaire. Of that school-based sample, a random sample of over 15,000 adolescents were stratified by grade and gender and were selected to complete in-home interviews. The in-home interview also included an interview with a parent of one of the adolescents. Sampled adolescents have now been followed across multiple waves of data collection with the most recent data collection (wave V) completed in 2018. The Add Health study used a multi-stage sampling strategy with stratification which creates bias in both the point estimates and standard errors due to non-independence of observations. Sampling weights are used to correct this bias and ensure the sample is representative of the population (Chen & Harris 2020). The public use dataset is a random sample approximately one-third the size of the full sample.

Participants

Following the previous analyses of ACEs in the Add Health data (Easterlin et al., 2019; LeTendre & Reed, 2017), the sample for this study consists of adolescents who have both a sample weight at Wave IV, and complete data for the ACE indicators which are measured across Waves I, III and IV. This resulted in a sample of n = 2865. At Wave IV the average age was M = 28.7 (SD = 1.75) with 43.7% identifying as male and 56.3% as female. 70.85% identified as European American, and 9.2% reported Hispanic ethnicity. The average parental income, reported during Wave I was $49,840 ($SD$ = $58,190). Table 1 contains information on the demographics as well as the relevant study variables, described below.

Measures

ACE Indicators

Selection of Indicators

A total of 9 indicators were selected to construct an ACE scale. These indicators represent three categories of ACEs: exposure to neglect, violence/abuse, and household dysfunction. Although there is no consensual definition of what items should be included in an ACE scale, these three categories are consonant with McLaughlin's (2016) definition of adversity: "exposure during childhood or adolescence to environmental circumstances that are likely to require significant psychological, social, or neurobiological adaptation by an average child and that represent a deviation from the expectable environment" (p. 363). Deviations from the expectable environment include either absence of expected inputs (e.g., absence of a primary caregiver) or unexpected inputs (e.g., exposure to violence). McLaughlin (2016) clarifies and expands this definition to include two dimensions of childhood adversity: exposures to threat (e.g., abuse, or other violence) and deprivation (e.g., neglect or parental absence).

In this study, the ACE indictors were: neglect (supervisory or not meeting material needs), physical abuse, emotional abuse, sexual abuse, parental incarceration, parental alcohol misuse, parental separation, witnessing violence, and being a victim of violence. Each of these indicators represents one of the dimensions of adversity (deprivation or threat) and can be considered a deviation from the expectable environment that may require significant adaptation on the part of a typically developing child (i.e., likely to have lasting impact on important developmental processes). For example, parental incarceration may result the absence of an attachment figure in a child's life, or a disruption in their attachment or relationship to their parent or caregiver. Witnessing or experiencing violence, physical abuse, emotional abuse, or sexual abuse are examples of exposure to threat.

Inclusion of parental alcohol misuse is commonly included as an ACE but may or may not meet the definition of an ACE provided by McLaughlin (2016). Severe alcohol use from a parent or caregiver may impair their ability to parent effectively, can hamper the development of a secure attachment and may increase the risk of exposure to other ACEs (Dube et al., 2001). Without further information about how alcohol use impaired parenting or increased exposure of other ACEs, it is not certain if alcohol misuse is an ACE itself (McLaughlin 2016). Similarly, parental separation or divorce can affect a child's attachment with the non-residential parent and represents a disruption from their environment. Experiencing divorce can also affect a parent's ability to engage in sensitive and responsive parenting. More specific information on how alcohol use or divorce affected the parent's ability to engage in sensitive and responsive parenting, or increased risk for other ACEs would more strongly support including these items as ACEs. Despite limited knowledge on the specific effects of divorce or alcohol use on a particular individual, including these items as ACEs increases consistency and comparability in the results to previous studies that use the Add health data.

Construction of the ACE scale

Each indicator was recoded into a dichotomous variable to represent either no exposure (*0 = no exposure*) or exposure to the potentially traumatic experience (*1 = indication of exposure*). Response options varied across the different items. For items measuring abuse or neglect, response options ranged from *0 = this did not occur to me* to *5 = occurred 10 times or more*. Researchers using the Add health dataset differ on their selection of where to dichotomize the indicators chosen. The choice of where to dichotomize an item affects the prevalence estimate of that item. Although a choice of where to dichotomize the items is not always given, the choice of where to dichotomize these items for this study was based on previous research using the Add health data and to ensure levels of exposure to ACEs in this sample are similar to national estimates of abuse and neglect (Brumlee et al., 2019). Table 2 contains information on the items used to measure ACEs and the frequency of ACEs in this sample.

Neglect was measured using endorsement of either of the two following items "*How often had your parents or other adult-caregivers left you alone when an adult should have been with you?" (0 = never happened 1 = 10 times or more)* or *"How often had your parents or other adult-caregivers not taken care of your basic needs, such as keeping you clean or providing food or clothing?" (0 = never happened 1 = 2 times or more).* Physical Abuse was measured with one item *"How often had your parents or other adult caregivers hit you with a fist, kicked you, or thrown you down on the floor, into a wall, or down the stairs?" (0 = never happened 1 = three times or more).* Emotional abuse was measured with the following item "*How often did a parent or other adult caregiver say things that really hurt your feelings or made you feel like you were not wanted or loved?" (0 = never happened 1 = 10 times or more).* Parental incarceration was measured with endorsement of any of the following four items *"Has/did your biological mother*

(mother figure) or father (father figure) ever spent time in jail or prison?" (0 = none 1 = at least one). Parental alcohol misuse was measured by parent self-report with the following item *"How often in the last month have you had five or more drinks on one occasion?" (0 = 1 time or less, 1 = 2 times or more)*. Parental separation/divorce was measured with parental self-report of marital status *(0 = married 1 = any other option).* Witnessing extreme violence was measured with the following item *"You saw someone shoot or stab another person*" *(0 = never 1 = 1 time or more)*. Being a victim of violence was measured with three items *"During the past 12 months how often did the following happen: a)someone pulled a knife or gun on you; b)someone cut or stabbed you; c)someone shot or stabbed you" (0 = none 1 = yes to any*).

The list of ACEs were closely similar to the ACE items used in Quinn et al., (2017, 2019) with the following two exceptions: The measure of violent victimization combined items measuring threat of violence (someone pulling a knife or gun on the youth) and being a victim of violence (someone cut or stabbed you/shot or stabbed you) which is consistent with how other researchers have measured exposure to violent victimization (e.g. Lee et al., 2020). Both of these items represent an exposure to threat of violence, which is a single type of ACE, which justifies combining them as a single item. This list also included an item measuring parental separation which is commonly measured in other studies on ACEs, but was omitted from the Quinn et al. (2017).

The items were summed together to create an ACE index, which is a measure of cumulative exposure to different childhood adversities. Because ACEs tend to co-occur and there is a lack of evidence for differential effects for individual ACEs (Green et al., 2010), it is common practice to add the number of ACEs together to form an index representing how many different types of ACEs an individual reported experiencing. Although using an ACE index has been criticized, there is no consensus on whether alternative approaches yield superior results (Bethell et al., 2017).

Although every measurement strategy has limitations, there are several advantages to using an ACE score. An ACE score is simple, and easy to interpret. For example, it is relatively easy to interpret that for every exposure to a different type of adversity, there is a 34% increased risk of alcohol use disorder (LeTendre & Reed 2017). It is also noteworthy that the association between the number of ACEs and numerous health and mental health outcomes is replicated across a diverse number of studies, samples, and operational definitions (Hughes et al., 2017). This indicates the effect of ACEs are robust and consistent, despite many definitional differences.

Protective Factors

Parental Bond

Five items from wave I were used to measure parental warmth: "*How close do you feel to your mother/father?" "How much do you think she/he cares about you?" "Most of the time, your mother (father) is warm and loving toward you," "you are satisfied with the way you and your mother/father communicate"* and *"overall you are satisfied with your relationship with your mother/father."* The items were measured on a 5-point Likert-type scale and were coded such that higher scores indicate higher levels of parental warmth. These items have been previously used in research (Wilkinson et al., 2019) and when summed into a scale have an acceptable level of internal consistency. Cronbach's alpha was acceptable for these items with $\alpha = .85$ for mothers and $\alpha = .88$ for fathers.

Parental Monitoring

Seven items from wave I were used to measure parental monitoring. These items have been used in previous Add Health studies to measure several related constructs: parental control (Harris-McKoy, 2016), parental autonomy-granting (Deutsch et al., 2017), and parental monitoring (Donaldson et al., 2016; Roche et al., 2008). These items ask whether the adolescent's parents allow them to make decisions about various domains in their life. Example items include "*Do your parents let you make decisions about the time you must be home on weekend nights*?" and "*Do your parents let you make decisions about the people you hang around with?"* Response options are dichotomous *(0 = no 1 = yes).* Cronbach's alpha for this scale is .62, which is considered low (Nunally 1978). However, results from a confirmatory factor analysis (CFA) indicate that a unidimensional factor structure fits the data well, with a χ^2= 154.91 (14) RMSEA = .96 and a CFI = .96 and all standardized factor loadings are large (>.4) and significant.

School Bonding

Three items asked during wave I were used to measure school bonding. Items were recoded to a *1 = strongly disagree to 5 = strongly agree* scale with higher values indicating higher levels of school bonding. The items included "*You felt close to people at your school," "You feel like you are a part of your school," "You are happy to be at your school."* School bonding had an acceptable alpha with α= .78. These items have been used in previous research to measure levels of school connection or school attachment (Olufowote et al., 2020).

Low friend involvement in drugs/alcohol

Three items were used to measure the number of friends who drink alcohol or use drugs in wave I. Items were coded such that higher scores indicated having more friends who smoke cigarettes, drink alcohol, or use marijuana. Scores ranged *from 0 =no friends to 9 = having three best friends who smoke cigarettes daily, drink alcohol and smoke marijuana*. This variable is used in previous studies to measure peer involvement in drug or alcohol use (Watts & Iratzoqui 2019). Alpha was acceptable for this scale with α= .75.

Mentor

Having a mentor was measured with one item during wave III which asked, *"Other than your parents or step-parents, has an adult made an important positive difference in your life at any time since you were 14 years old?"* This item has been used previously in Add Health studies to measure natural mentoring relationships (Whitney, Hendricker, & Offutt 2011).

Self-Esteem

Four items from wave I were used to measure self-esteem. Example items included *"How often have you thought you had many good qualities?"* and *"How often have you felt like you liked yourself?"* Response options ranged from 1=strongly agree to 5 = strongly disagree. These items have previously been used to measure self-esteem in the Add Health data (e.g., Whitney, Hendricker & Offutt 2011). Cronbach's alpha was computed with an acceptable score of α= .79.

Low Self-Control

There is no consensus on the best way to measure self-regulation in the Add Health dataset (Bunch, Iratzoqui & Watts 2018) and multiple items and scales have been proposed and used (Wolfe & Hoffman 2016). Researchers have commonly summed approximately 23 items from wave I that measure multiple dimensions of self-control such as impulsivity and difficulty with problem-solving (Beaver 2020). However, Wolfe and Hoffman (2016) conducted confirmatory factor analyses and found these items do not represent a simple unidimensional construct, but instead represent multiple independent factors. Two factors in their study, a measure of difficulties with attention and focus and problem-solving were selected to be included in this study. These two factors were selected because they tap into both top-down (reflective problem solving) and bottom-up (difficulty concentrating or maintaining focus) processes associated with impairment in self-control that are related to the development of alcohol use problems (Chassin et al., 2013).

Inattention. For this study, 5 items from wave I were selected to measure low attention difficulties. Items included questions that asked how frequently the adolescent reported difficulty getting along well with teachers, difficulty paying attention in school, difficulty completing homework, difficulty focusing, and trouble getting along with friends. Items were measured on a zero to four Likert scale with response options ranging from *0 = never to 4 = every day.* These items were selected to measure bottom-up processes associated with impairment in self-control. In the previously described study (Wolfe & Hoffman 2016), these five items all loaded highly on one factor. Additionally, these items have subsequently been used in research on low self-regulation and deviance (Boccio, Schwartz, & Beaver 2020). A confirmatory factor analysis of these items found the items fit the data relatively well with $\chi^2 = 123.73$ (5), RMSEA = .08, CFI = .97. Additionally, all standardized factor loadings were significant and were large (>.4). Cronbach's alpha was acceptable with α=.70.

Problem-Solving. To measure top-down processes associated with self-control, four items from wave I were selected. These items have been used to measure problem-solving (Boccio et al., 2020), and all load onto the same factor (Wolfe & Hoffman 2016). Example items include, "When attempting to find a solution to a program, you usually try to think of as many different ways to approach the problem as possible" and "After carrying out a solution to a problem, you usually try to analyze what went right and what went wrong." Response options were coded so that higher scores represent higher problem-solving abilities. Response options ranged from *1 = strongly disagree to 5 = strongly agree*. A confirmatory factor analysis of these items fit the data relatively well with $\chi^2 = 52.22$ (2), RMSEA = .08, CFI = .99. Additionally, all factor loadings were significant and large (>.5). Cronbach's alpha was acceptable with α=.75

Alcohol Use

Two items measured during wave IV were used to measure alcohol use. One item measured the typical number of drinks consumed when one drank in the past 12 months. Response options ranged from one to 18 drinks. This item has been used previously in research using the Add Health data to capture frequency of drinking (e.g., Goings et al., 2020; Green et al., 2014). The second item measured how frequently drinking occurred: "During the past 12 months, on how many days did you drink alcohol?" response options included*: 0 = none 1 = 1 or 2 days in the past 12 months; 2 = once a month or less (3 to 12 days in the past 12 months); 3 = 2 or 3 days a month; 4 = 1 or 2 days a week; 5 = 3 to 5 days a week; 6 = every day or almost every day.* This item has also been used to assess drinking behaviors (Alexopoulos & Cho, 2019).

Covariates

Demographic variables included as covariates in this study were: age, biological sex, race, ethnicity, and parental income. Age was calculated at wave IV using variables for the participants date of birth and the date of survey administration to create a variable measuring their age in years. Biological sex was coded as a dichotomous variable (0 = male and 1 = female). Race was dummy coded as (0 = White/Non-Hispanic and 1 = All others), and ethnicity was coded as (0 = Non-Hispanic and 1 = Hispanic). Annual household income was measured during wave I by parent-report and was coded so that 0 = no income to 999 = $999,000 or more.

Analysis Plan

All substantive analyses were conducted using Mplus version 8.4 (Muthen & Muthen 1998-2019) and R Studio version 4.1 (R studio team 2020). Missing data were handled using full information maximum likelihood estimation with robust standard errors (MLR) for the structural equation model trees as it can handle missing data, nonindependence, and sampling weights (Yuan & Bentler, 2000). Additionally, Multiple Imputation was used for the regression mixture model to prevent case wise deletion which occurs when employing the automatic three-step approach in Mplus to measure predictors of class membership. Multiple imputation was executed in Mplus using 10 imputed datasets.

Analytic Strategy

To understand how the association between ACEs and alcohol use may vary across individuals, and what factors predict that variability, two complementary analytic strategies were used: regression mixture modeling (RMM) and structural equation model trees (SEM trees). These two strategies are both suitable for identifying heterogeneity in the association between exposure to ACEs and alcohol use. Because both strategies are forms of exploratory data analysis, comparing the results from the strategies can be a useful way of determining the robustness of the results (Jacobucci et al., 2017).

Regression Mixture Model Building Strategy

A RMM is a finite-mixture model similar to latent class analysis (LCA) or growth mixture modeling (GMM). Mixture models are used to examine heterogeneity by empirically identifying homogeneous, normally distributed latent subgroups (classes). In a mixture model, the dependent variable in this analysis is modeled as a mixture (weighted sum) of a finite number of normally distributed groups (Van Horn et al., 2009).

RMM differs from other forms of mixture modeling such as latent class analysis (LCA) or growth mixture modeling (GMM). LCA and GMM identify latent classes who differ in their means and variances (LCA) or the means and variances of the intercept and growth factors (GMM) (Van Horn et al., 2015). This does not test for individual differences in the strength of association between a predictor and outcome variable. In contrast, RMM can be conceptualized as a moderator analysis (see figure 1 for a conceptual diagram). In RMM, classes also differ on the parameters of a regression model (e.g., intercepts and slope coefficients). RMM models the joint distribution of an outcome variable conditioned on a predictor (Y on X). This allows the different classes to differ in the regression weights, or the strength of the association between a predictor variable and outcome variable. Class membership can then be predicted based on a set of covariates. The set of covariates can predict class membership using multinomial logistic regression (Van Horn et al., 2015).

For this study, the regression model consisted of simultaneously estimating the effect of exposure to ACEs on two related measures of alcohol use: the number of days alcohol was consumed, and the typical number of drinks consumed. Because the number of drinks consumed is a count variable, it was modeled using a negative binomial distribution. Negative binomial is appropriate for count data and can handle data with a large number of zero scores (Lanza et al., 2014). A negative binomial distribution relaxes the equidispersion assumption (equality of mean and variance) in a Poisson regression by including a dispersion parameter which measures the variability in the number of drinks consumed (Atkins & Gallop 2007). Negative binomial regression has successfully been used in RMM to measure adolescent delinquency (Lanza et al., 2014). Relevant demographic covariates (gender, race, ethnicity, parental income during adolescence, and age at the time of study) were also included as well as the sampling weight to correct for sampling design (Chen & Harris 2020).

The first step in RMM is to determine the number of latent classes that best characterize the data. Following previous studies and simulations on class enumeration in regression mixture modeling, I used the Bayesian Information Criteria (BIC) and the penalized (adjusted) Bayesian Information Criteria (ABIC) to determine model fit, with lower values representing better model fit. In addition to model fit, interpretability and substantive justification guided model selection (Ram & Grimm, 2009).

Entropy, a measure of the degree of separation in model fit, was recorded but was not used to determine class sizes. Although Regression mixtures tend to have low entropy, this may not be a sign of poor fit and entropy is not recommended or commonly used to determine class enumeration (Van Horn et al., 2009). Similarly, although it is commonly used in other mixture models, the bootstrapped likelihood ratio test, performs poorly in regression mixtures and is not recommended for class enumeration (Jaki et al., 2017).

I followed the model-building strategy of Kim et al., (2016) for selecting the number of classes as well as adding in demographic covariates and predictors of class membership. Class enumeration was determined by estimating a series of unconditional models (i.e., no covariates or predictors of class membership) and sequentially increasing the number of classes from one class to five classes. After selecting the number of classes to retain, covariates and predictors of class membership were added into the model. Following both previous research (Van Horn 2009), and recommendations from simulation studies (Lamont, Vermunt, & Van Horn, 2016), the inclusion of the covariates (i.e., race, ethnicity, gender, age, and parental income during adolescence) in the regression mixture were held constant across different classes. This is because the effects of the covariates are used to adjust for differences in alcohol use related to these variables.

The predictors of class-membership (i.e., the hypothesized protective factors) were estimated using the three-step approach described by Asparouhov and Muthén (2014). In this approach the number of classes is first determined (step one) and then individuals are assigned to the most likely class based on their posterior probabilities while considering the possibility of misclassification (step two). Lastly, multinomial logistic regression is used to determine predictors of class membership (step three). For the BCH approach, the possibility of misclassification is considered using a weighted multiple group model with the most likely class membership treated as a known group, with weights that reflect measurement error in classifying class membership. Various protective factors across ecological levels (e.g., parental monitoring or self-control) were then used to predict class membership.

After identifying the optimal number of classes and appropriately including covariates in the analysis, I examined what protective factors predict class membership using the automatic three-step procedure in Mplus (Asparouhov & Muthen 2014). Whether to include auxiliary variables (i.e., predictors of class membership) during class enumeration is debated on both theoretical and methodological grounds (Asparouhov & Muthen 2014). Including the auxiliary variables while determining class membership may lead to substantial shifts in the number of classes which may render the results meaningless (Asparouhov & Muthén, 2014).

Structural Equation Model Tree

The second analysis used a structural equation model tree (SEM tree) to identify heterogeneity in the association between exposure to ACEs and alcohol use (Brandmaier et al., 2016). Structural equation model trees combine structural equation modeling with decision trees.

Decision trees are a non-parametric regression that use recursive partitioning to create groups of individuals who are similar on an investigated outcome (Strobl et al., 2009). SEM trees are a form of exploratory multiple group SEM, where group membership is empirically determined based on a set of covariates. In SEM trees, a SEM and set of covariates are specified. The data is repeatedly split on all possible values of all covariates. A SEM is fit for each possible split, with the split that results in the greatest improvement in model fit retained, creating a new "node." This process is repeated along each node until a stopping criteria, such as non-significant improvement in model fit, is reached. This creates a tree-like structure with well-defined groups whose parameters in the terminal nodes can be compared. Following the path (i.e., decision points) to the terminal nodes can be used to examine which set of factors determine belonging to that group.

For this study the SEM was identical to the regression used in the RMM. Two regressions were estimated simultaneously, one for the number of days someone drank in the past year, and the typical number of drinks consumed. Each outcome was predicted by the number of ACEs and the same set of demographic covariates (i.e., biological sex, racial group, ethnicity, parental income during adolescence, and age). The typical number of drinks consumed was also specified using a negative binomial regression. Additionally, the sampling weight was included to allow the results to be nationally representative. The groups were divided based upon the values of the same list of protective factors used as predictors of class membership for the RMM. In the SEM tree literature, any variable used to partition the data is called a "covariate;" the overlap in the terminology between a demographic covariate and a covariate in SEM trees used to partition data is confusing. To reduce this confusion, I have used demographic covariates to refer to covariates used to adjust the association between a predictor variable and an outcome variable in a regression analysis, and refer to the “covariates” used to partitioning the data in SEM trees as simply protective factors.

Because SEM trees are an exploratory data-driven analysis, Serang et al. (2020) recommend explicitly describing the strategy used to construct the SEM tree. SEM trees use recursive partitioning to repeatedly split the data into two groups based on all possible values of every covariate. Whether a candidate split is retained, is based on comparing the deviance (-2logliklihood) of the two models. If a candidate split improves, model fit it is retained creating a node, and the data are then divided on all possible values until a stopping-criteria is reached.

I used the R package Mplus Trees to fit the SEM trees (Serang et al. 2020). Mplus-Trees (Serang et al. 2020) uses several parameters to control whether a split is retained, and when the algorithm stops. The complexity parameter, cp, determines the relative (proportional) improvement in model fit needed to retain a node. Additionally, a second criteria used is the minimal number of observations needed for a terminal node. Following the recommendations of Serang et al (2020) I varied the complexity parameter (cp) using values of .001 and .01, as well as the minimum sample size for retaining a group. I varied the minimum sample size requirement using two values: 200 (approximately 5% of the sample) and 400 (10% of the sample).

CHAPTER 4: RESULTS

Regression Mixture Model

Identification of Latent Classes

To determine the number of classes that best fit the data, I fit models by sequentially increasing the number of latent classes from one to five. Table 3 provides information on fit indices for each model estimated. As can be seen in Table 3, the BIC and ABIC value continued to decrease up through five classes. However, the largest drop in BIC occurred from class one to two with the next largest drop from class two to three. The two-class model was chosen because the three-class and subsequent models did not converge to an interpretable solution, which is an indicator of estimation difficulties and poor model fit (Ram & Grimm 2009).

After selecting the two-class solution, I then added covariates into the model. Following both previous research (Van Horn 2009) and recommendations from simulation studies (Lamont, Vurmont & Van Horn & 2016), the inclusion of the covariates (i.e., race, ethnicity, gender, age, and parental income during adolescence) in the regression mixture were held constant across different classes.

Interpretation of Class Results

The parameter estimates for the final model is presented in Table 6. The first class, termed the harmful effects class, consists of 72.6% of the sample. After controlling for biological sex, racial group, ethnicity, parental income and age, there is a non-significant association between ACEs and the number of days alcohol was consumed (B = .01 SE = .03 p = .83) and a positive significant association between ACEs and the number of drinks consumed (B = .05 SE =.02 p =.001). The second class, the resilient group, consists of approximately 26.2% of the sample and is characterized by a non-significant association between exposure to ACEs and both the number of days alcohol is consumed (B=-.04 SE =.02 p=.07) and number of drinks (B=-.33 SE =.20 p=.09).

Predictors of Class Membership

To determine which factors predict class membership, I implemented a three-step approach that regressed the theoretically determined resilient factors (non-parental adult mentor, having few friends who drink alcohol or use drugs, school bonding, maternal and paternal bonding, parental monitoring, self-esteem self-regulation, and problem solving) onto class membership. Three of the protective factors were significantly associated with class membership. Having a mentor during adolescence was negatively associated with belonging to the resilient class (B= -.35 se = .12 p=.004) while school bonding (B= .05 se = .02 p=.04) and problem solving (B= .06 se = .02 p=.01) were positively associated with belonging to the resilient class. None of the other theoretically determined predictor variables were significantly associated with class membership.

Structural Equation Model Tree

Construction of the Tree

Using a cp value of .01 and the default setting for the minimum sample size for group membership (100 individuals) resulted in a model with no splits in the data (i.e., only one group). Conversely, using a cp value of .001 and the default sample size setting resulted in approximately thirty groups. This large number of groups is difficult to interpret and may be a sign of overfitting. I then re-ran the analyses using a cp value of .001 but varied the minimal sample size requirements using values of 200 (5%) and 400 (10%) individuals. These values were chosen to ensure the sample size in the terminal nodes is large enough to accurately estimate the SEM.

Using a sample size of 200 individuals resulted in 9 terminal nodes, with samples ranging from 248 individuals (6%) to 1053 (25%) of the sample. The first split was based on having a mentor during adolescence. Five of the seven splits related to the self-esteem variable with splits based on a difference of one point. The remaining splits were based on the number of friends who consume alcohol or drugs. Using a minimum sample size of 400 (10%) resulted in three groups split by two variables, *having a mentor* and *self-esteem*. The sample sizes ranged from 934 (22%) to 2221 (53% of the sample). The first split was based on the presence of a mentor, and the next split was based on the level of self-esteem.

The final model selected was chosen based on model parsimony and the interpretability of the results. Using a minimum sample size of 200 per group resulted in creating multiple groups based off the same variable (self-esteem). The self-esteem variable has one of the largest range of values (16) in the set of splitting variables. Because recursive partitioning is more likely to select a variable with many values, it is likely that the multiple splits based off of this variable are due to chance, and result in overfitting (Serang 2021). To reduce the chance of overfitting, I retained the tree based on a cp value of .001 with a minimal sample size of 400 individuals to interpret for analysis.

Description of the Model

A plot of the tree is given in figure 2, and Table 5 contains the parameter estimates for the terminal nodes. Although significance tests are presented, they should be interpreted cautiously given the exploratory nature of the analysis (Serang et al. 2020). There are two splits, with three terminal nodes. The first split is based on whether the participant reported having a mentor during adolescence. The second split was based on the whether the adolescent had self-esteem above 16 (the median).

The first group which consisted of 22% of the sample reported not having a mentor during adolescence. As noted in Table 5, in this group, there was not a significant association between exposure to ACEs and either number of days alcohol was consumed ($B = -.02$ $SE= .06$ $p =.75$) or the typical number of drinks consumed ($B = .01$ $SE = .04$ $p = .61$). Sex, age, and income were all significantly associated with the number of days alcohol was consumed, and sex and age were significantly associated with the number of drinks consumed. The intercept, which is the predicted value for the outcome variable when all predictors are zero, was 7.18 for the number of days drank and 5.3 for the number of drinks consumed.

The second group, which consisted of 25% of the sample, was characterized as having a mentor and below average self-esteem. In this group there was not a significant association between exposure to ACEs and either the number of days alcohol was consumed ($B=0.03$ $SE= 0.06$ $p = 0.63$) or the typical number of drinks consumed ($B = 003$ $SE = .03$ $p =.92$). Sex and race were associated with the number of days alcohol was consumed; and sex, race, and ethnicity were associated with the number of drinks consumed as can be seen in Table 5 The intercept for number of days alcohol was consumed was 2.86, and for number of drinks consumed was 2.49.

The last group, which consists of 55% of the population reported having a mentor during adolescence and above average self-esteem. In this group there was not a significant association between ACEs and the number of days someone drank ($B =-.01$ $SE = .05$ $p =.75$) but there was a significant association between ACEs and the typical number of drinks consumed ($B= .06$ $SE = .03$ $p =.04$). As seen in Table 5, sex, race, age, and income were all significantly associated with the number of days alcohol was consumed; and sex, race, and age were associated with the number of drinks. The intercept for number of days alcohol was consumed was 5.7, and for the typical number of drinks was 3.1.

CHAPTER 5: DISCUSSION

Individuals who are exposed to multiple ACEs are at an increased risk of problematic drinking (Hughes et al. 2017). However, not all individuals who are exposed to ACEs develop alcohol use problems. There is an increasing call for research to examine both ACEs and protective factors to better understand why some individuals exposed to ACEs drink problematically while others do not (McLaughlin, 2016). The difference in the effect of exposure to ACEs on alcohol use is an example of a differential effect (Van Horn et al. 2009). Little empirical research has examined resilience to ACEs, and even fewer have specifically examined alcohol use (Brown & Shillington, 2017). No study has specifically examined differential effects in the association between ACEs and alcohol use.

The aim of this study was to examine differential effects in exposure to ACEs and alcohol use to empirically identify a resilient group of individuals. The study used novel analytic tools to achieve these aims: Regression Mixture Modeling (RMM) and Structural Equation Model Trees (SEM trees). Both analyses identify groups of individuals who are similar to one another on parameters of interest (e.g., the association between ACEs and alcohol use) and are capable of identifying what factors predict belonging to a particular group (Jacobucci et al., 2017). This study was driven by two research questions 1) How can heterogeneity in the association between ACEs and alcohol use best be characterized? 2) What factors predict group membership?

Summary of Results

Heterogeneity in the Association of ACEs and Alcohol Use

The regression mixture model identified two groups, a harmful effects group and a resilient group. The majority of the sample (72.6%) were classified into the harmful effects group. In the harmful effects group, there was a significant association between exposure to

ACEs and the number of drinks typically consumed when drinking. In the second group, the resilient group (26.2%), there was no significant association between exposure to ACEs and either the number of days alcohol was consumed, or the number of drinks consumed.

The results of the SEM tree were somewhat similar to the results of the RMM. Instead of two groups, the SEM tree divided the data into three groups based on two variables – an adult mentor and the level of self-esteem. Although significance tests should be interpreted with caution, in two of the groups there was no significant association between exposure to ACEs and alcohol use. Taken at face-value, this would indicate these two groups are resilient to the harmful effects of ACEs. The third and largest group was characterized by adolescents who reported having a mentor and above average self-esteem. In this group there was a significant association between exposure to ACEs and the number of drinks consumed. This would suggest that having a mentor during adolescence and higher self-esteem may be risk factors for consuming larger quantities of alcohol during adulthood.

Comparison of Methods

Although both analyses can be used to identify heterogeneity, they differ in how groups are formed. The RMM identifies latent groups of individuals who are most like one another on the parameters of interest (e.g., intercept and slope coefficients), while the SEM tree creates groups based on the values of observed covariates (Jacobucci et al., 2017; Van Horn et al., 2009). In RMM the groups are latent, and then theoretically identified protective factors can be tested to determine if there is a significant association with group membership. In contrast, the splits in RMM are based solely on the values of the researcher determined covariates (Serang et al., 2020).

This difference in how groups are formed may account for the difference in findings between the two models. Results from the RMM indicate most of the protective factors were not significantly associated with group membership. This suggests these protective factors may not be well-suited for examining resilience to ACEs. Because the SEM tree partitions the data into groups only based on the values of the chosen covariates, it is limited to the quality of covariates chosen. The RMM suggests these covariates may not be optimal for creating groups, which would limit the quality of the results of the SEM tree.

Both strategies found that individuals who reported having a mentor during adolescence were at an increased risk for alcohol related outcomes associated with exposure to ACEs. However, the SEM tree did not replicate the findings that higher levels of school bond or self-control were associated with resilience. In contrast, adolescents who reported both having higher self-esteem and a mentor were more likely to have alcohol related problems. This finding is contrary to what was expected as low self-esteem has previously been associated with increased alcohol use (Scheier et al., 2000) and high self-esteem is associated with resilience in maltreated children (Cicchetti et al., 1993). However, the association between self-esteem and alcohol use is stronger among younger adolescents, as well as among females (Bartsch et al., 2017). Research has also found that higher self-esteem in men is associated with increased frequency of drinking (Blank et a., 2015). Lastly, in this study, self-esteem was measured during adolescence, while the frequency and amount of drinking was measured during early adulthood which may also have affected the results. Self-esteem does change during adolescence, and self-esteem during adolescence may not be associated with alcohol use during young adulthood due to these changes (Scheier et al., 2000).

Predictors of Resilience in RMM

Mentorship

One consistent finding between both analyses was the negative association between reports of having a mentor and the number of typical drinks. This finding is somewhat surprising given that some previous research has found that having a mentor during adolescence can have positive protective effects (Whitney et al., 2011). However, Whitney et al. (2011) found the quality of mentorship influenced whether mentoring was associated with alcohol use during early adulthood. Youths with a low-quality mentor were more likely to have alcohol use problems, but there was no difference in alcohol problems comparing high-quality mentoring vs no mentor. Because the quality and type of mentoring was not examined in this analysis, it is difficult to determine if the risk of mentoring is due to low quality mentoring. Adolescents who have been exposed to ACEs and have a low-quality mentor may have been more likely to drink compared to adolescents with no mentor.

Another possible explanation is a selection effect and that individuals who were at a greater risk for experiencing alcohol use problems were also more likely to have a mentor during adolescence. Important adults in the adolescent's life may have taken a stronger interest in the adolescent because of their greater risk. Depending on the mentor's own alcohol use, it is possible that the mentor may have normalized drinking. Lastly, it is also possible the mentorship exhibited positive effects in other domains (e.g., academic functioning) but not for alcohol use.

School Bonding

School bonding was associated with an increased likelihood of being in the resilient group. This finding is consistent with previous research on protective factors for alcohol use

(Chassin et al., 2013). Adolescents who report higher levels of belonging to their schools are less likely to engage in risky alcohol use during adolescence (Guo et al., 2001).

There are several reasons why school bonding may be associated with lower alcohol use. Adolescents who have a connection to their school may associate with fewer deviant or alcohol using peers or may be engaged in a greater number of extra-curricular activities which may limit their amount of unsupervised time, which is a risk factor for alcohol use (Hodder et al., 2018; Hoffman 2006). Similarly, adolescents who report high levels of school bonding may been able to develop supportive relationships with important non parental adults such as teachers or coaches.

Problem Solving

Previous research also indicates individuals who have higher levels of self-regulation are at a lower risk for problematic drinking (Patock-Peckahm et al., 2001). This demonstrates the robustness of school bonding and self-control for preventing alcohol use, even in the context of exposure to ACEs. Research on resilience in maltreated children found the related construct of ego overcontrol to be associated with resilient functioning (Cicchetti 2013). Individuals who are able to develop a controlled and rational way of interacting with others may be better able to adapt to an adverse home environment by being better attuned to their surroundings (Cicchetti 2013). Likewise, adolescents who have higher self-control may be less prone to engaging in risky behaviors in general and may be less susceptible to peer influence on drinking alcohol.

Lack of Significance in Other Protective Factors

None of the other protective factors were significantly associated with class membership. This is surprising given the protective factors were identified based on a review of relevant protective factors across ecological predictors (Chassin et al., 2013; Cleveland & Feinberg 2012;

Jorm et al., 2010). However, it appears these factors did not seem to exert a protective influence in the context of ACEs. As there are multiple pathways to alcohol abuse (Chassin et al. 2013), factors that reduce the risk for drinking in other contexts (e.g., peer use) may not be applicable in the context of ACEs.

Of the three significant effects, two were relatively small effects and one (having a mentor) was a risk factor for alcohol use. Although there is a wealth of research attesting to the effects of the identified protective factors, this study suggests these factors may not be applicable in the context of ACEs. Existing research on ACEs and resilience has derived the list of protective factors from previous research on resilience in other contexts (Bethell et al., 2019; Narayan et al., 2018). Although this is a logical starting point, the unique effect of exposure to ACEs may necessitate broadening the list of what items are included in protective factors. In a review of research on resilience in maltreated children, Cicchetti (2013) noted that while relational factors (e.g., parent-child relationship) are often associated with resilient functioning in non-maltreated children, personality and other individual characteristics may be more important in maltreated children.

Exposure to ACEs may also adversely affect many of the identified protective factors (Hays-Grudo et al., 2021). For example, several of the ACEs consist of experiences of parental abuse or neglect, which would adversely affect the parent-child relationship. Likewise, both self-esteem and self-control may also be adversely influenced by exposure to ACEs (Hays-Grudo & Morris, 2020). However, research on resilience to childhood maltreatment found that self-esteem was related to resilient functioning (Cicchetti 2013), indicating some individuals are able to develop healthy self-esteem despite exposure to maltreatment. Nonetheless, it is possible many of the identified protective factors may be better understood as mediators, rather than moderators of the association between exposure to ACEs and alcohol use. For example, it may be that the association between ACEs and alcohol use occurs through impaired development of self-esteem, or that ACEs damages the parent-child relationship, leading to affiliation with substance using peers which increases the risk for drinking during adolescence (Cicchetti & Masten 2010).

Intersection of Protective Factors and Sociodemographic Variables

Although school bonding was associated with belonging to the resilient class in this study, it is worth noting this association may vary across demographic variables. Levels of school bonding may vary across different ethno-racial groups. Although school bonding was associated with belonging to the resilient class in the entire sample, it is possible that this affect may be less strong in some groups. African American adolescents experience higher rates of school expulsion and disciplinary actions when compared to other racial or ethnic groups. African American adolescents may also be exposed to racial hostility from peers, teachers, or other school officials, which may reduce their experience of school bonding (Okonofua, Walton & Eberhardt 2016). Likewise, due to structural factors, such as funding for public schools, access to high quality schools may vary across racial-ethnic groups. It could be that the effects of school bonding could vary across economic levels or gender.

Although covariates were included in both sets of analyses, the actual relationships between the predictor variables and these important contextual factors may not have been captured in these analyses. Because of the potential differences in the effect of school bonding on race, gender and economic class, future research may consider examining if the protective factors vary across different groups. It may be that other protective factors are more salient in certain cultural contexts, or that some of the identified protective factors are not associated with resilient functioning which may not have been captured in this study.

Overlap and Differences Between the Research Methods and Questions

The first two analyses both examine heterogeneity in the effect of ACEs on alcohol use problems. Regression mixture modeling and SEM trees are complementary methods for uncovering heterogeneity in data (Jacobucci et al., 2017; Strobl et al., 2009). The first analysis uses mixture modeling to derive latent classes that differ in the effects of ACEs on alcohol use, with protective factors used to predict class membership. SEM trees use PACEs as predictors of differences in the model parameters (e.g., the β coefficient between ACEs and PACEs). The analyses start at opposite ends: RMM starts by examining heterogeneity in the direct effect, and then PACEs are used to predict class membership; SEM trees start with using PACEs to partition the data into different groups of individuals who are most similar in the parameters of the model, but different from the other groups.

In instances where there is little theoretical reasoning and few previous studies to guide group selection, Jacobucci et al. (2017) recommend using both methods concurrently and comparing their results for interpretability and statistical plausibility. Both approaches have advantages and disadvantages. RMM identifies heterogeneity that can be either observed or unobserved which creates greater flexibility in identifying potential groups. However, RMM is limited because it assumes a linear relationship between the predictor variables and class membership and interactions between variables must examined manually. Conversely, SEM trees automatically examine all possible interactions when partitioning the data. In SEM trees the data is partitioned using covariates by determining which split results in the greatest improvement in model fit. Analyzing the resulting tree structure and interpreting the model parameters in the terminal nodes can be used to determine which PACEs and combinations of PACEs affect the association between ACEs and alcohol use, and in what way. However, the data is partitioned based solely on the specified and observed covariates, which may limit how the groups are determined.

Implications for Couple and Family Therapists

There are multiple clinical implications for this study for therapists working with adolescents who have been exposed to ACEs. This study provides empirical evidence for the existence of a resilient group to ACEs: there is no significant association between exposure to ACEs and later alcohol use for approximately one in four adolescents. There were two factors that were found to contribute to belonging to the resilient group: effective problem solving and school bonding. For therapists working with adolescents who may be exposed to ACEs, therapists should assess for the adolescent's connection to their school and attempt to increase the adolescent's level of bonding to the school. Adolescents who report lower levels of school bonding may benefit from exploring ways to increase connection to the school. Therapists may try to help adolescents identify teachers they feel closer to, classes they enjoy or excel at or other positive aspects of the school experience (Allen et al. 2018). Therapists could also explore increasing involvement in school sponsored clubs or activities which may increase school bonding (Allen et al. 2018) and has also been found to be protective against alcohol use more generally (Hoffman 2006).

Secondly, therapists should also assess the adolescent's level of self-regulation (problem solving). Adolescents who have higher self-control may be at a lower risk for alcohol use, and adolescents who struggle with self-control may benefit from interventions that specifically target increasing self-control. Exposure to multiple ACEs can lead to a dysregulated stress response that can impair self-regulation (Hays-Grudo et al., 2021). Dysregulated stress responses are characterized by increased activation of the sympathetic nervous system which could lead to difficulties with problem-solving and self-control. Interventions that target reducing the dysregulated stress response system by eliciting the relaxation response and activating the parasympathetic nervous system may be beneficial for adolescents who struggle with lower self-control (Hays-Grudo et al., 2021).

Therapists can target mindfulness and mind-body (MBMB) interventions that can elicit the relaxation response such as meditation, yoga or tai-chi (Bethell et al., 2016). Stress regulation and problem-solving are also key components of multiple existing evidence-based practices for youths exposed to trauma or other ACEs such as Trauma-Focused Cognitive Behavioral Therapy (TF-CBT) (Cohen et al., 2012) or Trauma Affect Regulation Guide for Education and Therapy (TARGET) (Ford & Hawke 2012). The results of this study support therapists incorporating these practices in working with youths exposed to ACEs.

Even though there was no direct evidence that supportive parental relationships were associated with reduced alcohol use in this study, it is worthwhile to note caregiver involvement is an important component of these evidence-based practices. Further, self-regulation skills in children and adolescents are best learned through effective co-regulation with responsive adults (Hays-Grudo et al., 2021). Thus, including parents in treatment may still be beneficial and provide adolescents and their parents practice in developing important problem-solving and self-regulation skills related to lowered alcohol use.

Lastly, it is important to note that the lack of significance of several factors (e.g., parental bonding) in predicting resilience does not imply these factors are not salient for prevention work (Biglan et al., 2017; Nurius et al., 2020). Reducing exposure to ACEs by increasing competent, warm, and sensitive parenting is equally important for promoting resilience (Morris et al., 2021). Efforts to improve parenting practices, may lead to increased sensitive and responsive parenting and in turn decreased negative parenting practices which may reduce exposure to physical or emotional abuse. Research on multiple parent training and interventions have demonstrated success at increasing parental competence and even reducing subsequent reoffending for parents (Biglan, Van Ryzin, & Hawkins 2017). In a review of interventions to improve outcomes associated with ACEs, Marie-Mitchell & Kostolansky(2019) found in 12 of the 14 reviewed studies that measured parent-child relationship led to improvements in positive parenting, reduced harsh punishment or increased maternal sensitivity. However, the majority of these studies were with younger children, not adolescents. Although multiple evidence-based family therapy practices exist to improve adolescent drinking or substance use (Baldwin et al., 2012), how the role of ACEs or how trauma may influence substance use is not as clear. Incorporating trauma-informed care in family therapy could be advantageous when working with families with adolescent substance use.

Limitations and Future Directions

This study is not without limitations. Although using a secondary data-analysis allows access to large nationally representative longitudinal data, researchers are limited to the measures available in the dataset. This affected the study in the measurement of ACEs and the protective factors. Although there is no consensus on the best way to measure ACEs, there is emerging research suggesting retrospective reports of ACEs may be biased and do not always correspond to prospective research (Baldwin et al., 2019). Further, researchers measuring ACEs often make multiple decisions related to both the items they select as well as the choice of where or how to dichotomize the ACE indicators. Future research could examine how these analytic decisions affect the association between ACEs and alcohol use, as well as other outcomes.

Additionally, research could consider McLaughlin's (2016) dimensional approach to childhood adversity that consists of exposure to threat and deprivation when measuring ACEs. The dimensions of adversity may differentially influence the association between ACEs and alcohol use. Likewise, each dimension may be associated with disruptions in different developmental systems. Research that identifies which developmental systems are disrupted by threat may provide clues to identify future protective factors (McLaughlin 2016). For example, exposure to threat may lead to increased impulsivity, which is a risk factor for alcohol use (Chassin et al., 2013; McLaughlin 2016). If so, strategies to increase adolescent self-control may be more appropriate for adolescents exposed to threat. Future research may benefit from not only focusing on protective factors to ACEs, but also identifying mediators between ACEs and alcohol use.

A second limitation of the study is related to the questions used to measure the protective factors, as well as the timing of the questions. For example, the lack of significance of having a non-parental adult mentor could be related to limitations in how mentorship was measured in this study. Further information on the quality of the mentorship, the duration of the mentorship, the content or approach of the mentorship could have affected the results. Future research that more precisely measures the quality of mentorship could more closely examine the association between having a mentor and substance use in the context of ACEs.

Because of the timing of when the protective factors were measured (Wave I for all items except having a mentor), the protective factors only provided a snapshot of an adolescent's report of their relationship with peers, school, and family. These relationships are dynamic and can change drastically during adolescence (Steinberg & Morris 2000). Future research that measures these variables at multiple time points may be better able to examine the association between the protective factors and resilience (Cicchetti 2013).

A longitudinal approach to measuring protective factors is also more in line with the Relational Developmental Systems (RDS) (Lerner 2006) approach previously discussed. Future research that measures both exposure to ACEs and protective factors across time may more fully capture the complexities of the association between exposure to ACEs, protective factors, and alcohol use that may interact in complex ways. The timing of exposure to a particular ACE may affect the risk of exposure to other ACEs in the future. For example, experiencing parental divorce or separation may increase risk of exposure to poverty, or parental depression, or parental substance use. Likewise, parental substance use may increase the risk for neglect or physical abuse.

Additionally, these factors may affect exposure to positive experiences as well. For example, experiencing parental divorce could lead to an adolescent attending a new school which could affect the level of school bonding, or affect an adolescent's friend group which may increase (or decrease) their exposure to deviant or substance using peer groups. This in turn may affect the parent's level of parental monitoring or supervision, which could also influence adolescent alcohol use. Future research that measures exposure to ACEs prospectively, protective factors, and alcohol use across multiple timepoints, may be better able to capture the dynamic nature of how ACEs, protective factors and alcohol use all intersect over time.

Conclusion

This study examined heterogeneity in the association between exposure to ACEs and alcohol use using two analytic strategies, regression mixture modeling and structural equation model trees. Evidence for a resilient group of individuals was found, and school bonding and self-control emerged as likely protective factors that are associated with resilience. There was evidence adolescents who report having a mentor and higher self-esteem may be at a higher risk for experiencing negative outcomes from ACEs, although the results are inconclusive. Future research on ACEs and alcohol use should examine a wide variety of protective factors across a larger period of development to better understand what factors are associated with resilience.

APPENDICES

APPENDIX A.

Tables

Table 1. *Descriptive Statistics for Study Variables and Controls*

Variables	α	Range	M (SD) or %
Parental Bond (mother)	0.85	1-5	4.4 (.65)
Parental Bond (father)	0.88	1-5	4.2 (.76)
Parental Monitoring	0.62	0-1	.27 (.22)
School Bond	0.78	1-5	2.3 (.88)
Low-Alcohol Use in Peers	0.75	0-3	2.2 (.87)
Mentor		0 -1	78%
Self-Esteem	0.79	1-5	4.1 (.64)
Inattention	0.7	1-5	2.8 (.66)
Problem Solving	0.75	1-5	3.8 (.63)
Number of days Alcohol Consumed		0-6	2.23 (1.81)
Typical Number of Drinks		1-18	2.36 (3.04)
Sex	-	-	-
Male	-	-	44.58%
Female	-	-	55.42%
Race	-	-	-
White	-	-	68.21%
Non-White	-	-	31.79%
Ethnicity	-	-	-
Non-Hispanic	-	-	90.11%
Hispanic	-	-	9.89%
Parental Income	-	0-999	$49,840 ($58,190)
Age	-	25-34	28.7 (1.75)

Table 2. *Correlations Among Study Variables*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Esteem	-													
2. Problem Solving	.30	-												
3. Focus	.29*	.18*	-											
4. M. Bond	.38*	.16*	.22*	-										
5. P. Bond	.37*	.12*	.27*	0.53*	-									
6. Monitoring	0.0	0.0	.01	.02	.05*	-								
7. School Bond	-.32*	-.19*	-.36*	-.25*	-.29*	-.06*	-							
8. Mentor	.02	.01	.01	.01	.02	-.02*	-.04*	-						
9. Sex	-.17*	-.03	.12*	-.1*	-.01	-.02*	.03	.06*	-					
10. Income	.01	-.05*	.02	.01	.02	-.06*	-.02	.07*	.02	-				
11. Age	-.06*	.09*	-.02	-.14*	-.16*	-.38*	.11*	-.05	-.05*	.01	-			
12. Ethnicity	-.3*	-.01	-.03	0.0	-.03*	.06*	0.0	-.06	.01	-.09*	-.02	-		
13. Race	-.06*	-.09*	0.0	-.01	.03*	-.05*	0.0	.08*	-.01	.15*	-.06*	-.23*	-	
14. Drink	.03	-.05**	-.03	0.0	.04*	-.03*	-.03*	.05	-.2*	.14*	-.09*	-.03*	.16*	-
15. ACEs	-.12*	0.0	-.23*	-.18*	-.22*	-.01	0.19*	-.05	-.06*	-.15*	.05	.06*	-.15*	-.04*

Esteem Self Esteem *M. Bond* Maternal Bond *P. Bond* Paternal Bond *Monitoring* Parental Monitoring

* p <.01

Table 3. *Information on Measures Included in Adverse Childhood Experiences Index*

Measure	Informant	Wave Assessed and Item	Response Range	Recoded variable	Percentage of Sample
Neglect (supervisory or material)	Adolescent	Wave III: (supervisory) "By the time you started 6th grade, how often had your parents or other adult care-givers left you home alone when an adult should have been with you? (material) " How often had your parents or other adult caregivers not taken care of your basic needs, such as keeping you clean or providing food or clothing?	0=never happened, 5 = more than 10 times	0=no supervisory or material neglect 1 = supervisory (10 or more times) or material (2 or more times) neglect	12.00%
Physical Abuse	Adolescent	Wave IV: "Before your 18th birthday, how often did a parent or adult caregiver hit you with a fist, kick you, or throw you down on the floor, into a wall, or down stairs?"	0=never happened, 5 = more than 10 times	0=2 times or less, 1=three times or more	14.01%
Emotional Abuse	Adolescent	Wave IV: Before your 18th birthday, how often did a parent or other adult caregiver say things that really hurt your feelings or made you feel like you were not wanted or loved?	0=never happened, 5 = more than 10 times	0=less than 10 times, 1= 10 times or more	11.60%

Table 3. *Continued*

Sexual Abuse	Adolescent	Wave IV: How often had one of your parents or other adult caregivers touched you in a sexual way, forced you to touch him or her in a sexual way, or forced you to have sexual relations?	0=never happened, 5 = more than 10 times	0=never, 1 = one or more times	7.72%
Parental Incarceration	Adolescent	Wave IV: Has/did your biological mother (mother figure) or father (father figure) ever spent time in jail or prison?	Yes/No	0=no parent/guardian imprisoned, 1 = at least one parent/guardian	4.35%
Maternal Alcoholism	Parent	Wave I: How often in the last month have you had five or more drinks on one occasion?	0=never, 6=five or more times	0=1 time or less a month 1 = two or more times	11.17%
Marital Separation/ Divorce	Parent	Wave I: What is your current marital status?	1=single, never married 2 = married 3 = widowed 4 = divorced 5 =separated	0=married 1 = any other response option	26.27%
Witness Violence	Adolescent	Wave I: "You saw someone shoot or stab another person"	0=never 1=more than once	0=no exposure 1=any exposure (i.e., "1" on at least one item)	10.19%
Violence Victimization	Adolescent	Wave I "Someone pulled a knife or gun on you"," someone shot or stabbed you", someone "cut or stabbed you", " you were jumped"	0=never 1=more than once	0=no exposure 1=any exposure (i.e., "1" on at least one item)	4.35%

Table 4. *Fit Indices for Regression Mixture Model*

Number of Classes	BIC	ABIC	entropy	number of free parameters
1	27198.48	27179	1.00	6
2	**24781.76**	**24743.63**	**0.9**	**12**
3	23812.47	23755.28	0.87	18
4	22977.57	22901.31	0.98	24
5	22665.74	22570.42	0.96	30

Note: * p <.05 ** p<.01 *** p <.001

Table 5. *Parameter Estimates, Standard Errors for the Two-Class Regression Mixture Model*

Parameter	Harmful effects Class (72.6%)		Resilient Class (27.4%)	
	B	*SE*	*B*	*SE*
Number of Days Alcohol Consumed in a Week				
ACEs	0.01	0.03	-0.03	0.03
Sex	-0.63	0.05**	-0.63	0.05**
Parental Income	0.003	0.001**	0.003	0.001**
Age	-0.01	0.01	-0.01	0.01
Hispanic	-0.08	0.08	-0.08	0.08
Race	0.15	0.06*	0.15	0.06*
Intercept	3.5	0.44	0.55	
Typical Number of Drinks Consumed				
ACEs	0.05	0.02**	-0.15	0.18
Sex	-0.41	0.04**	-0.41	0.04**
Parental Income	0	0.001	0	0.001
Age	-0.04	0.01**	-0.04	0.01**
Hispanic	0.11	0.06	0.11	0.06
Race	0.17	0.05**	0.17	0.05**
Intercept	2.49	0.32	0.46	0.52
Dispersion	0.19	0.01	3.8	1.26

Note: * p <.05 ** p<.01 *** p <.001

Table 6. *Parameter Estimates, Standard Errors for the Structural Equation Model Tree*

	No mentor (22%)		Low self-esteem (25%)		High-Self Esteem (55%)	
Parameter	*B*	*SE*	*B*	*SE*	*B*	*SE*
Number of Days						
ACEs	-0.02	0.06	0.03	0.06	-0.01	0.05
Sex	-0.96	.16***	-0.71	.12**	-0.66	0.11*
Parental Income	0.01	.002**	0.004	.001*	0.004	0.001**
Age	-0.14	0.05*	-0.04	0.03	-0.11	.03**
Hispanic	-0.25	0.26	0.17	0.2	-0.16	0.19
Race	0.38	0.21	0.52	.14**	0.68	.14*
Intercept	7.18	1.57	2.86	0.95	5.7	1.04
Number of Drinks						
ACEs	0.01	0.04	-0.003	0.03	0.06	0.03*
Sex	-0.55	.1**	-0.41	.07**	-0.45	.08*
Parental Income	0	0.001	-0.001	0.001	0.001	0.001
Age	-0.13	.03**	-0.03	0.02	-0.08	0.02
Hispanic	0.01	0.18	0.19	0.12	0.17	0.12
Race	0.26	0.14	0.5	.09*	0.32	.10**
Intercept	5.3	0.82	2.49	0.57	3.1	0.63
Dispersion	0.9	0.16**	0.61	0.06**	0.66	.06**

Note: * p <.05 ** p<.01 *** p <.001

APPENDIX B.

Figures

Figure 1. *Regression Mixture Model Conceptual Diagram*

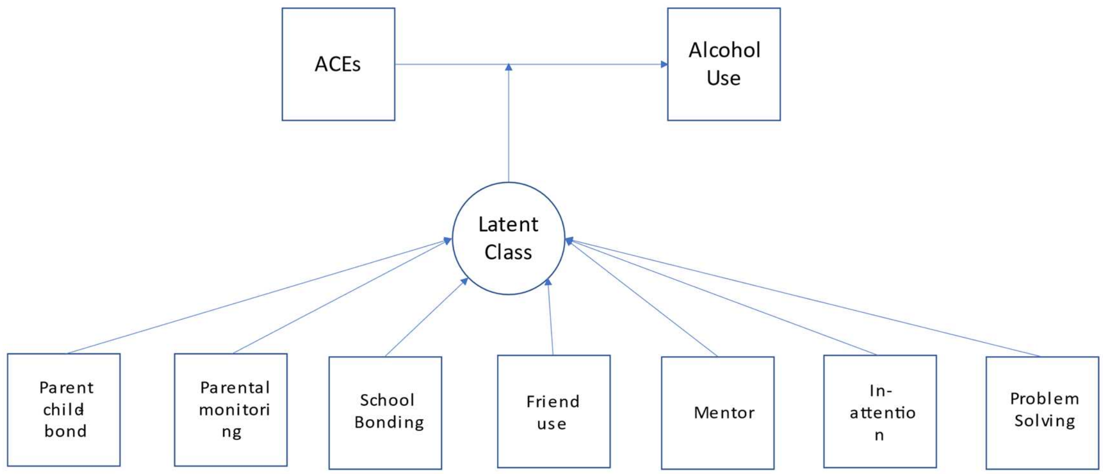
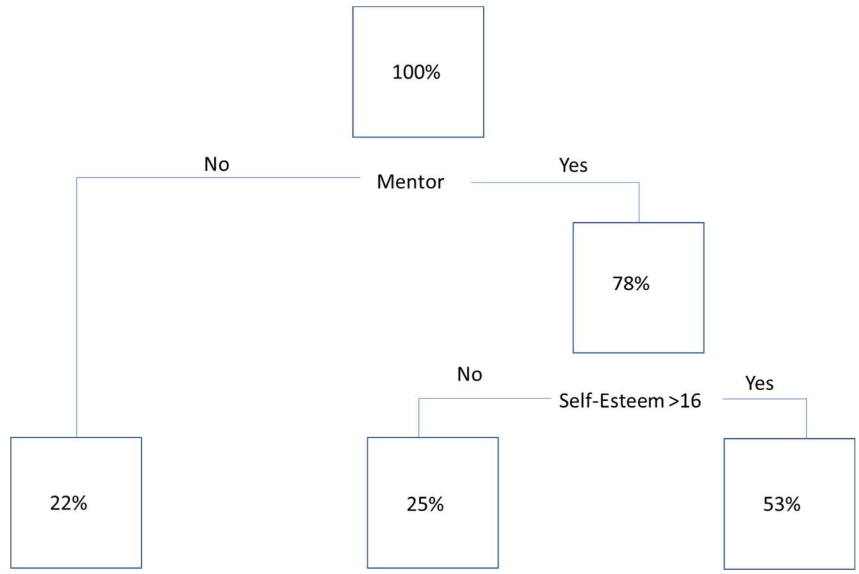


Figure *2. Structural Equation Model Tree*



Note: Percent sign refers to the percent of the sample in each group

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