Polyvictimization and Associated Substance Use in College Students:

A Latent Class Analysis

Dissertation

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Abstract

Collegiate polyvictimization is a serious, but understudied, phenomenon. Scientific knowledge regarding polyvictimization in college students has been hindered by a focus on non-collegiate populations, use of a limited number of outcome variables, or examination of only a singular victimization experience. The major consequence of these limitations has been the emergence of apparent knowledge gaps in the existing polyvictimization literature. As such, this dissertation aimed to complete a latent class analysis (LCA) using a sample of college students (n = 36,986), from a national dataset, to identify typologies of victimization and associated substance use. Through LCA, four classes distinguished by victimization emerged: *high/poly*, *verbal/discrimination*, *sexual/discrimination*, and *low/no*. Logistic regression models suggest that students allocated to the *high/poly, verbal/discrimination*, and *sexual/discrimination* classes have higher rates of substance use than the *low/no* class – with students in the *high/poly* class reporting the highest use of substances overall. Casual mediation analyses also suggest that psychological distress is higher in all classes, save for the *low/no* class, and that psychological distress partially mediates the relationship between latent class membership and substance use. Findings indicate an urgent need for screening and early identification of polyvictimization to improve collegiate mental health outcomes.

Keywords: victimization, college students, psychological distress, substance use

Dedication

This dissertation is dedicated to my friends. Thanks to all of you, I have been able to become a person of perseverance, joy, curiosity, resilience, intellect, hope, and love. Through you, I have found laughter and reprieve from the challenges of this journey. Even when things got hard, and I did not know if I could go on, none of you doubted me – not even for a second. You have cheered with me during my successes and cried with me during my failures. I thank you all so much for caring for me. I am so blessed to have such wonderful friends. I would also like to dedicate this dissertation to my mother. Thank you, mom, for being there for me throughout this journey. Thank you for the never-ending phone calls, the words of encouragement, and for always cheering me on. I hope I have made you proud.

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Fields of Study

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Chapter 1. Introduction

For many, college matriculation marks the start of a new chapter in life – one full of challenges and opportunities. However, not all college students have a collegiate career free of harm. Of the 20 million college students currently in the United States (U.S.), it is estimated that around 22% (4.4 million) will report experiencing at least one type of victimization on-campus (Jennings et al., 2007). This equates to slightly more than 20 students out of every 100 (Jennings et al., 2007). With a majority of victimization experiences going underreported, this estimate represents a fraction of the total number of students who will experience victimization during their collegiate career.

While the *Jeanne Clery Disclosure of Campus Security Policy and Crime Statistics Act* requires U.S. postsecondary institutions to report annual campus crime data, there is no requirement for the reporting of crimes that occur outside of campus bounds or on property not owned by the institution (Clery Center, 2022). Further, with differences in crime reporting based on jurisdiction, prevalence rates for off-campus victimization are challenging to determine. Thus, the total number of college students who experience victimization, both on-campus and off-campus, likely exceeds 22%.

The reasons for elevated victimization rates among college students are multifaceted, but often are centered around participation in high-risk activities, target suitability, and reduced supervision (Fisher et al., 1998; Swan et al., 2021). For students affiliated with Greek-letter organizations, student government, athletics, or student unions, the risk of experiencing victimization is especially elevated – due to proximity to harm inflictors (Gardella et al., 2015; Snyder et al., 2021; Swan et al., 2021). Heightened risk of victimization can also be found among college students who attend a public institution, have a disability, are in a relationship, are younger in age, have low or no institutional grade point average (i.e., first semester student), are a sexual or gender minority, are a racial or ethnic minority, have a preexisting psychopathology, or live within campus bounds (DeKeseredy et al., 2021; Fisher et al., 1998; Gardella et al., 2015; Hayes et al., 2021; Porter & Williams, 2011; Snyder et al., 2021).

Defining Victimization

Victimization is the experience of, or a lack of protection from, direct or indirect harm resulting from the actions of another person (Ford, 2017). Historically, victimization has been viewed dichotomously, with those involved categorized as either a "victim" (i.e., the harm target) or a "perpetrator" (i.e., the harm inflictor) (Park & Kim, 2019). Victimization is often categorized based on the type of harm experienced. While the number of victimization types abound, common types routinely seen in the literature include: maltreatment, harassment, abuse, assault, theft, fraud, bullying, stalking, kidnapping, trafficking, homicide, genocide, torture, and violence (Ford, 2017; Office for Victims of Crime [OVC], 2020). These broad victimization types can further be distinguished based on the intent, also referred to as the "context," of harm (e.g., mental, psychological, physical, emotional, sexual, verbal, financial) and the harm target (e.g., minority group, intimate partner, suitable stranger) (OVC, 2020).

Primary and Secondary Victimization

Occasionally, victimization is classified as being "primary" or "secondary." With primary victimization, an individual has been harmed directly (e.g., experienced sexual assault); whereas with secondary victimization, an individual has indirectly heard about or witnessed harm (e.g., bystander witnessed robbery at gunpoint) (Carrera-Fernández et al., 2022). Secondary victimization of individuals who have experienced primary victimization is also possible. In these situations, individuals who have experienced victimization are exposed to four possible secondary victimization dimensions: (1) avoidance of the individual, (2) blaming of the individual, (3) minimization of the individual's suffering, and (4) devaluation of the individual – as a result of having experienced victimization (Carrera-Fernández et al., 2022). When one or more of these dimensions occur, the individual who experienced victimization can be subjected to further post-victimization harm, which may be classified as secondary victimization.

Cybervictimization

With the rapid expansion of information and communication technologies, more individuals are being subjected to victimization online or through electronic devices. Termed "cybervictimization," many of the same types of victimization mentioned previously can now occur in a digital space or on a social media platform. Typically, cybervictimization is classified with the same considerations as other types of victimization, only with an added prefix of "cyber" (e.g., cyberbullying, cyberstalking) to denote that it occurred electronically. Cybervictimization has some unique qualities not seen with traditional victimization, such as: harm inflictor anonymity, broader victimization audience, and unlimited internet capacity (i.e., abusive content is available for longer periods or can be downloaded/reuploaded) (Arató et al., 2020).

Defining Polyvictimization

Polyvictimization, also known as "multiple victimization" or "cumulative victimization," is the experience of two or more types of victimization occurring over a set period of time (Finkelhor et al., 2007; Ford, 2017). Commonly, across the literature, in order for polyvictimization to occur, the types of victimization experienced must be distinct from one another. Or, to put it simply, each type of victimization results in a differing type of harm – which is often distinguished through predetermined categories originating in psychology and criminology (Ford, 2017). For example, sexual harassment and sexual assault both have a sexual intent of harm. Despite being two separate experiences with differing meaning, because they both are classified as having a sexual intent, they would not be considered polyvictimization if combined together. In a case with physical assault and sexual assault, however, the criteria for polyvictimization would be met, as the intent of harm is physical for one experience and sexual for the other – making the experiences distinct.

Differences in Defining Polyvictimization Across the Literature

It is imperative to note that polyvictimization is an emerging term. Thus, there are some differences across the literature regarding how polyvictimization is studied. While a majority of studies accept the definition put forth by Finkelhor et al. (2007), some studies also include additional criteria for polyvictimization. One such criterion is the inclusion of a differing harm inflictor. For example, if one experienced physical assault and sexual assault by an intimate partner (i.e., the same harm inflictor), despite the intent of harm being distinct, the harm inflictor is not. In this example, these two types of victimization could be combined together and considered one type of victimization: intimate partner victimization. So, for these studies, this victimization combination would not meet this specific definition of polyvictimization. For other studies, the consideration for harm inflictor is not considered, and thus polyvictimization would have occurred using this specific definition.

Another criterion occasionally seen in the literature relates to the time of life when polyvictimization occurs. For some studies, combinations of victimization at specific time points are emphasized, while others examine the entire lifespan. Often, these set timelines are discipline specific, with some disciplines concerned with polyvictimization across the lifespan, in childhood alone (e.g., as adverse childhood experiences), during periods of growth and development, or during periods of interest (e.g., while enrolled in college, during incarceration, or while serving in the military).

Polyvictimization Versus Revictimization

It is imperative to note, however, that polyvictimization is not synonymous with revictimization. With revictimization, a person experiences repeat or subsequent episodes of *a singular victimization type* (i.e., with the same intent of harm and/or harm inflictor) over a specified period (Snyder et al., 2021; Widom et al., 2008). While with polyvictimization, a person experiences *two or more distinct victimization types* (i.e., with differing intent of harm and/or harm inflictor) over a specified period.

In cases where an individual has experienced both primary and secondary victimization, classification is again based on victimization experience distinctness. As aforementioned, any experience causing harm through the actions of another person is victimization, be it direct or indirect. Thus, experiencing primary and secondary victimization can be considered polyvictimization. However, if these primary and secondary victimization experiences are the same victimization type, or related to the same victimization experience, they could be considered revictimization.

Collegiate Victimization

As aforementioned, an estimated 22% of all college students will report experiencing at least one victimization type on-campus (Jennings et al., 2007). This prevalence percentage originates from a landmark survey completed by 564 undergraduate college students at a large, southeastern U.S. university in 2005 (Jennings et al., 2007). For this particular survey, victimization was divided as being direct (i.e., primary) or indirect (i.e., secondary), with 21.5% of students reporting direct victimization (i.e., person, property, or sexual assault) and 45.9% of students reporting indirect victimization (i.e., person or property) (Jennings et al., 2007).

Since 2005, other studies have been completed to help determine the prevalence of victimization among college students, but most narrow in on only a singular victimization type or specific student population (e.g., sexual and gender minority, Greek-letter organization affiliated). While college students can experience any type victimization, the most prevalent in this population are often cited as being: intimate partner violence, psychological abuse, sexual assault, physical assault, bullying, stalking, and theft (Caravaca-Sánchez et al., 2021; Wang et al., 2020).

Sexual Victimization and the Red Zone

According to the 2019 Association of American Universities (AAU) Campus Climate Survey on Sexual Assault and Misconduct, which surveyed 181,752 college students across 27 U.S. campuses, sexual victimization rates are on the rise (Cantor et al., 2020). Sexual contact through physical force or inability to consent, since enrolling in college, was reported by 13% of all students completing the AAU survey – up 3.0, 2.4, and 1.4 percentage points in undergraduate female, graduate female, and undergraduate male students, respectively, since 2015 (Cantor et al., 2020).

Penetration involving physical force or inability to consent since enrolling in college was reported by 15.4% of female, 13.7% of sexual and gender minority, and 3.5% of male students (Cantor et al., 2020). General nonconsensual sexual contact was reported among 25.9%, 9.7%, 6.8%, and 2.5% of undergraduate female, graduate female, undergraduate male, and graduate male students, respectively (Cantor et al., 2020). An alarming 22.8% of undergraduate and 14.5% of graduate students identifying as transgender, nonbinary, genderqueer, or gender questioning reported nonconsensual sexual contact (Cantor et al., 2020). Sexual harassment rates in the AAU survey topped 41.8% among all students, with the highest rates reported by undergraduate female (59.2%) and other sexual and gender minority (65.1%) students (Cantor et al., 2020).

In a literature review of male college students aged 18-24, sexual victimization on college campuses was reported by 3.2% to 28.7% of all men surveyed (Forsman, 2017).

Another literature review, which examined general campus sexual assault from 2000 to 2015, found prevalence rates of 6% to 44.2% among female students and 1.4% to 3.2% among male students (Fedina et al., 2018). Another study, of male and female undergraduate students across 12 U.S. universities, found a sexual victimization rate of 24.2% for female students and 15.6% for male students (Jouriles et al., 2022). More alarmingly, in a study of male students associated with a Greek-letter organization, 27.5% reported sexual victimization – with 13.7% and 25.5% reporting penetrative or attempted penetrative sexual assault (Luetke et al., 2021). One study, of 800 U.S. community college students, found that 48.8% of students reported experiencing sexual victimization – with a majority being female, younger than 26, non-heterosexual, and non-White (Howard et al., 2019).

Unfortunately, due to the alarming number of sexual victimization experiences among college students, a moniker has been designated to bring awareness to those most at-risk: "red zone." The red zone refers to the first few weeks of the fall academic term. It is during this time where college students, especially freshmen, are considered to be at the greatest risk of experiencing a nonconsensual sexual encounter (Flack et al., 2008). There are several proposed risk factors as to why this time period is associated with such an uptick in sexual victimization (e.g., Greek-letter organization recruitment, increased substance use, invitation to student welcoming events), however, regardless of risk factors, several prior studies have findings which support the existence of the red zone (Flack et al., 2008).

Intimate Partner Victimization

The prevalence of intimate partner, or "dating," victimization among college students is estimated to fall between 20% and 50% depending on the type of harm inflicted (Nabors, 2010). In a study of 1,028 New York college students, 9.5% reported sexual abuse and 43.1% reported psychological abuse from an intimate partner (Porter & Williams, 2011). For those students who did report sexual abuse from an intimate partner, sexual and gender minority students were five times as likely to report, while racial and ethnic minority students were twice as likely (Porter & Williams, 2011).

Physical abuse by an intimate partner was also assessed in the Porter and Williams study, which found 35.7% of deaf and hard-of-hearing, 11.9% of sexual and gender minority, 21.7% of racial and ethnic minority, and 45.1% of female students reporting physical abuse by a partner (2011). Physical abuse by an intimate partner was also reported among 88.1% of heterosexual, 78.3% of White, and 55.1% of male students (Porter & Williams, 2011). Rape by an intimate partner was reported among 1.7% of students; attempted rape was reported among 2.2% (Porter & Williams, 2011).

A secondary data analysis, of the American College Health Association-National College Health Association II survey, found that out of 26,685 college students across the U.S., 18% of students with a disability and 10% of students without a disability reported psychological, physical, or sexual intimate partner victimization (Scherer et al., 2016). Of the students who completed the AAU survey, 10.1% reported experiencing sexual intimate partner victimization, with the highest rates being reported among undergraduate female (14.1%) and sexual and gender minority (21.5%) students (Cantor et al., 2020).

Another study, of 1,938 college students, found that approximately 30.1% of college students physically assault their intimate partner (Nabors, 2010).

Stalking, Bullying, Cyberbullying, and Peer Victimization

Peer victimization is estimated to occur among 8% to 25% of college students (Cole et al., 2020). In a 2020 study, using the Peer Victimization in College Survey, out of 733 full-time college students in the U.S., 75% reported at least one type of peer victimization (Cole et al., 2020). Bullying, be it by a peer or non-peer, is also prevalent among college students. In a 2017 literature review of bullying victimization in the postsecondary setting, 20% to 25% of all college students across 14 studies reported being bullied while in college (Lund & Ross, 2017).

In this same literature review, the mean prevalence of bullying victimization of men and women were 19.3% and 17.4%, respectively (Lund & Ross, 2017). In a 2004 study of collegiate bullying, out of 1,025 undergraduate students, 33.4% of students reported witnessing students bully classmates; 18.5% reported experiencing bullying by a classmate themselves (Chapell et al., 2004). Another 29.4% reported witnessing an instructor bully classmates, with 14.5% reporting bullying by an instructor themselves (Chapell et al., 2004). Around 10% to 15% of college students report experiencing cyberbullying while in college (Lund & Ross, 2017).

Stalking is also commonplace among college students. In a study of 800 U.S. community college students, 14.3% of all students reported being stalked since enrolling in college (Howard et al., 2019). In another study, of 4,266 college students, 2.3% of students reported being stalked in the past year (Brady et al., 2017). Looking at the 2019

AAU survey, 5.8% of students reported experiencing stalking since being in college, with 31.1% reporting they knew who was stalking them (Cantor et al., 2020). In a study by Reyns and Scherer (n = 43,000), students with a disability were two times more likely to have experienced being stalked – with 5% of non-disabled and 10% of disabled students self-reporting a stalking experience in the past year (2018).

Discrimination, Theft, and Criminal Victimization

In 2019, the National Center for Education Statistics (NCES), through the U.S. Department of Education, found that there were 18.7 on-campus crimes (i.e., burglary, motor vehicle theft, aggravated assault, robbery, and arson) per 10,000 full-time college students (2022). In addition to this, 20 students were killed via homicide and 757 students experienced a hate crime (NCES, 2022). These hate crimes included intimation, vandalism, destruction, and simple assault. It is important to note that these only include reported incidents of victimization, and do not include estimates for those students who did not report the incident to local law enforcement.

Discrimination is also problematic among college students. In a study of 2,230 college students, past year discrimination by a stranger was reported by 32% of students – with members of all racial/ethnic groups reporting experiencing discrimination (Bravo et al., 2021). In a secondary data analysis of Black college students seeking services at Penn State Counseling and Psychological Services, 27.1% reported experiencing racial/ethnic or cultural discrimination in the past six months; 9.9%, 6.1%, 3.0%, 2.5%, and 1.6% reported discrimination based on their gender identity, sexual orientation, nationality, disability, and religion, respectively (Tan & Magruder, 2022). In another secondary data analysis examining 426,245 student respondents from the 2015-2019 American College Health Association-National College Health Assessment, discrimination in the past year was reported by 7.9% of all students (Qeadan et al., 2022).

In this same analysis by Qeadan et al., across the 2018-2019 academic term, 30.1% of transgender, non-binary, genderqueer, and other gender diverse students reported experiencing discrimination; while 20.9% of gay, lesbian, and bisexual students reported experiencing discrimination (2022). Black students (16.6%), biracial/multiracial students (16.0%), and American Indian/Alaska Native/Native Hawaiian students (12.9%) reported more discrimination than their White peers (Qeadan et al., 2022).

Hazing

Hazing is an ongoing problem in the collegiate setting, especially among students affiliated with Greek-letter organizations, athletic teams, and other extracurricular student organizations. Several different forms of hazing (e.g., binge drinking, humiliation, isolation, sleep-deprivation, beating, branding, confinement, forced consumption, pledge servitude, and sex acts) are routinely experienced in student-lead groups (Allan & Madden, 2012; Finkel, 2002). In a 2018 study of collegiate hazing, out of a sample of 404 first-year college students, 79% of students reported being involved in unofficial hazing – with 43% reporting that their experience of hazing was involuntary (Pečjak & Pirc, 2019). Another study, from 2005, found that out of 736 college students – 36% reported experiencing hazing, with those in Greek-letter organizations and student athletics being among those most likely to engage with hazing (Campo et al., 2005). In another study, of

5,880 students across seven research universities, 26% of students reported experiencing a hazing behavior (Allan et al., 2019).

Collegiate Polyvictimization

For studies focused on collegiate polyvictimization, emphasis is often placed on victimization in childhood and later in adulthood – with polyvictimization occurring solely during the college years receiving less attention. In the studies that do focus on polyvictimization occurring only during college, patterns of prevalence vary. In a study by Snyder et al., 4,000 female college students were surveyed about singular victimization and polyvictimization (2020). Of these 4,000 students, 32% experienced polyvictimization, with 54% experiencing two or more types of victimization and 32% reporting three or more (Snyder et al., 2021).

Looking back at the 2019 AAU survey, while 9.5% of students reported one type of victimization, 16.4% reported experiencing at least two types of victimization since enrolling in college (Cantor et al., 2020). In a study of 800 U.S. community college students, 12.2% reported two types of victimization, 6.6% reported three types of victimization, and 4.7% reported four or more types of victimization since enrolling (Howard et al., 2019). A study by Ross et al., found that 15% of male college students and 22.5% of female college students reported combination intimate partner abuse, sexting coercion, and sexual coercion (2019).

Defining Psychological Distress

As explained by Ridner (2004), psychological distress is a "unique discomforting, emotional state experienced by an individual in response to a specific stressor or demand that results in harm, either temporary or permanent" (p. 539). While the concept of psychological distress can vary slightly, it is often cited as being a state of emotional suffering, in which one experiences non-specific symptoms of depression (e.g., hopelessness, sad mood, anhedonia) and anxiety (e.g., restlessness, irritability). Occasionally, an individual may also experience somatic symptoms, such as fatigue or pain. There are five defining attributes of psychological distress: 1) perceived inability to effectively cope with a stressor, 2) change in emotional state, 3) mental discomfort, 4) communication related to mental discomfort, and 5) harm (Ridner, 2004). While not a technical diagnosis, psychological distress has the potential to be persistent or increase risk of development of an explicit psychopathological disorder.

Psychological Distress Among College Students

The risk of developing psychological distress is already elevated in college students – as postsecondary education brings with it a number of stressors that could surpass a student's ability to cope, either alone or in combination (Vázquez et al., 2012). In fact, one study of 5,784 college students in India found that psychological distress was reported by 34.8% of students (Ts et al., 2017). More alarmingly, this same study found that college students who reported psychological distress had higher rates of substance use, suicidality, sexual abuse, and academic failure (Ts et al., 2017). Another study, of 1,400 college students in China, found that 90.86% of students reported having psychological distress (Zhang et al., 2018). In Italy, a study of 4,760 university students found a psychological distress prevalence rate of 78.5% (Porru et al., 2021). Elevated rates of psychological distress have also been found in the United States. In 2022, a study of 7,012 students found that almost two-thirds (64%) of students reported psychological distress via non-specific depressive symptoms (Giovenco et al., 2022).

Psychological Consequences of Victimization

The mental health consequences of experiencing collegiate victimization are vast. Numerous studies have identified an association between singular victimization and subsequent psychological distress, anxiety, depression, posttraumatic stress disorder, and substance use in college students (Assari & Moghani Lankarani, 2018; Bridges-Curry & Newton, 2022; Holt et al., 2017; Parks et al., 2014; Straight et al., 2003; Weingarten et al., 2018; Wright, 2016). Physical, psychological, and sexual types of victimization have been repeatedly associated with psychological distress, posttraumatic stress disorder, and depression in college students – with greater frequency and severity of victimization resulting in more severe symptoms (Sabina & Straus, 2010).

Cybervictimization (e.g., cyberstalking, social media impersonation) during college has been linked with reports of increased anxiety, depression, and suicidal ideation (Wright, 2016; Weingarten et al., 2013). Relational aggression and intimate partner violence have been associated with increased psychological distress (Dahlen et al., 2013; Weingarten et al., 2018). In one study of 18,335 university students across 25 countries, experiencing sexual victimization or physical intimate partner victimization was associated with heightened depression and posttraumatic stress disorder symptoms (Pengpid & Peltzer, 2020). Peer victimization has also been linked with elevated stress, depression, and anxiety symptoms (Cole et al., 2020).

Psychological Consequences of Polyvictimization

While a singular victimization experience is serious and has been linked with several negative psychological symptoms, polyvictimization has been associated with the development of a greater number and greater severity of negative psychological symptoms due to accumulation of trauma (Bridges-Curry & Newton, 2022; Elliott et al., 2019; Finkelhor et al., 2007; Ford, 2017). In fact, research has found polyvictimization to be a better predictor of psychological distress and trauma symptomology than any singular type of victimization alone (Elliott et al., 2019). Polyvictimization has also been associated with higher rates of depression, anxiety, and posttraumatic stress disorder compared to singular or no victimization (Elliott et al., 2019; Sabina & Straus, 2008).

Collegiate Substance Use

Substance use is already pervasive among college students. Be it for recreational or experimental use, overall prevalence rates are striking. In 2019, the National Survey on Drug Use and Health indicated that 52.5% of full-time college students (aged 18 to 22) drank alcohol in the past month; another 33% binge drank and 6.4% engaged in heavy alcohol use (National Institute on Alcohol Abuse and Alcoholism [NIAAA], 2022). Findings from the 2020 Monitoring the Future (MTF) study found similar prevalence rates, with 56% of all students using alcohol in the past month, 28% being drunk in the past month, and 24% reporting binge drinking (National Institute on Drug Abuse [NIDA], 2021).

In this same 2020 MTF study, 44% of college students reported using cannabis – up from 38% in 2015 (NIDA, 2021). In 2020, past month use of vaped nicotine was reported among 19% of college students, while 12% of this same sample reporting vaping cannabis; past-month cigarette smoking was reported by 4% of college students (NIDA, 2021). Use of nonmedical amphetamines, nonmedical prescription opioids, and hallucinogens were reported by 6.5%, 1%, and 9% of students (NIDA, 2021).

Fear of Colligate Victimization and Substance Use

Fear of experiencing victimization has been associated with substance use in college students. In a study by Couture et al. (2020), 1,415 urban university students completed a survey regarding fear of experiencing 11 different victimization types (i.e., physical assault, sexual assault, arson, robbery, theft, vandalism, homicide, hate crimes, hate speech, verbal threats, and microaggression). Students that participated in the study were broken up into quartiles by level of reported fear (i.e*., no/little fear, moderate fear, high fear,* or *very high fear*). Results of this study showed that *high fear* and *very high fear* levels were reported more by female students (26.6% and 33.1%) than male students (19.8% and 16.3%) (Couture et al., 2020).

When looking at substance use, female students reporting *moderate fear*, *high fear*, and *very high fear* were more likely to engage in hazardous drinking – 1.63, 1.87, and 1.64 times higher than females with *no/little fear* (Couture et al., 2020). Female students with *very high fear* were over two times more likely to report tobacco use compared to female students with *no/little fear* (Couture et al., 2020). Cannabis rates among female students with *high fear* and *very high fear* were 1.82 and 2.41 times higher than the *no/little fear* female group (Couture et al., 2020). These same associations were not seen among the male students who participated, however, it is important to note that a majority of the sample (73.5%) was female (Couture et al., 2020).

Collegiate Victimization, Polyvictimization, and Substance Use

While the association between polyvictimization and substance use has yet to be fully examined among college students, prior research has found that adolescents who have experienced polyvictimization are three to five times more likely to use substances than their non-polyvictimized peers (Ford et al., 2010). In fact, one study of female college students found that experiencing intimate partner dating victimization predicted cannabis use the following day (Shorey et al., 2017). Another study found that stalking victimization, from a dating partner, was related to alcohol and drug use in college students, even when controlling for age, gender, relationship duration, and physical aggression victimization (Strauss et al., 2019). Among the studies that have examined substance use and polyvictimization in college students, findings suggest that experiencing polyvictimization is associated with greater frequency/quantity of, and shorter latency to, substance use (Berzenski & Yates, 2011; Caravaca-Sánchez et al., 2021; Klanecky et al., 2015; Priolo-Filho & Williams, 2019; Sherman et al., 2021).

Psychological Consequences and Substance Use

While victimization has been associated with substance use among college students, the psychological symptoms following victimization have also been associated with substance use (Mofatteh, 2020). In Canadian college students, use of cannabis and tobacco have been associated with depressive symptoms; while use of alcohol has been associated with anxiety (Esmaeelzadeh et al., 2018). Psychological distress and posttraumatic stress disorder have also been linked to problematic alcohol consumption, heavy or hazardous drinking, and diagnosis of a substance use disorder while in college (Borsari et al., 2008; Read et al., 2015).

Specific Aims and Research Purpose

The primary purpose of this study is to uncover the typologies of victimization that manifest in the collegiate student body and examine associations between these typologies and use of substances as a means to cope with victimization-related trauma symptomology. Through this, the broader purpose of this dissertation is to expand on current victimization research and examine if any differences in substance use among college students can be identified based on the types of victimization they have experienced. It is the overarching goal of this dissertation to lay the groundwork for a future program of research focused on the development of trauma-informed screening tools, prevention programs, and interventions that reduce substance use prevalence and related consequences in college students who have experienced victimization in any form, number, or context.

As aforementioned, scientific knowledge regarding polyvictimization in college students has been hindered by a focus on non-college specific populations, use of a limited number of outcome variables, or examination of only a singular victimization experience. The major consequence of this has been the emergence of apparent knowledge gaps in the existing polyvictimization literature. As such, this study aimed to confront several of these knowledge gaps through three specific aims: 1) identify typologies of victimization experience among college students; 2) determine which typologies of victimization are associated with risk of substance use; and 3) examine if psychological distress functions as a mechanism (i.e., mediator) through which typologies of victimization may contribute to substance use.

Chapter 2. Literature Review and Theoretical Framework

Polyvictimization and Substance Use in Emerging Adulthood

A literature review, looking at polyvictimization and associated substance use across emerging adulthood, without the inclusion of explicit college enrollment, was completed. This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Five databases (MEDLINE, Cumulative Index to Nursing and Allied Health Literature [CINAHL], APA PsycINFO, PubMed, and SocINDEX) were searched in August of 2021 using a variety of terms related to variables of interest (see Table 1). Boolean connectors "AND" and "OR" were used to link search terms. Included databases were accessed through the EBSCOhost database system. Results retrieved from the EBSCOhost database system were subsequently transferred to a review management account using the web-based software Covidence. Duplicate publications were accounted for, and removed, using Covidence.

The initial search yielded 828 studies. Upon removal of 170 duplicates, 658 studies were subject to title and abstract screening. Studies were included if they (1) contained at least two distinct measures of trauma or victimization, (2) included at least one measure of substance use, (3) focused on participants aged 18-30 (± 5 years), (4) were available in English, and (5) were peer-reviewed. Studies were excluded if they (1) examined trauma or substance use in relation to a physical injury or medical condition,

(2) focused on use of a substance given under medical direction or supervision, (3) included substance use as a risk factor and not an outcome, or (4) included measures of perpetration and not victimization. The requirement for college enrollment as an inclusion criterion was omitted when search results yielded too few articles.

After screening, 534 studies were excluded due to irrelevant titles or abstracts. Full-text review was then completed on the remaining 124 studies. Completion of the full-text review resulted in another 92 studies being excluded – yielding 32 total studies. During data extraction, two additional studies were excluded, as deeper exploration of study tables identified no polyvictimization measure. Thus, leaving the final number of included studies for final analysis at 30 (see Figure 1).

Variables of Interest	Related Search Terms
Polyvictimization	“polyvictim,” “poly-victim,” “poly victim,” “polyvictims,” “poly-victims,” “poly victims,” “polytrauma,” “poly-trauma,” “poly trauma,” “polyvictimization,” “poly-victimization,” “poly victimization,” “multiple types of victimization,” “multiple kinds of victimization,” “multiple forms of victimization,” “multiple types of trauma,” “multiple kinds of trauma,” “multiple forms of trauma,” “multiple types of traumatization,” “multiple kinds of traumatization,” “multiple forms of traumatization,” “cumulative victim,” “cumulative victimization,” “cumulative trauma,” “cumulative traumatization”
Substance Use	“substance use,” “substance abuse,” “substance misuse,” “drug use,” “drug abuse,” “drug misuse,” “alcohol use,” “alcohol abuse,” “alcohol misuse,” “addiction,” “dependence,” “substance use disorder,” “polysubstance,” “poly substance,” “poly-substance”

Table 1. Literature Review Search Terms

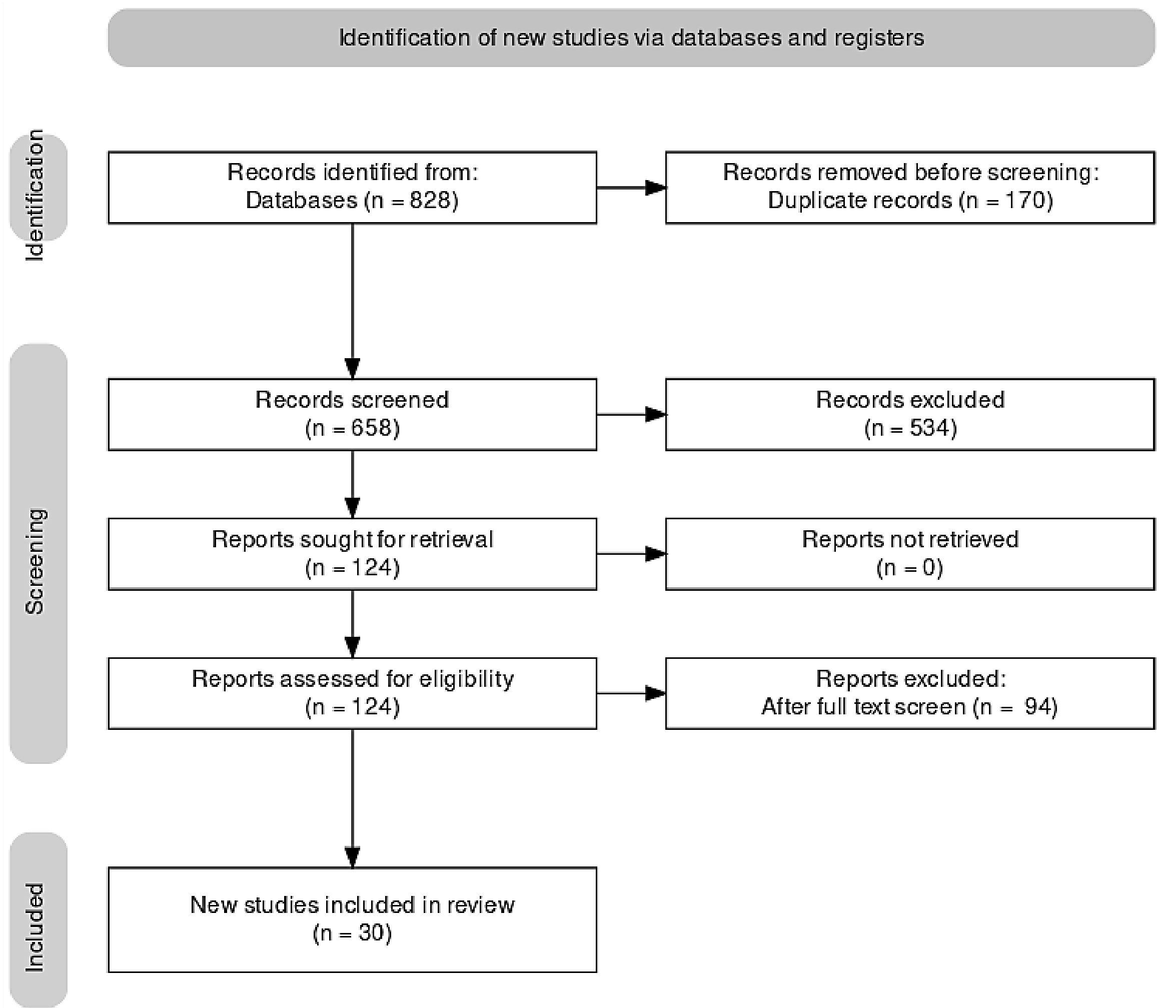

Figure 1. Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) Flow Diagram for Literature Review

Key Literature Review Findings

Sample sizes of included studies ranged from 115 to 15,960. Twenty-one of the included studies took place in the U.S., while the remaining were conducted in Canada (*n* = 2), Honduras (*n* = 1), Sweden (*n* = 2), Switzerland (*n* = 1), Brazil (*n* = 1), Spain (*n* = 1), and El Salvador (*n* = 1). Several populations were explored across the studies; four examined college students, two examined homeless or sheltered individuals, five examined sexual and gender minorities, two examined individuals in treatment for a substance use disorder, and three examined emerging adults charged as juvenile offenders. The remaining 14 studies focused on general emerging adulthood or community-based samples. Twenty studies were longitudinal in nature, while the remaining 10 were cross-sectional.

Overall, 29 of the 30 included studies identified an association between experiencing polyvictimization and engaging in substance use. Collectively, studies found polyvictimization to be associated with shorter latency to use (*n* = 3), increased use (*n* = 20), and problematic or disordered use (*n* = 7). Adverse childhood experiences, or ACEs, were explored as a form of polyvictimization in five studies – with all five finding higher ACE scores to be associated with a proportional increase in substance use (Davis et al., 2021; Kappel et al., 2021; Mersky et al., 2013; Schilling et al., 2007; Shin et al., 2018). Alcohol was examined in 22 studies, of which half (*n* = 11) found an association between polyvictimization and binge, heavy, problematic, or risky drinking. Nineteen studies found a link between polyvictimization and increased alcohol use.

Cannabis was explored in 10 studies, of which eight found an association between polyvictimization and increased or problematic cannabis use. All eight studies examining tobacco use found an association between experiencing polyvictimization and increased use of tobacco. Illicit drug use, general substance use, and other drugs (e.g., cocaine, heroin) were found to be linked to polyvictimization in 16 studies. In the study by Quin et al., experiencing polyvictimization was also alarmingly associated with an increase in injection drug use and related consequences – with the odds of injection drug use being higher in those experiencing polyvictimization (2016).

Measures of Victimization and Polyvictimization

Measures of victimization and polyvictimization were not consistent in type or number across included studies. While all studies included at least one victimization measure, the number of items which aggregated to form that victimization measure varied widely. Further, in a number of studies, the term "victimization" was not explicitly used to define the measure. Instead, terms such as "violence," "trauma," "abuse," "conflict," or "maltreatment" were used. Polyvictimization was primarily analyzed as a summed count, cumulative score, or combination of included study victimization measures. Depending on the study, some counts greater than two were combined to represent polyvictimization, while other studies looked at differences based on summed count (e.g., differences between a count of two, three, four, et cetera).

Measures of Substance Use

Substance use measures also varied across included studies. Alcohol, included in 22 of the studies, was the most frequently measured substance. Cannabis was measured in nine studies, while tobacco was measured in eight. Substance-related consequences and problems were measured in only three studies (Cater et al., 2014; Charak et al., 2019; Shin et al., 2018). One study examined drinking self-efficacy beliefs (Klanecky et al., 2015). Outside of alcohol, cannabis, and tobacco, measures of other substances were mixed. The other named substances in these studies include cocaine, heroin, ecstasy, methamphetamine, mushrooms, inhalants, phencyclidine, lysergic acid diethylamide, prescription drugs, and non-prescription drugs. The inclusion of these drugs differed across studies.

In 10 studies, “substance use” or “illicit use” was used to capture use of any or all substances. Injection drug use was explored in only one study, which found the odds of injection drug use were 5-7 times higher in those reporting 4-5 types of victimization (Quinn et al., 2016). A majority of studies measured substance use as being yes/no over some time period. Thirteen studies looked at substance use in the prior year, while others examined use of substances at different time points (i.e., past week $n = 1$; past month $n = 5$; past three months $n = 2$; past six months $n = 2$; lifetime $n = 3$).

Collegiate Studies

When it comes to the studies that did focus on college students, only two took place in the U.S. (Berzenski & Yates, 2011; Klanecky et al., 2015). The remaining two, completed by Priolo-Filho and Williams (2019) and Caravaca-Sanchez et al. (2021), originated from Brazil and Spain, respectively. Sample sizes of these studies ranged from 200 to 2,637. Both of the studies completed in the U.S. focused on undergraduate students, while the other two focused on the collective college student body.

When reviewing the findings of these studies, results suggest a proportional relationship between polyvictimization and substance use, that is, as the amount and number of victimization experiences increase, so too does the rate of substance use. Further, in the study by Klanecky et al. (2015), college students who experienced multiple trauma exposures (i.e., polyvictimization) were found to have reduced insight and poorer drinking refusal self-efficacy than those who experienced no victimization or singular victimization. Overall, these four studies all identified an association between victimization and substance use among college students – with a greater number of victimization experiences being linked to a greater use of substances.

Conclusions and Research Priorities

Aggregate findings of this review indicate the need for a clear, unified definition of polyvictimization. Measures of victimization and substance use were inconsistent and no standardized measure for either concept was identified – making comparison of results across studies a challenge. Studies were mixed in approach for defining polyvictimization and incorporating victimization counts into analyses. Most studies examined polyvictimization beginning in childhood and not solely in emerging adulthood. Collectively, these studies express a growing need for research regarding polyvictimization and substance use in emerging adulthood – especially for those enrolled in college.

Based on the findings of these studies, future research priorities should revolve around polyvictimization and substance use in minority populations, in developmental and transitional periods other than childhood, in those residing in areas with high substance use rates, and in those who have a preexisting psychopathology. Attention should also be given to different combinations of polyvictimization and related substance use (e.g., type, frequency, quantity, route, duration, and consequences). Additionally, this literature review points towards the growing need for a trauma-informed, standardized screening tool that can identify those at-risk of both singular victimization and polyvictimization – with their respective consequences.

The Self-Medication Hypothesis

This study is guided by the Self-Medication Hypothesis (SMH), a causal theory that postulates that substances are used as a method to reduce unwanted or unpleasant trauma-related psychological symptoms in those who have experienced a stressor (Hall & Queener, 2007; Khantzian, 1997; Turner et al., 2018). The basic premise of the SMH is that the experience of a stressor induces some degree of traumatic psychological response (Khantzian, 1997). Depending on the context of the stressor, this response can manifest as any number of trauma-related psychological symptoms with differing levels of severity and duration. Per the SMH, individuals seek out alternative strategies to cope with these trauma-related psychological symptoms, as they are found to be unwanted or unpleasant (Khantzian, 1997). One such strategy is the use of substances – like drugs or alcohol (Khantzian, 1997; Turner et al., 2018).

When it comes to the type of substance used, the SMH dictates that the choice is often made based on which substance best ameliorates or relieves the psychological symptoms found to be problematic or painful (Hawn et al., 2020; Khantzian, 1997). For example, one may use alcohol as an attempt to alleviate anxiety – as alcohol has sedating properties. Another may use amphetamine, a known stimulant, to decrease poor concentration. However, while substances have the ability to reduce unwanted or unpleasant psychological symptoms, their effects are often temporary and lead to short-term negative reinforcement (Hawn et al., 2020). This creates a cycle where repeated and increased use of substances is necessary to continue to cope, allowing for substance use to progress into problematic or disordered use (Hawn et al., 2020).

As substance use transitions from recreational to problematic or disordered, the risk of experiencing substance-related consequences increases. Given that victimization and substance use are already prevalent among college students and knowing that polyvictimization is a known risk factor for the development of substance use problems, the SMH has been used to create an adapted conceptual model for this study (see Figure 2). The SMH has been adapted for use in several other studies examining similar concepts with success (Hawn et al., 2020).

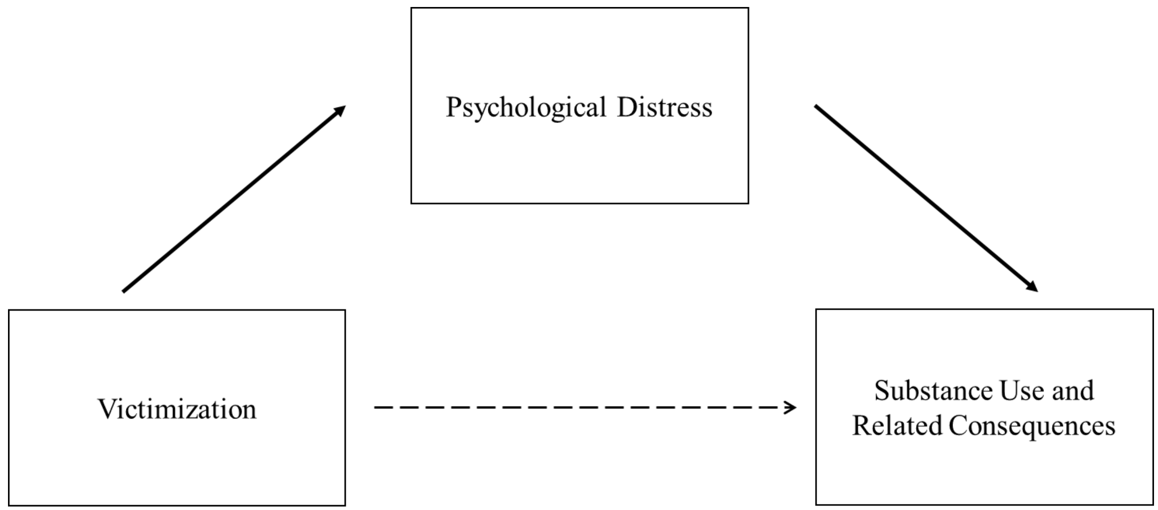

Figure 2. Self-Medication to Cope with Victimization Conceptual Model
Note: The dashed arrow represents a direct pathway, while the solid arrows represent indirect pathways.

However, use of the SMH is not without limitations. Firstly, the SMH is not always conceptually clear when addressing persons who present with dual diagnosis (i.e., have both a substance use disorder and psychopathology), making empirical support challenging to evaluate (Henwood & Padgett, 2007). Secondly, the SMH was originally established based on the review of case studies involving clinical samples with severe heroin use disorder – limiting casual conclusions and generalizability to lower acuity samples or to individuals who used substances at less severe levels or who use a substance other than heroin (Alexander & Ward, 2018). Despite these limitations, prior studies have found evidence to support the SMH even in lower acuity, dual diagnosis, and non-heroin use populations (Alexander & Ward, 2018).

The Self-Medication to Cope with Victimization Conceptual Model

For this study, the SMH is valuable in that it provides a framework for understanding the potential associations between victimization and substance use. The SMH also allows for the testing of psychological distress as a mediator. Based on the basic tenants of the SMH, it is implied that substance use becomes a coping mechanism for the alleviation of unwanted or unpleasant trauma-related psychological symptoms following a stressor. In this case, the stressor acts as an independent variable, substance use acts as a dependent variable, and unwanted or unpleasant trauma-related psychological symptoms (i.e., psychological distress) act as mediators. With this in mind, the SMH has been used to create an adapted conceptual model to guide this study.

The *Self-Medication to Cope with Victimization Conceptual Model* (see Figure 2) was designed to focus on victimization in any form, number, or context. In this model, victimization acts as the stressor (i.e., the independent variable), substance use acts as the coping mechanism (i.e., the dependent variable), and psychological distress acts as the unwanted or unpleasant trauma-related psychological symptoms (i.e., the mediator). When it comes to addressing current knowledge gaps, the *Self-Medication to Cope with Victimization Conceptual Model* allows for an understanding of the direct and indirect pathways that may connect the concepts of victimization and substance use and related consequences together. Thus, allowing for future research studies to target one of these indirect or direct pathways if potential associations are uncovered.

Chapter 3. Methods and Analytics

To achieve the aforementioned aims of this study, a secondary data analysis was completed. Data used in this secondary analysis have been extracted from a dataset provided by the American College Health Association (ACHA). The ACHA is a U.S.-based organization representing over 700 institutions of higher education (ACHA, 2022). The ACHA serves as the principal leadership organization for the advancement of college student and campus community health across the U.S. (ACHA, 2022).

Data Collection and Organization

In order to obtain the ACHA-National College Health Assessment (NCHA) III data for secondary analysis, the primary investigator first had to become a member of the ACHA. After ACHA membership was confirmed through submission of an assigned member number, a data use request form was completed. Due to the ACHA not allowing requests for the full ACHA-NCHA III dataset, only questions related to student demographics, mental health, substance use, and victimization were requested. Once obtained, a thorough review of survey questions was completed. Only questions related to the aims of the study were retained. See Appendix B and C for copies of the ACHA Data Use Permission Letter and Data Use Guidelines that pertain to this study. Upon approval of the data request form, a *SPSS* file of requested data was provided via electronic mail. In order to keep the received data protected, the *SPSS* file was uploaded to a secured server immediately upon receipt. The requested data were de-identified by the ACHA Research Team prior to data retrieval.

Per correspondence with the ACHA Research Team, an error was detected with the categorization of the Kessler 6 Distress Scale (K6) in the ACHA-NCHA III. While the K6 raw scores were identified as being correct in the data file received, the categorical variable RKESSLER6 collapsed the KESSLER6 variable into the categories of *no/low*, *moderate*, or *serious* levels of psychological distress – which is incorrect. As explained by the ACHA Research Team, "the original cutoff used for the MODERATE psychological distress category was a score of 9. A cutoff score of 5 to indicate MODERATE psychological distress is what is supported in the literature and what should have been used" (T. Klenner, personal communication, August 29, 2022). As a result, the *SPSS* syntax for recoding RKESSLER6 was provided by the ACHA Research Team. This syntax was run to correct this error before data was transferred from *SPSS* to *R*.

Data Management, Storage, and Protection

Being that this study utilizes secondary data, risk to participants is low. However, this study also embeds additional human subject protection. Data retrieved from the ACHA Research Team will remain de-identified and stored in a designated folder on a secured server (i.e., "R drive") through The Ohio State University College of Nursing. Use of de-identified data, and a secured server, will protect the primary study respondents from potential harm originating from this study. No attempts will be made to connect participants to any of the used secondary data. Any files that contain ACHA-NCHA III data will also be saved in the aforementioned folder on the secured server. Permission to access this folder has only been granted to the study team; ability to access the data in the folder has been restricted to the primary investigator, the co-investigator, and the consulting statistician. This study has also been subject to review, by The Ohio State University Behavioral and Social Sciences Institutional Review Board, who approved this study through an expedited review.

Data

The ACHA-NCHA is a nationally recognized health survey centered around college student health habits, behaviors, and perceptions (ACHA, 2021). Developed by the ACHA in 2000, the ACHA-NCHA serves as a tool for comprehensive understanding of present U.S. college student health; the metrics originating from the ACHA-NCHA provide postsecondary institutions the ability to benchmark selected health outcomes in comparison to a national sample (Lederer & Hoban, 2022). The overall purpose of the ACHA-NCHA is to collect national-level data on college student demographic characteristics, substance use, mental health, personal safety, violence exposure, preventative health practices, physical health, relationship difficulties, sexual health, and academic performance. There have been several ACHA-NCHA surveys since initiation of the pilot program in 2000, with each survey updated or revised to include emergent health issues observed by the ACHA.

The ACHA-NCHA III is an 86-question, web-based survey. While not required, participating postsecondary institutions are granted the ability to add their own supplemental campus-based questions; all supplemental campus-based questions are added to the ACHA-NCHA III as items under an 87th question at the end of the survey (i.e., N3Q87). First collected in the Fall of 2019, the ACHA-NCHA III has been delivered to U.S. college students during fall and spring academic terms, with each of these terms serving as a distinct wave. For each wave, the survey is completed by a new group of student participants, resulting in distinct samples of cross-sectional data.

The current study examines one wave (i.e., Fall 2019) of ACHA-NCHA III data. The ACHA-NCHA III was selected for use in this study because: (1) it contains a large, nationally representative sample of current college students; (2) it assesses several types of collegiate victimization experiences; and (3) it assesses the use of multiple substances. It is important to note that, despite the ACHA-NCHA III being the third survey in the ACHA-NCHA series, it is not appropriate to make comparisons between previous ACHA survey measures.

Institution Survey Request and Survey Setting

Any public, private, two-year, or four-year postsecondary institution in the U.S. is eligible to request the ACHA-NCHA III survey for use. Managed by the ACHA and select institutional coordinators, participating colleges are provided the ACHA-NCHA III survey in a web-based form after paying a fee for survey access. The ACHA-NCHA III is then delivered to students through their respective postsecondary institution as a confidential, voluntary, web-based survey.

Requests to complete the survey are delivered to students via the email address held by the participating institution. Upon completion of the ACHA-NCHA III survey by all participating students, the ACHA provides each respective postsecondary institution with their own institution's dataset, frequency report of results, and executive summary of key findings (Lederer & Hoban, 2022). Participating institutions are also provided an aggregated results report and executive summary of key findings from all institutions that participated in that wave (Lederer & Hoban, 2022).

Students selected for participation are free to complete the survey on any web-accessible device of their choice. The survey can be completed in multiple sessions, as students can save their responses and return to the survey at another time. When returning to complete the survey, students can use a device that differs from the one used prior, but they may only use one device at a time (ACHA, 2020). Once the "Submit Survey" button on the last page of the survey is submitted, the link between the student's email address and survey responses is destroyed (ACHA, 2020).

Recruitment, Informed Consent, and Respondent Privacy

Recruitment of ACHA-NCHA III survey respondents was undertaken by the participating postsecondary institution through a randomized sampling method. *Qualtrics Research Suite* software was used to generate unique survey links for each student on the mailing list. The unique survey link was connected to a randomly generated response identification number, allowing for de-identification of students who participated. The response identification number allows for: 1) prevention of more than one survey submission per student participant, 2) follow-up with only non-responders with survey reminder messages, 3) facilitation of a random drawing to award incentives at the close of the survey, and 4) ability for students to complete the survey in multiple sessions from more than one device. Those requesting ACHA-NCHA III data are not provided student response identification numbers. Respondents completed the informed consent process upon receiving the survey; an overview of the survey was provided prior to participation. Students were then able to opt in or out of the survey after reading the overview.

Several privacy protections were embedded into the ACHA-NCHA III. Student email addresses provided by participating postsecondary institutions were used for the sole purpose of requesting student participation in the study. Student email addresses were used only for a single survey effort and were not retained. The file containing student email addresses were uploaded into *Qualtrics Research Suite* software. Student emails were not shared with another party nor used for any other purpose. To ensure that no copies of student email addresses were retained, files containing student email addresses were intentionally deleted from Trash folders in *Box* – which cannot be retrieved after a 14-day grace period through *Box* User Services Support Team. Additionally, the utilized ACHA-NCHA III study survey implementation protocol was made confidential.

Participants and Sample

To participate in the ACHA-NCHA III survey, students had to be attending a U.S. postsecondary institution that requested access to the survey from the ACHA. Recruitment of students occurred through each participating postsecondary institution during the Fall 2019 academic term. A total of 38,679 students, from 58 total postsecondary institutions, participated (see Table 2). Students who completed a former ACHA-NCHA survey were not eligible to participate again and were excluded. Students were required to be at least 18 years of age and provide informed consent to participate. No other criteria were used to include or exclude students from participating.

Institution Characteristic	*n*
Type of Institution	
Public	29
Private	29
Two-year	5
Four-year	53
Geographic Location	
Northeast (CT, ME, MA, NH, NJ, NY, PA, RI, VT)	11
Midwest (IL, IN, IA, KS, MI, MN, MO, NE, ND, OH, SD, WI)	13
South (AL, AR, DE, DC, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX, VA, WV)	25
West (AK, AZ, CA, CO, HI, ID, MT, NV, NM, OR, UT, WA, WY)	9
Institution Size	
< 2,500 students	12
2,500-4,999 students	11
5,000-9,999 students	14
10,000-19,999 students	9
≥ 20,000 students	12
Institution Setting	
Very large city (population > 500,000)	10
Large city (population 250,000-499,999)	4
Small city (population 50,000-249,999)	24
Large town (population 10,000-49,999)	16
Small town (population 2,500-9,999)	4
Rural community (population < 2,500)	0
Religious Affiliation	
Yes	15
No	43
Minority Institution	
Yes	12
No	46
Total Number of Institutions	**58**

Table 2. Demographics of Participating Postsecondary Institutions

Survey Layout and Skip Logic Mechanism

Survey items included on the ACHA-NCHA III are organized based on topic area: *Overall Health and Community; Weight, Nutrition, and Exercise; U.S. Department of Agriculture Food Security; Sleep; Safety; Alcohol, Tobacco, and Other Drugs; Sexual Health; Mental Health; Services Used; Medical; Chronic Conditions; Impediments to Academic Performance;* and *Demographic Characteristics*. If selected by the respective postsecondary institution, an additional topic area of *Firearms or Campus-Specific Questions* can also be added. Scales embedded into the ACHA-NCHA III are placed under the corresponding topic area where they are most relevant (e.g., the Kessler 6 Distress Scale under the topic area of Mental Health). Identification of survey items can be broken down into three parts: the ACHA-NCHA survey being used, the question number, and relevant sub-items. For example, item N3Q22A1 denotes use of the ACHA-NCHA III survey (i.e., N3), question number 22 (i.e., Q22), and a sub-item (i.e., A1).

The ACHA-NCHA III uses a built-in skip logic mechanism through *Qualtrics Research Suite* software. Skip logic allows for the survey to send respondents to a future point on the survey based on how they respond to a certain item. For the ACHA-NCHA III, the skip logic mechanism results in the triggering of sub-items based on general item response. For example, relevant to the current study, responding “yes” to *lifetime substance use* then triggers sub-item *past three-month substance use*. In cases where an item is answered in a way which does not prompt sub-item response, this same skip logic mechanism then skips over the connected sub-items and brings the respondent to the next main survey item.

Measures and Instrumentation

The current study uses selected items and scales from the ACHA-NCHA III. Details concerning the selected items and scales follow below.

Intimate Partner, Non-Intimate Partner, and General Victimization

All survey items related to victimization have been aggregated and condensed into three categories based on harm target: *intimate partner victimization*, *non-intimate partner victimization*, and *general victimization* (see Table 3). Intimate partner victimization, comprised of five questions (N3Q19A-E), has been further condensed into three victimization types based on intent of harm: psychological (N3Q19A-B), physical (N3Q19C), and sexual (N3Q19E). Similarly, six of the seven non-intimate partner victimization items (N3Q20B-G) have been condensed into four victimization types based on intent of harm: physical (N3Q20B), verbal (N2Q20C), sexual (N3Q20D-F), and stalking (NQ20G).

It is important to note that the first non-intimate partner victimization item (N3Q20A) has been omitted, as it does not denote if victimization occurred, only if one was involved in a physical fight. For general victimization, six items (N3Q47A13-18) have been condensed into four victimization types based on intent of harm: bullying/cyberbullying (N3Q47A13-14), hazing (N3Q47A15), microaggression/discrimination (N3Q47A16/18), and sexual (3Q47A17). All ACHA-NCHA III items pertaining to victimization asked respondents to report (yes/no) victimization experiences occurring in the past year.

Measure	Type of Victimization
Intimate Partner Victimization	**Psychological** *A partner called me names, insulted me, or put me down to make me feel bad.* (N3Q19A) *A partner often insisted on knowing who I was with and where I was or tried to limit my contact with family or friends.* (N3Q19B)
	Physical *A partner pushed, grabbed, shoved, slapped, kicked, bit, choked, or hit me without my consent.* (N3Q19C)
	Sexual *A partner forced me into unwanted sexual contact by holding me down or hurting me in some way.* (N3Q19D) *A partner pressured me into unwanted sexual contact by threatening me, coercing me, or using alcohol or other drugs.* (N3Q19E)
Non-Intimate Partner Victimization	**Physical** *I was physically assaulted (do not include sexual assault).* (N3Q20B)
	Verbal *I was verbally threatened.* (N3Q20C)
	Sexual *I was sexually touched without my consent.* (N3Q20D) *Sexual penetration (vaginal, anal, oral) was attempted on me without my consent.* (N3Q20E) *I was sexually penetrated (vaginal, anal, oral), or made to penetrate someone without my consent.* (N3Q20F)
	Stalking *I was a victim of stalking (for example: waiting for me outside my classroom, residence, or office; or repeated emails/phone calls). (*N3Q20G)
General Victimization	**Bullying/Cyberbullying** *Bullying (for example: making threats, spreading rumors, physical or verbal attacks, or excluding someone from a group)* (N3Q47A13) *Cyberbullying (use of technology to harass, threaten, embarrass, or target another person)* (N3Q47A14)
	Hazing *Hazing (rituals, challenges, and other activities involving harassment, abuse, embarrassment, ridicule, or humiliation used as a way of initiating a person into a group)* (N3Q47A15)
	Microaggression/Discrimination *Microaggression (a subtle but offensive comment or action directed at a minority or other non-dominant group, whether intentional or unintentional, that reinforces a stereotype)* (N3Q47A16) *Discrimination (the unjust or prejudicial treatment of a person based on the group, class, or category to which the person is perceived to belong)* (N3Q47A18)
	Sexual *Sexual Harassment (unwelcomed sexual advances, requests for sexual favors, and other verbal or physical conduct of a sexual nature)* (N3Q47A17)

Table 3. Measures of Victimization

Past Three-Month Substance Use

Substance use is measured on the ACHA-NCHA III with the Alcohol, Smoking, and Substance Involvement Screening Test (ASSIST; α=.89; Humeniuk et al., 2006; World Health Organization [WHO], 2002). The ASSIST is used to screen for problematic or risky use of tobacco, alcohol, cannabis, cocaine, sedatives, prescription stimulants, prescription opioids, inhalants, hallucinogens, and other drugs (Humeniuk et al., 2006; WHO 2002). For the current study, two embedded ASSIST items are being used: *lifetime use* (i.e., item N3Q22A) and *past three-month use* (i.e., item N3Q22B).

Lifetime use and *past three-month use* are both broken down into 12 sub-items based on substance class. For example, if a student responds “yes” to *lifetime use* for at least one substance class, the ACHA-NCHA III survey then triggered the *past three-month use* item for that respective substance. If the student selected “no,” they skipped item N3Q22B due to the ACHA-NCHA III survey skip logic feature. Despite the skip logic mechanism resulting in missing data for *past three month use*, if *lifetime use* had a “no” survey response, all missing values for those responding “no” will be recoded to also show a value of “no.”

For this study, all classes of substances captured by the ACHA-NCHA III embedded ASSIST (N3Q22A1-11) were entered into analyses separately – except for prescription opioids (N3Q22A11) and heroin (N3Q22A10), which have been condensed into a single *opioid* class. The other substance classes examined in this study include: *nicotine*, *alcohol*, *cannabis*, *cocaine*, *prescription stimulants*, *sedatives*, *hallucinogens*, *methamphetamine*, and *inhalants*. All analyses focused on substance use occurring in the past three months, rather than the lifespan. See Table 4 for a full list of included ASSIST items and corresponding substance classes.

Past Two-Week Binge Drinking Frequency

Despite the ASSIST capturing past three months use of alcohol, due to differences in alcohol use contexts, item N3Q28 (i.e., *Over the last two weeks, how many times have you had five or more drinks (males) or four or more drinks (females) containing any kind of alcohol at a sitting?*) has also been added into study analyses. This item assesses binge drinking episodes over the past two weeks. Respondents were prompted to select a response ranging from none to ≥10. For this study, binge drinking frequency has been reduced into three analytic categories: *no binge episodes*, *1-10 binge episodes*, and *≥10 binge episodes*.

Substance Use Measure	Type of Substance
ASSIST *In your life, which of the following substances have you ever used? For prescription medications, please report nonmedical use only. "Nonmedical use" means taking prescription drugs just for the feeling or experience they cause or taking them more often or at higher doses than prescribed.* (N3Q22A)	**Nicotine** *Tobacco or nicotine delivery products (cigarettes, e-cigarettes, Juul or other vape products, water pipe or hookah, chewing tobacco, cigars, etc.).* (N3Q22A1)
	Alcohol *Alcoholic beverages (beer, wine, liquor, etc.).* (N3Q22A2)
	Cannabis *Cannabis (marijuana, weed, hash, edibles, vaped cannabis, etc.).* (N3Q22A3)
	Cocaine *Cocaine (coke, crack, etc.).* (N3Q22A4)
	Prescription Stimulants *Prescription stimulants (Ritalin, Concerta, Dexedrine, Adderall, diet pills, etc.).* (N3Q22A5)
	Methamphetamine *Methamphetamine (speed, crystal meth, ice, etc.).* (N3Q22A6)
	Inhalants *Inhalants (poppers, nitrous, glue, gas, paint thinner, etc.).* (N3Q22A7)
	Sedatives *Sedatives or Sleeping Pills (Valium, Ativan, Xanax, Klonopin, Librium, Rohypnol, GHB, etc.).* (N3Q22A8)
	Hallucinogens *Hallucinogens (Ecstasy, MDMA, Molly, LSD, acid, mushrooms, PCP, Special K, etc.).* (N3Q22A9)
	Opioids *Heroin.* (N3Q22A10) *Prescription opioids (morphine, codeine, fentanyl, oxycodone [OxyContin, Percocet], hydrocodone [Vicodin], methadone, buprenorphine [Suboxone], etc.).* (N3Q22A11)

Table 4. Measures of Substance Use

Note: ASSIST = Alcohol, Smoking, and Substance Involvement Screening Test

Psychological Distress Severity

The Kessler 6 Distress Scale (K6; α=.89) is a truncated version of the Kessler 10 Distress Scale (K-10; α=.93), which functions as a measure of psychological distress and overall emotional state (Kessler et al., 2003). Comprised of six Likert scale questions, the K6 contains items focused on the presence of nervousness, hopelessness, worthlessness, fatigue, irritability, and negative affect over the past 30 days (Sunderland et al., 2011). Scores on the K6 range from zero (no items selected) to 24 (all items selected); the higher the score, the higher the level of psychological distress (Sunderland et al., 2011).

The K6 items embedded into the ACHA-NCHA III survey are rated on a five-point scale ("none of the time" = 0; "a little of the time" = 1; "some of the time" = 2; "most of the time" = 3; "all of the time" = 4) with a score of zero denoting no experience of a symptom and a score of four denoting experience of a symptom continuously (Sunderland et al., 2011). For this study, K6 scores were examined as a continuous variable. Following latent class analysis, K6 scores were incorporated into a series of causal mediation analyses as a mediator. The K6 scores of the entire sample were then compared to each latent class and categorized based on latent class average: *no/low psychological distress* (0-4), *moderate psychological distress* (5-13), and *severe psychological distress* (13-24) (Prochaska et al., 2012). The K6 can be found listed as item N3Q44 on the ACHA-NCHA III survey. See Table 5 for a full description of the embedded K6 and related sub-items.

Psychological Distress Measure	Type of Psychological Distress Symptom
K6 *During the past 30 days, about how often did you feel...*	*...nervous?* (N3Q44A)
	...hopeless? (N3Q44B)
	...restless or fidgety? (N3Q44C)
	...so sad nothing could cheer you up? (N3Q44D)
	...that everything was an effort? (N3Q44E)
	...worthless? (N3Q44F)

Table 5. Measures of Psychological Distress
Note: K6 = Kessler 6 Distress Scale

Student Demographic Characteristics

To examine differences in victimization, substance use, and psychological distress across student groups, several demographic characteristics were included in analyses: sexual orientation, gender identity, race/ethnicity, place of residence, disability status, year in school, enrollment status, and extracurricular student organization involvement (i.e., student athletics and Greek-letter organization). Demographic items, with responses totaling less than 5% of the total wave sample, have been condensed into other categories for analysis purposes. Sexual orientation (N3Q68) has been condensed into four categories based on percent of respondents: *straight*, *bisexual*, *gay/lesbian*, and *other sexuality* (see Table 6). Similarly, gender identity (N3Q67C) was condensed into five categories based on prevalence percentage: *female*, *male*, *transgender*, *nonbinary*, and *other gender identity* (see Table 6).

Race/ethnicity (N3Q75A) was compressed into five categories based on percentage of the wave sample reporting: *White*, *Black*, *Asian*, *Hispanic*, and *other race/ethnicity* (see Table 6). Having an item response choice of biracial/multiracial, a sixth category of *biracial/multiracial,* was also examined. Students who selected more than one race, but did not explicitly select the item response of biracial/multiracial on the survey, were added to those already identified as biracial/multiracial manually and recoded. Residence (N3Q78 *Where do you currently live?*) was analyzed in this study as *on-campus* or *off-campus*.

Affiliation with a Greek-letter organization was also explored. Students who reported being a member of a Greek-letter organization (N3Q77A *Are you a member of a social fraternity or sorority?*) were categorized as either a *Greek-letter affiliate* or *non-Greek-letter affiliate*. A similar approach was taken with student athletics (N3Q81 *Do you participate in organized college athletics at any of the following levels?*), which condenses three items (i.e., *varsity, club sports, intramurals*) into two categories: *college athlete* and *non-athlete.*

Year in college (N3Q72) was assessed through three categories: *1st year undergraduate*, *2nd to 5th year undergraduate*, and *graduate* (i.e., master's and doctoral). Enrollment status (N3Q73) was simply examined as *full-time* or *part-time*. Students reporting at least one of the seven disability responses (N3Q82), were categorized as having a disability (i.e., *disability*), while those selecting none of the responses were categorized as not having a disability (i.e., *no disability*). All demographic characteristic categories were coded and incorporated into analyses as dichotomous variables, with a value of 1 denoting the value of the variable of interest (e.g., 1 = athlete, 0 = non-athlete).

Student Demographic Measures	Demographic Analytic Category
Sexual Orientation *What term best describes your sexual orientation?* (N3Q68)	Straight
	Bisexual
	Gay/Lesbian
	Other Sexuality: *Pansexual. Queer. Questioning. Asexual.*
Gender Identity *Which term do you use to describe your gender identity?* (N3Q67C)	Female
	Male
	Transgender
	Nonbinary
	Other Gender Identity: *Genderqueer. Agender. Genderfluid. Intersex.*
Race/Ethnicity *How do you usually describe yourself?* (N3Q75A)	White
	Black
	Asian
	Hispanic
	Other Race/Ethnicity: *Middle Eastern/North African or Arab Origin. Native Hawaiian or Other Pacific Islander. American Indian or Native Alaskan.*
	Biracial/Multiracial

Table 6. Student Sexual Orientation, Gender Identity, and Race/Ethnicity Measures

Data Analysis Plan

A latent class analysis (LCA) was performed in *R Version 4.2.1* using the poLCA package (Linzer & Lewis, 2011). Data were examined independently to identify how many latent classes, based on reported victimization, are present at this specific ACHA-NCHA III data collection point. Latent class analysis can be described as a statistical procedure that allows for the identification of qualitatively different classes among individuals who share similar characteristics. It is a person-centered mixture model that identifies subgroups in a sample (i.e., latent classes) using patterns of responses across survey questions, assessment indicators, and scales (Weller et al., 2020).

Identified subgroups, or "latent classes," are detected in LCA using unobserved heterogeneity (Weller et al., 2020). It is important to note, however, that latent class membership is not based on an individual's responses, rather latent class membership is based on probability. The basic premise of LCA is that being in a certain latent class will explain an individual's responses to certain categorical indicators (Weller et al., 2020). Or, to put it plainly, in LCA, an individual's responses to categorial indicators do not drive their latent class membership – their latent class membership drives their responses to categorical indicators.

After a sample has been chosen, indicators are selected to define the hypothesized latent classes, estimators are determined, and the dataset is structured (Weller et al., 2020). For this study, an LCA was performed using *intimate partner victimization, non-intimate partner victimization,* and *general victimization* survey items as indicators. Students from the ACHA-NCHA III survey, who did not have missing data for these indicators, were included in analyses. Data management and manipulation were conducted using *R*.

Latent class models were run multiple times while testing differing numbers of classes, starting with a two-class model. With each model generated, the number of classes increased by one (e.g., two-class model, three-class model, four-class model, et cetera). With LCA, model quality improves with each additional class; when model quality begins to deteriorate, additional classes are no longer added (Weller et al., 2020). When additional models no longer improve quality, the final number of generated models are compared to choose the model with the "best fit."

Latent Class Determination

Model fit was determined by examining Akaike information criterion (AIC), Bayesian information criterion (BIC), Lo-Mendell-Rubin (LMR) likelihood ratio tests, and relative entropy which helped to select the appropriate number of latent classes (Dziak et al., 2014; Lo et al., 2001; Nylund et al., 2007; Tofighi et al., 2008). Both AIC and BIC are considered reliable indicators of LCA model fit; the lower the information criterion value (i.e., lower BIC and AIC value) the better fit of a model (Weller et al., 2020). With BIC and AIC, lower values represent parsimony in models, indicating a better fit with the "best" number of classes.

Use of LMR likelihood ratio tests allow for the generation of a *p*-value for each model – which can help indicate if a LCA model with an additional class is a statistically a better fit than a previous model with fewer classes (Nylund et al., 2007; Weller et al., 2020). Relative entropy, on the other hand, is a diagnostic statistic that indicates how accurately a LCA model defines classes; relative entropy values from 0 to 1, with a value closer to one indicating a more accurate model (Weller et al., 2020). Typically, a relative entropy value greater than 0.80 is acceptable, but models that achieve relative entropy >0.95 are ideal. Use of these model fit statistics allow for a more accurate LCA model selection.

Smallest Latent Class Size Selection and Class Interpretability

Often, latent class models return different models with similar best fit statistics. In order to select the final, most appropriate latent class model, smallest class size and interpretability were examined. For smallest class size, a cut criterion of 5% was used. In cases where the proportion of the sample dedicated to each latent class is less than 5%, the model was considered cut from consideration – unless the class had theoretical significance and its presence in the model can be defended in the existing literature. Thus, models with latent classes containing less than 5% of the total sample from that wave were disregarded unless theoretically supported. A 5% cut criterion was set, as classes with less than 5% of the sample are difficult to replicate and would pose challenges for future work using these latent classes.

Further, interpretability was used to offer theoretical support for certain models; interpretation of generated models through a theoretical perspective allowed for the selection of a model which is best supported by the existing literature. For example, if a three-class model is the best fit statistically, but four classes are supported by the literature, then consideration would be made for a selection of a four-class model rather than a three-class model. To examine interpretability, line plots were generated using victimization endorsement probabilities, to examine how responses are divided between the latent classes. These line plots were examined to make a substantive decision on which model is the most interpretable.

Logistic Regression and Latent Class Associations

After latent classes were estimated, interpreted, and an appropriate model was selected, a demographic and descriptive statistics report was run on each class to describe the demographic makeup of each class. In order to examine proportional differences between classes, Chi-square testing was completed for each demographic under each latent class. In the case of age, however, a *t*-test proportional differences were generated – due to age being a continuous variable. Next, logistic regressions were run to examine the likelihood of substance use based on latent class membership. For these regressions, latent class associations were used to predict likelihood rates for certain substance use classes and substance use overall. Casual mediation analyses, with psychological distress (i.e., K6 scores) added as a mediator, were then completed. Use of the K6 scores were used to examine the average amount of psychological distress across the sample, in comparison to each latent class.

Management and Omission of Missing Data

While completing the ACHA-NCHA III, students are able to skip any questions they do not wish to answer. Based on the sensitivity of the questions pertaining to this study, a certain degree of missingness was expected. Further, due to the triggering of the skip logic mechanism built into the survey, questions answered "no" prevent the triggering of the next set of items pertaining to the question, leading to a high percent of missingness for several items by default. Due to this skip logic mechanism, some items had high degrees of missingness.

Missing responses will be examined for patterns and trends across included items. In cases where over 5% of survey item responses were missing, data was examined for evidence of missingness due to the skip logic mechanism. Further, to control sample size and obtain appropriate latent classes, only respondents who answered all ACHA-NCHA III survey items relating to variables of interest (i.e., *intimate partner victimization*, *non-intimate partner victimization, general victimization*, and *psychological distress*) were included. Even with the omission of students with missing item responses, a total of 95.6% of student respondents were retained – making the total final sample 36,986. With less than 5% missing data, it is considered acceptable in the literature to proceed with the analysis without use of missing data procedures (Dong & Peng, 2013; Kang, 2013).

Power and Effect Size

Power for LCA was calculated using power curves and benchmark sample size tables calculated by Dziak and colleagues (2014). These indicate that even with small differences in the likelihood of experiencing each type of victimization across classes (Cohen's w = .06), this sample provides more than adequate power to correctly detect the appropriate number of classes, as a sample of 1,600 provided power > .80 with a similar number of indicators (i.e., 12-16). Further simulation studies indicate that a sample size of 2,000 is adequate (power > .80) to detect small associations between latent class membership even with small differences in the likelihood of experiencing victimization across classes (w = .06) (Geiser & Wurpts, 2014; Wurpts, 2012). Therefore, the total sample of 36,986 was sufficient to examine associations between latent class membership, substance use, and related consequences. Monte Carlo simulations were used to determine power for indirect effects. Results indicate that this study was adequately powered to detect indirect effects resulting from small to moderate effects (rs = .20; indirect effect = .04) even for outcomes with a prevalence of less than 5% (power > .80).

Despite omission of participants with missing response items, this study is high powered. Effect sizes were attended to in order to ensure that errors are not made due to the large sample size and resulting high power. Effect sizes smaller than the benchmarks for a small effect size (e.g., r = .20) were interpreted with caution. If results suggested that findings are overpowered (e.g., very small effects that are significant with an alpha of 0.05), alpha for analyses were decreased (e.g., from 0.05 to 0.01 or 0.001) to reduce the likelihood of Type I errors that may arise from the large sample size.

Strengths and Limitations of Analytic Plan

Data analyzed in this study is cross-sectional in nature. Use of cross-sectional data prevents analysis of potential longitudinal associations that may be present between victimization and substance use. Further, this study used cross-sectional data to conduct preliminary tests of hypothesized mediation effects. There are noted limitations to the use of cross-sectional data for mediation, including inability of such analyses to determine the temporal order of variables and distinguish associations that co-occur in time from prospective associations (Maxwell & Cole, 2007; O'Laughlin et al., 2018). Additionally, due to a low percentage of responses for certain demographic items, some important minority groups were compressed into single categories. This does not allow for deeper exploration of select minority groups that may be particularly at-risk.

Despite these limitations, the examination of mediation utilizing cross-sectional data is a first step in identifying potential mechanisms that may help to explain expected associations between victimization and substance use. Additionally, LCA can be subject to naming fallacy. With LCA, the names assigned to identified latent classes are made based on available information about the classes. Due to the complexity of classes, one may advertently name a class in a way that does not accurately reflect class membership, creating a case where a latent class is not appropriately named (Weller et al., 2020).

While this study has several noted limitations, it also has several strengths. Firstly, this study is adequately powered, allowing for indirect effects to be detected. Secondly, the primary study includes participants from 58 U.S. colleges and universities, not a single site or state – allowing for greater generalizability of findings. Further, being a secondary data analysis, the risk to human subjects is low – as included data have already been de-identified by the ACHA Research Team. This study also allowed for associations to be made across a range of substances, demographic characteristics, and victimization types. With several prior studies looking only at a small number of substances, victimization types, or specific populations – this study was innovative and capable of capturing potential associations yet to be identified.

Chapter 4. Findings

Data were cleaned and recoded, per the aforementioned plan, using *R Version 4.2.1.* Using the poLCA package, a null one-class model was fit. Following this, the number of latent classes generated was increased by one (i.e., to a two-class model) to compare model fit to the original sample (i.e., the null one-class model). Subsequent models were generated, adding one new latent class each time (i.e., three-class model, four-class model, et cetera). Best fit statistics (Table 7) and victimization endorsement probabilities were generated for all latent classes with each new model. Once model quality began to deteriorate, no further latent classes were added.

Best fit statistics for all models were then compared to identify the models that were the best fit statistically. Line plots were created using victimization endorsement probabilities for each respective model, to examine patterns across the latent classes. These line plots, along with the victimization endorsement probabilities, were then used to name latent classes generated in each model (e.g., a latent class with low or no levels of probability endorsement across all types of victimization would be named the "*low/no*" class; a latent class with high levels of probability endorsement across all types of victimization would be named the "*high/poly*" class). Smallest latent class size and class interpretability were then used to determine which model was the best fit theoretically.

A final, preferred LCA model was then selected by consensus – picking the model that was the best fit both statistically and theoretically. Demographic reports were generated to examine the makeup of each individual latent class in the selected model. It is imperative to note, however, that student respondents who selected ≥ 2 races were coded as being under the category *biracial/multiracial*. After *R* recoding, those students were combined with the students who responded that they were "biracial or multiracial" on the ACHA-NCHA III survey. Coding was completed in order to avoid recounting students who selected multiple races *in addition to* the biracial/multiracial response option (e.g., selected Black, Hispanic, and biracial/multiracial rather than just biracial/multiracial without specifying) (see Appendix 1).

Chi-square and *t*-test proportional differences were also generated to examine differences between latent classes via demographic makeup. After model selection, a series of logistic regressions were run for the latent classes within the selected LCA model. Using each latent class as a predictor, separate logistic regressions were completed for each substance use outcome. Findings of logistic regressions were compared across all substances. Casual mediation analyses, with the addition of psychological distress (i.e., K6 scores) as a mediator, were then completed – to examine if psychological distress functions as a mechanism through which typologies of victimization may contribute to substance use across latent classes.

Latent Class Determination

A series of latent class models were generated, with the number of latent classes included increasing by one with each subsequent model. Commonly accepted best fit statistics (i.e., BIC and AIC) were examined and models were compared – with smaller values denoting a better model fit. As subsequent latent classes were added, BIC and AIC values decreased (see Table 7). The lowest BIC and AIC values were seen with the final, eight-class model; whereas the highest BIC and AIC values were seen with the two-class model – excluding the one-class model as it is a null model generated only for comparison to the original sample. Model deterioration (i.e., relative entropy value below 0.80) began with the eight-class model, so models with nine or more latent classes were not included in comparisons.

One likelihood based index was used, LMR, which provided a *p*-value to compare models with one less latent class (e.g., two-class model compared to a one-class model; three-class model compared to a two-class model). For all models generated, the *p*-value was found to be significant ($p < 0.001$). Due to this, LMR did not contribute to the decision of which model was preferred. Relative entropy values varied across models. All models, save for the eight-class model, had a relative entropy value above 0.80 (see Table 7). With a relative entropy value closer to 1 being ideal, this LCA suggested that, based on entropy alone, the models with the "best fit" were those with five- (0.84), six- (0.86), and seven-classes (0.86). However, all models, excluding the eight-class model, met the 0.80 minimum threshold for selection. It is important to note, however, that due to *R* generating entropy and not relative entropy, additional coding was added to change entropy into an interpretable form. See Appendix 1 for all *R* coding used in this LCA.

Smallest Class Size and Class Interpretability

Using the victimization endorsement probabilities for each latent class, line plots were generated to examine differences in victimization by students allocated to each class. Line plots were created for the four-class, five-class, six-class, and seven-class models – as a four-class or five-class model are the most routinely supported by the literature and the five-class, six-class, and seven-class models were the most "significant" per the best fit statistics. Using a cut criterion of 5%, models with multiple latent classes containing less than 5% victimization probability endorsement were excluded from consideration. The seven-class model, followed by the six-class model, were excluded based on not meeting the set 5% cut criterion across several latent classes.

Comparisons between the four-class and five-class model were then made. Being that the five-class model also had latent classes with less than 5% endorsement, and since one of the classes created with the five-class model had a low level of interpretability, a consensus was reached with statistical consultation to exclude the five-class model. Specifically, through the five-class model, a *physical assault/discrimination* latent class was generated. This latent class was not theoretically clear, and student allocation demonstrated no interpretable connections based on student demographics (e.g., lack of support for minority victimization as demographics showed no significant differences across minority demographics). A review of the literature also lacked justification for the inclusion of the *physical assault/discrimination* latent class.

While the five-class model also included an *intimate partner* latent class (characterized primarily by physical and psychological intimate partner victimization), this same class siphoned students from the *high/poly* latent class from the four-class model. As latent classes are added to each model, students get re-allocated. Thus, students can be allocated to differing latent classes across models – as what groups students together in the latent classes can change with each model. Being that this dissertation is focused on polyvictimization, and not solely intimate partner victimization, the decision to select the four-class model was also made based on retention of a *high/poly* class with a slightly higher student allocation.

Despite having a higher AIC/BIC, and a lower relative entropy (0.81 versus 0.84), the four-class model was selected based on interpretability and theoretical support. The four-class model generated the following latent classes: *high/poly* (class one; n = 954; 2.6% of sample), *verbal/discrimination* (class two; n = 3,267; 8.8% of sample), *sexual/discrimination* (class three; n = 2,426; 6.5% of sample), and *low/no* (class four; n = 30,171; 81.6% of sample).

Naming the Latent Classes

The *high/poly* latent class was characterized by high victimization endorsement probabilities across a majority of included victimization types – and thus named as such. A victimization endorsement probability of at least 50% was seen across six types of victimization in the *high/poly* latent class: *intimate partner physical, intimate partner psychological, intimate partner sexual, non-intimate partner verbal, non-intimate partner sexual,* and *general sexual* (see Table 8). All other types of victimization were also endorsed in the *high/poly* latent class, albeit below the 50% mark – with *non-intimate partner physical* being the lowest reported at 26%.

The *verbal/discrimination* latent class predominantly contained victimization endorsement probabilities relating to *non-intimate partner verbal* and *general discrimination* – both slightly above 39%. *Intimate partner psychological* (36%) and *general bullying* (25%) types of victimization were also endorsed within this class, but the naming of this class was based on the two highest reported victimization types. While other forms of victimization also had a probability of endorsement, a majority were at an endorsement probability at, or below, 10% (see Table 8).

Similarly, the *sexual/discrimination* class was aptly named after the top three victimization endorsement probabilities: *non-intimate partner sexual* (45.1%), *general sexual* (79.8%), and *general discrimination* (55.2%). *Non-intimate partner verbal* (25.3%) and *general bullying* (22%) were the next two highest seen probabilities in this class. The other possible victimization types also had some reported endorsement probabilities, but at lower percentage levels (see Table 8).

Finally, the *low/no* class was named due to a majority of victimization types being under 10% - with only one victimization type (i.e., *general discrimination*) getting above 10%. In fact, the second highest victimization probability came from *intimate partner psychological* – with an endorsement probability of only 5.7%. All other types of victimization had endorsement probabilities below 5% (see Table 8). See Figure 3 to see all endorsement probabilities, across all four latent classes, presented in a visual form.

Demographics and Proportional Differences Across Latent Classes

When examining students from all latent classes together, a majority of the students represented in this LCA were White, heterosexual, cis-gendered females. A majority of these students were also enrolled fulltime, classified as undergraduate, lived off-campus, were not athletes, were not disabled, and were not Greek-letter organization affiliated (see Table 9). However, simply going off the number and percentages of the students of various demographic characteristics does not allow for patterns between classes to be easily seen.

In order to examine proportional differences between classes, Chi-square testing was completed for each demographic characteristic for each latent class. In the case of age, however, *t*-test proportional differences were generated – due to age being a continuous variable. Through this, patterns could then be examined through the proportion of the total number of students identifying with a demographic characteristic falling into a respective latent class compared to other classes. It is important to note, however, that confidence and reliability of these tests decrease when looking at a demographic containing less than 5% of the class. Also, it is imperative to remember that for disability, year in college, enrollment status, residence, athletics, and Greek-letter organization affiliation – variables are dichotomous (i.e., recall that a value of 1 means the student reported the variable of interest).

Race/Ethnicity

When examining student race/ethnicity, for students identifying as Black: there were 89 (10% of the class) students allocated to the *high/poly* class, 337 (11% of the class) allocated to the *verbal/discrimination* class, 201 (8% of the class) allocated to the *sexual/discrimination* class, and 2,348 (8% of the class) allocated to the *low/no* class. Proportional differences were significant in the *verbal/discrimination* class compared to the *sexual/discrimination* and *low/no* classes. Specifically, these results demonstrate that Black students made up a larger proportion of the *verbal/discrimination* class than the *sexual/discrimination* and *low/no* class. No proportional differences were observed between *high/poly* and the other three classes.

Examining the proportion of White students making up each class revealed, 452 (49%) in the *high/poly* class, 1,615 (50%) in the *verbal/discrimination* class, 1,404 (59%) in the *sexual/discrimination* class, and 16,760 (56%) in the *low/no* class. Proportional differences were significant between the *sexual/discrimination* class and the other three classes, indicating that White students made up a larger proportion of the *low/no* and *sexual/discrimination* classes compared to the other two classes. Further, significant differences were found between the *verbal/discrimination* and *low/no* class; a larger proportion of White students made up the *low/no* class compared to the *verbal/discrimination* class.

For Hispanic students, 133 (14%) were in the *high/poly* class, 470 (15%) were in the *verbal/discrimination class*, 232 (10%) were in the *sexual/discrimination* class, and 4,139 (14%) were in the *low/no* class. Significant differences were noted only in the *sexual/discrimination* class compared to the other three classes; demonstrating that a smaller proportion of students identified as Hispanic in the *sexual/discrimination* group.

Looking at Asian students, 77 (8%) were in the *high/poly* class, 299 (9%) were in the *verbal/discrimination class*, 155 (6%) were in the *sexual/discrimination* class, and 3,336 (11%) were in the *low/no* class. Proportional differences were significant in the *low/no* class compared to the other three classes; *verbal/discrimination* and *sexual/discrimination* also proportionally differed – indicating that Asian students made up a larger proportion of the *low/no* class compared to the other classes, and a smaller proportion of Asian students made up the *sexual/discrimination* class than the *verbal/discrimination* class.

For students identifying as biracial or multiracial: there were 157 (17%) students allocated to the *high/poly* class, 413 (13%) allocated to the *verbal/discrimination* class, 364 (15%) allocated to the *sexual/discrimination* class, and 2,807 (9%) allocated to the *low/no* class. Significant proportional differences were noted between the *low/no* class and the other three classes; demonstrating that a small proportion of students identifying as biracial or multiracial made up the *low/no* class. Significant proportional differences were also detected between *verbal/discrimination*, *high/poly,* and *sexual/discrimination*. These results indicate that a larger proportion of students in the *high/poly* and *sexual/discrimination* classes are biracial or multiracial.

Students identifying with another race or ethnicity comprised a small percentage of the entire sample; only 1-2% of each class contained students identifying with another race/ethnicity. Due to this, the confidence and reliability of Chi-square testing in this case is decreased. However, at face value, students identifying with another race or ethnicity had a proportional difference that was significant between *low/no, high/poly,* and *verbal/discrimination*. No proportional differences were observed between *sexual/discrimination* and the other classes. Despite having a small number of students in these classes (i.e., *high/poly* $n = 23$ [2%], *verbal/discrimination* $n = 69$ [2%], *sexual/discrimination* $n = 35$ [1%], and *low/no* $n = 377$ [1%]), a larger proportion of the *high/poly* and *verbal/discrimination* classes were comprised of students identifying with another race or ethnicity.

Gender Identity

Female students made up a majority of all latent classes, with 689 (73%), 1,902 (58%), 2,021 (84%), and 18,567 (65%), allocated to the *high/poly, verbal/discrimination, sexual/discrimination*, and *low/no* classes, respectively. When examined proportionally, significant differences can be seen across all classes. These proportional differences across all classes demonstrate that female students are more likely to be in the *high/poly* and *sexual/discrimination* classes. A smaller proportion of female students can be found in the *verbal/discrimination* class compared to the *low/no* class.

For students identifying as male, 215 (23%) were in the *high/poly* class, 1,229 (38%) were in the *verbal/discrimination class*, 275 (11%) were in the *sexual/discrimination* class, and 11,108 (37%) were in the *low/no* class. Significant proportional differences were detected between *high/poly* and all other classes; *verbal/discrimination* and *low/no* were significantly, proportionally different than *sexual/discrimination* and *high/poly* – indicating that a larger proportion of the *verbal/discrimination* and *low/no* classes were male. A smaller proportion of males can be found in the *sexual/discrimination* class.

Students, with a gender identify other than female or male, make up a very small percentage of the entire sample. Thus, proportional comparisons across these groups have decreased reliability. However, at face value, when looking at nonbinary students: 11 (1%), 43 (1%), 49 (2%), and 150 (<1%) make up the *high/poly, verbal/discrimination,* *sexual/discrimination*, and *low/no* classes, respectively. Statistically, the *low/no* class differed from all three other classes, with nonbinary students making up a smaller proportion of all classes except *sexual/discrimination.*

All students identifying as transgender (i.e., *high/poly n* = 7 [1%], *verbal/discrimination n* = 25 [1%], *sexual/discrimination n* = 13 [1%], and *low/no n* = 65 [<1%]) or "other" (i.e., *high/poly n* = 24 [3%], *verbal/discrimination n* = 59 [2%], *sexual/discrimination n* = 62 [3%], and *low/no n* = 217 [1%]) also made up a small percentage of the entire sample. Students identifying as transgender, or another non-specified gender, had significant proportional differences between the *low/no* class and all other classes. This demonstrates that transgender students made up a smaller proportion of the *low/no* class.

Sexual Orientation

For students identifying as "straight" or "heterosexual:" 625 (66%) were in the *high/poly* class, 2,452 (76%) were in the *verbal/discrimination class*, 1,485 (61%) were in the *sexual/discrimination* class, and 25,478 (85%) were in the *low/no* class. Significant differences were detected between *high/poly* and all other classes; all classes were proportionally different from one another in a significant way. Thus, straight students made up a larger proportion of the *low/no* class, followed by the *verbal/discrimination* class, the *high/poly* class, and the *sexual/discrimination* class.

Bisexual students comprised 18% (*n* = 171), 13% (*n* = 410), 19% (*n* = 468), and 7% (*n* = 2,205) of the *high/poly, verbal/discrimination, sexual/discrimination*, and *low/no* classes, respectively. Significant proportional differences were detected between *low/no* and all other classes regarding these students. The *sexual/discrimination* and *verbal/discrimination* classes also differed. Together, results indicate that bisexual students made up a larger proportion of the *sexual/discrimination* class, followed sequentially by *high/low, verbal/discrimination,* and *low/no.*

Students identifying as gay or lesbian, combined together for analyses in this sample, made up 4% (*n* = 42), 5% (*n* = 158), 5% (*n* = 219), and 3% (*n* = 882) of the *high/poly, verbal/discrimination, sexual/discrimination*, and *low/no* classes, respectively. Proportional differences were significant for the *low/no* class compared to all other classes. No other proportional differences were seen, demonstrating that the smallest proportion of these students were allocated to the *low/no* class. For those students who identified with another sexual identity: 105 (11%) were in the *high/poly* class, 226 (7%) were in the *verbal/discrimination* class, 334 (14%) were in the *sexual/discrimination* class, and 1,462 (5%) were in the *low/no* class. Of these, significant differences in proportions were found across all classes; with gay and lesbian students making up a larger proportion of the *sexual/discrimination* class, followed sequentially by *high/*poly, verbal*/discrimination*, and *low/no.*

Year in College, Enrollment Status, and Residence

Year in college, for this study, was divided into three categories: first year undergraduate, 2nd to 5th year undergraduate, and graduate. First year undergraduate students made up 25% (*n* = 232), 23% (*n* = 739), 21% (*n* = 498), and 23% (*n* = 6,937) of the *high/poly, verbal/discrimination, sexual/discrimination*, and *low/no* classes. Differences in class allocation proportions were detected between *sexual/discrimination* and the *high/poly* and *low/no* classes. No differences were seen between *verbal/discrimination* and any other class; demonstrating that freshman students made up a larger proportion of the *high/poly* class followed by the *low/no* and *sexual/discrimination* classes.

For undergraduate students in their 2^{nd} to 5^{th} year: 589 (63%) were allocated to the *high/poly* class, 1,836 (57%) were allocated to the *verbal/discrimination class*, 1,479 (62%) were allocated to the *sexual/discrimination* class, and 16,449 (55%) were allocated the *low/no* class. Proportional differences were significant in the *high/poly* class compared to the *verbal/discrimination* and *low/no* classes; the *sexual/discrimination* class also differed from the *verbal/discrimination* and *low/no* classes. Specifically, these results demonstrate that 2^{nd} to 5^{th} year undergraduate students made up a significantly larger proportion of the *high/poly* class followed by the *sexual/discrimination* class. Graduate students (i.e., *high/poly* n = 120 [13%], *verbal/discrimination* n = 635 [20%], *sexual/discrimination* n = 417 [17%], and *low/no* n = 6,280 [21%]) had similar proportional differences as the 2^{nd} to 5^{th} year undergraduate students, only with an extra proportional difference of significance between *sexual/discrimination* and *high/poly*, with graduate students making up a smaller proportion of the *high/poly* class compared to the *sexual/discrimination* class.

Students enrolled fulltime made up 89% (n = 836), 89% (n = 2,905), 92% (n = 2,220), and 91% (n = 27,337) of the *high/poly*, *verbal/discrimination, sexual/discrimination,* and *low/no* classes, respectively. When examining proportional differences between the classes, significant differences were seen between *sexual/discrimination*, *high/poly*, and *verbal/discrimination.* Additional differences in proportion were also seen between *low/no*, *high/poly*, and *verbal/discrimination.* These findings indicate that fulltime students made up a larger proportion of the *sexual/discrimination* class, sequentially followed by the *low/no* class.

Parttime students (i.e., *high/poly n* = 104 [11%], *verbal/discrimination n* = 351 [11%], *sexual/discrimination n* = 193 [8%], and *low/no n* = 2,731 [9%]) had proportional differences that were significant between *sexual/discrimination, high/low,* and *verbal/discrimination*; an additional proportional difference was detected between *low/no* and *verbal/discrimination.* Specifically, these results demonstrate that students reporting a parttime enrollment status made up a large proportion of both the *high/poly* and *verbal/discrimination* classes at an equal rate.

Student residence, which was categorized in this study as on-campus or off-campus, also had notable proportional differences. For those students living on-campus, 338 (37%) were allocated to the *high/poly* class, 1,171 (36%) were allocated to the *verbal/discrimination* class, 978 (41%) were allocated to the *sexual/discrimination* class, and 11,585 (39%) were allocated to the *low/no* class. Proportional differences were significant for these students between *sexual/discrimination, verbal/discrimination,* and *high/poly*; an additional difference was detected between *verbal/discrimination* and *low/no* – demonstrating that students living on-campus made up a larger proportion of the *sexual/discrimination* class followed by the *low/no* class. The same proportional configuration was seen for students residing off campus, but at an inverse rate.

Athletics and Greek-letter Organization Affiliation

A majority of students in this sample were not involved in college athletics. However, for those that were: 195 (20%), 683 (21%), 466 (19%), and 6,991 (23%) were sorted into the *high/poly*, *verbal/discrimination, sexual/discrimination,* and *low/no* classes, respectively. Looking at proportional differences across classes, students in the *low/no* class were significantly different than the *verbal/discrimination* and *sexual/discrimination* classes – with student athletes making up a larger proportion of the *low/no* class. No proportional differences were observed between the *high/poly* class and the other three classes.

When it comes to Greek-letter organization affiliation, for students who were a member of a fraternity or sorority: 109 (11%) were in the *high/poly* class, 286 (9%) were in the *verbal/discrimination* class, 264 (11%) were in the *sexual/discrimination* class, and 2,394 (8%) were in the *low/no* class. Significant proportional differences were seen between the *high/poly* class and the *verbal/discrimination* and *low/no* classes; indicating that students with Greek-letter affiliation made up a larger proportion of the *high/poly* class. Proportional differences were also detected between the *sexual/discrimination* class and the *verbal/discrimination* and *low/no* classes – showing that Greek-letter affiliates made up a smaller proportion of the *verbal/discrimination* and *low/no* classes compared to the *sexual/discrimination* class.

Disability Status

Looking at disability, a majority of the original sample reported not having a disability. However, when looking at proportional differences between classes, students reporting a disability made up a larger proportion of all classes but *low/no*. Specifically, 300 (31%) students with a disability were allocated to the *high/poly* class, 754 (23%) were allocated to the *verbal/discrimination* class, 634 (26%) were allocated to the *sexual/discrimination* class, and 4,242 (14%) were allocated to the *low/no* class. Significant differences in proportion were found between *high/low* and all other classes, *verbal/discrimination* and all other classes; *sexual/discrimination* and all other classes, and *low/no* and all other classes – demonstrating that students with a disability made up a larger proportion of all classes except *low/no.* Students with a disability made up the larger proportion of the *high/poly* class, subsequently followed by the *sexual/discrimination* class and the *verbal/discrimination* class .

Age

The mean age of the *high/poly* class was 21.8 years, whereas the mean ages for the *verbal/discrimination, sexual/discrimination,* and *low/no* classes were 23.1, 21.7, and 22.5 years, respectively. Proportional differences were significant between the *high/poly* class compared to the *verbal/discrimination* and *low/no* classes – but not the *sexual/discrimination* class.

Classes	Log Likelihood	Parameters	AIC	BIC	Entropy	LMR	*p*-value	RDF
1	-94987.66	11	189997.3	190091.0	N/A	N/A	N/A	2036
2	-84246.4	23	168538.8	168734.7	0.8243576	2504.255	p < 0.001	2024
3	-82954.59	35	165979.2	166277.3	0.819239	1519.875	p < 0.001	2012
4	**-82170.57**	**47**	**164435.1**	**164835.5**	**0.8079244**	**1096.227**	**p < 0.001**	**2000**
5	-81605.08	59	163328.2	163830.7	0.8370058	509.487	p < 0.001	1988
6	-81342.27	71	162826.5	163431.3	0.8601657	184.473	p < 0.001	1976
7	-81247.11	83	162660.2	163367.2	0.8561257	306.264	p < 0.001	1964
8	-81089.12	95	162368.2	163177.5	0.781028	130.531	p < 0.001	1952

Table 7. Best Fit Statistics for Generated Latent Class Models
Note: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; LMR = Lo-Mendell-Rubin Likelihood Ratio; RDF = Residual Degrees of Freedom

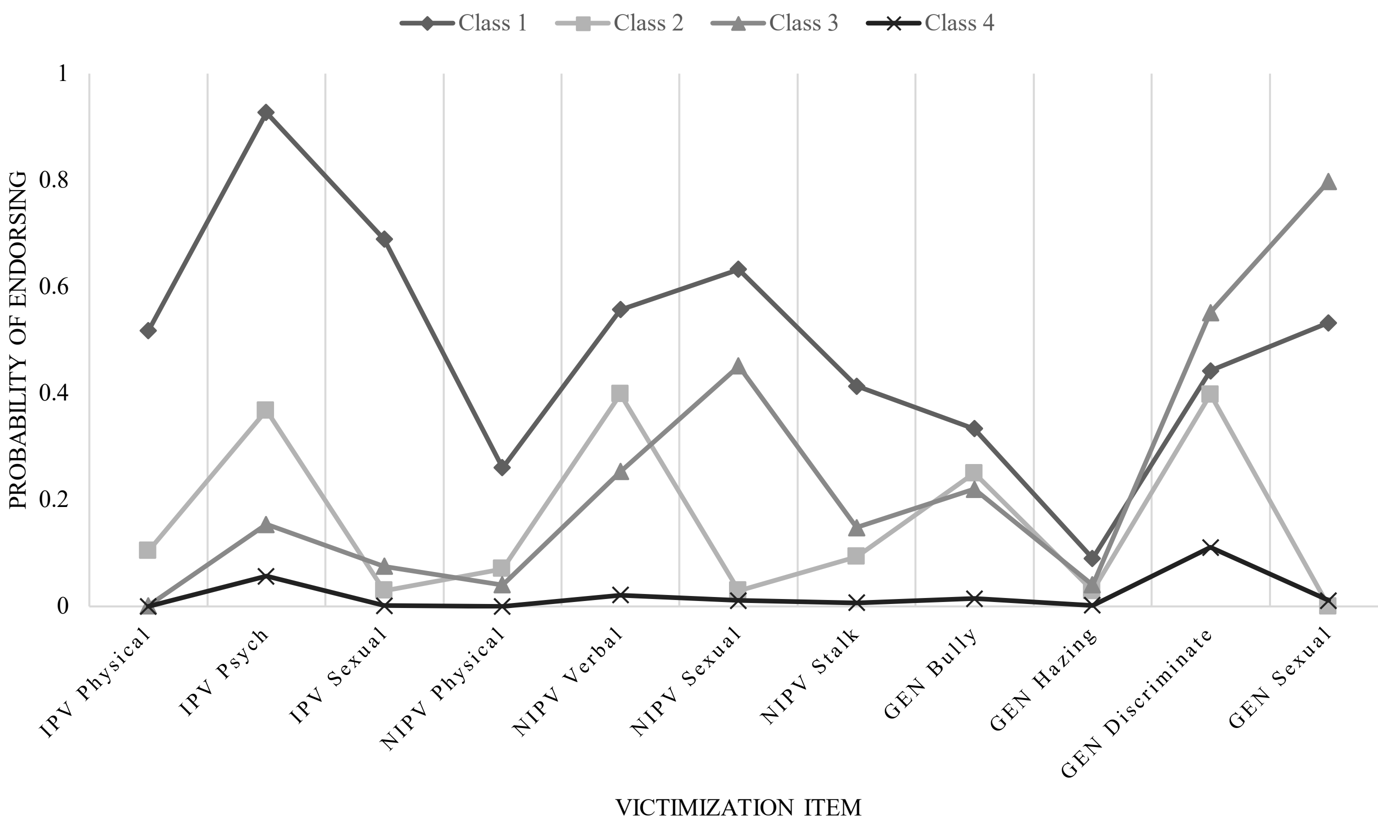

Figure 3. Four-Class Model Item Probability
Note: IPV = intimate partner victimization; NIPV = non-intimate partner victimization; GEN = general victimization.

Class	IPV Physical	IPV Psych	IPV Sexual	NIPV Physical	NIPV Verbal	NIPV Sexual	NIPV Stalk	GEN Bully	GEN Hazing	GEN Discriminate	GEN Sexual
1	0.5171	0.9267	0.6894	0.2604	0.5568	0.6325	0.4133	0.3338	0.0901	0.4424	0.5323
2	0.1044	0.3680	0.0299	0.0707	0.3983	0.0298	0.0932	0.2500	0.0292	0.3979	0.0000
3	0.0014	0.1541	0.0755	0.0405	0.2529	0.4511	0.1477	0.2198	0.0403	0.5515	0.7979
4	0.0000	0.0569	0.0016	0.0000	0.0213	0.0109	0.0066	0.0144	0.0019	0.1110	0.0108

Table 8. Probabilities of Endorsing Victimization Items by Latent Class
Note: IPV = intimate partner victimization; NIPV = non-intimate partner victimization; GEN = general victimization.

Logistic Regression and Latent Class Associations

In order to examine associations between latent class membership and use of substances, a series of logistic regressions were completed. For these logistic regressions, each latent class acted as a predictor, while each respective substance acted as the outcome of interest. Across the four latent classes, and 13 substance outcomes, 52 total logistic regressions were completed. Alpha level was set to 0.05 for all outcomes.

Odds ratios were also generated. Odds ratios (ORs) are a measure of association between an exposure and an outcome; essentially, the OR represents the odds that the outcome of interest will occur after some exposure – compared to no exposure at all (Szumilas, 2010). For this case, each latent class, with its own respective victimization types, serve as the “exposure.” Each independent substance type (e.g., opioids, sedatives, cannabis, alcohol) serve as an outcome. Logistic regressions were completed for each individual latent class. However, it is imperative to note that the reference group for each logistic regression is the other classes; the latent class of interest is given a value of one, while the other classes are given a value of zero (i.e., latent class of interest = 1, all other latent classes = 0).

High/Poly Latent Class

When it comes to the *high/poly* latent class, regression models suggest that all substance use outcomes, except for binge drinking, have a statistically significant, positive association with latent class membership (p <.001). Opioids, methamphetamine, and inhalants had the strongest associations with *high/poly* latent class membership, with an OR of 12.39, 61.31, and 12.02, respectively. It is imperative to note, however, that the number of students who used opioids, methamphetamine, and inhalants in this sample are few. So, while the ORs generated seem stark, a majority of students allocated to the *high/poly* class used these substances prior to allocation. To put it plainly, in this LCA, being in the *high/poly* class does not equate to higher use of opioids, methamphetamine, or inhalants – rather, the use of opioids, methamphetamine, or inhalants equates to *high/poly* latent class membership. Furthermore, binge drinking behaviors appeared to be positively associated with membership in the *high/poly* class – with bingeing 1-10 times and $\geq$10 times having an OR of 1.63 and 8.49, respectively. General alcohol use also had a statistically significant association, but had the lowest OR value (i.e., 1.43). See Table 10 for all *high/poly* latent class logistic regression outcomes.

Verbal/Discrimination **Latent Class**

Regression models show that, except for methamphetamine, membership in the *verbal/discrimination* latent class is significantly, and positively, associated with the use of all substances ($p < .001$). The strongest positive associations were observed with opioids (OR = 1.87), inhalants (OR = 1.89), and cocaine (OR = 1.74). Moreover, there was a significant, positive association between membership in the *verbal/discrimination* latent class and binge drinking with 1-10 episodes (OR = 1.15; $p < .001$) and binge drinking with $\geq$10 episodes (OR = 2.07; $p = .028$) – but no association with no binge drinking episodes (OR = 0.99; $p = .812$). See Table 11 for all *verbal/discrimination* latent class logistic regression outcomes.

Sexual/Discrimination Latent Class

Results from the *sexual/discrimination* regression models reveal that, similar to the *verbal/discrimination* latent class models, all substances, except methamphetamine, are significantly linked with latent class membership. Cannabis, hallucinogens, and stimulants showed the strongest positive associations with *sexual/discrimination* latent class membership, with ORs of 2.82, 2.60, and 2.56, respectively. In terms of binge drinking behavior, both 1-10 episodes (OR = 1.99) and ≥10 episodes (OR = 2.55) were significantly associated with latent class membership. See Table 12 for all *sexual/discrimination* latent class logistic regression outcomes.

Low/No Latent Class

When it comes to the *low/no* latent class, regression models indicate that all substance outcomes, except for no binge episodes, are negatively associated with latent class membership – with ORs ranging from 0.08 to 0.58 ($p < .001$). Methamphetamine had the strongest negative association with latent class membership, with an OR of 0.08. Binge drinking behavior is also negatively associated with membership in this latent class, with ORs ranging from 0.21 to 0.62. See Table 13 for all *low/no* latent class logistic regression outcomes.

Psychological Distress Mediation

To examine the mediating role of psychological distress, all latent classes and substance use outcomes were fit to models examining the indirect pathways laid out by the *Self-Medication to Cope with Victimization Conceptual Model* (i.e., victimization → psychological distress → substance use). In these models, each latent class model served as the independent variable. Psychological distress (i.e., K6 scores) were inserted into the models as a mediator, while each type of substance used acted as the dependent variable. All analyses were separated into three parts: 1) victimization → psychological distress, 2) psychological distress → substance use, and 3) mediation (see Appendix A). Upon generation of these models, it was found that the mean K6 score of all students in this sample was 7.61 – which corresponds to a *moderate* level of psychological distress (recall that scores on the K6 range from 0-24, with higher scores indicating a greater level of self-reported psychological distress).

Victimization → Psychological Distress Indirect Effects

To examine potential associations, via the indirect victimization → psychological distress pathway, models were fit which examined the association between allocation to the *high/poly* latent class (i.e., victimization) and K6 scores (i.e., psychological distress). This model showed a statistically significant, positive relationship between latent class membership and K6 scores ($b = 4.35$, $SE = 0.172$, $p < 0.001$). The adjusted R-squared for this model was 0.17, indicating that membership in the *high/poly* class explains 17% of the proportion of variance in student psychological distress. Per this model, students in the *high/poly* class had a K6 score 4.35 points higher than the original sample.

Other models, examining this indirect pathway, were fit for the remaining three latent classes. For these models, the latent class used as the independent variable was replaced with the next latent class in the sequence (i.e., *verbal/discrimination*, *sexual/discrimination*, or *no/low*). The second model (i.e., *verbal/discrimination*) showed a significant, positive relationship between latent class membership and K6 scores (b =

2.69, SE = 0.096, $p < 0.001$), suggesting that students in the *verbal/discrimination* latent class have higher levels of psychological distress – with K6 scores 2.69 points higher than the original sample. The adjusted R-squared for the *verbal/discrimination* latent class model was 0.02 – explaining a small portion of K6 score variance.

The third model fit (i.e., *sexual/discrimination*) also showed a significant, positive relationship between latent class membership and K6 scores (b = 2.92, SE = 0.110, $p <$ 0.001). This suggests that, like students in the *high/poly* and *verbal/discrimination* classes, students in the *sexual/discrimination* class have higher levels of psychological distress. For this model, however, students had a K6 score 2.92 points higher than the original sample. Again, a small portion of K6 variance was explained by the *sexual/discrimination* class, as the adjusted R-squared for this model was 0.02.

Lastly, a fourth model, examining the *low/no* latent class was fit. This model showed a significant, negative relationship between latent class membership and K6 scores (b = -3.43, SE = 0.069, t = -50.03, $p < 0.001$, adjusted R-squared = 0.06). This suggests that individuals in the *low/no* latent class have lower levels of psychological distress – a decrease of 3.43 K6 points. Overall, these analyses suggest that students in the *high/poly*, *verbal/discrimination*, and *sexual/discrimination* latent classes report higher levels of psychological distress – as opposed to students in the *low/no* latent class (see Tables 14-26).

Psychological Distress → Substance Use Indirect Effects

To examine potential associations, via the indirect psychological distress → substance use pathway, models were fit which examined the association between K6 scores (i.e., psychological distress) and use of each substance type. See Tables 14-26 for ORs and regression output generated for all substance outcomes.

***High/Poly* Latent Class**

Looking at binge drinking episodes (i.e., 1-10), K6 scores (b = 0.01, SE = 0.002, p = 0.014) and class allocation (b = 0.46, SE = 0.068, p < 0.001) were both positively associated with binge drinking. The odds of binge drinking 1-10 times were 1.01 times higher for each one-unit increase in K6 and 1.59 times higher for those allocated to the *high/poly* class. Binge drinking with ≥10 episodes also had a positive association with K6 scores (b = 0.08, SE = 0.021, p < 0.001) and class allocation (b = 1.75, SE = 0.336, p < 0.001); the odds of ≥10 binge drinking episodes were 1.09 times higher for each one-unit increase in K6 and 5.77 times higher for class allocation. Not binge drinking, however, differed from the other binge drinking outcomes. Both K6 scores (b = -0.02, SE = 0.002, p < 0.001) and class allocation (b = -0.30, SE = 0.085, p < 0.001) were negatively associated with not binge drinking; a one-unit increase in K6 predicted a decrease of 0.02, whereas as one-unit increase in class allocation predicted a decrease of 0.30.

The same analytical procedures were generated for the remaining 10 substance use outcomes for the *high/poly* latent class. When it comes to alcohol, while class allocation has a significant association (b = 0.35, SE = 0.076, p <0.001), K6 scores did not (b = 0.001, SE = 0.002, p = 0.604); a one-unit increase in K6 was associated with a no change, membership in the *high/poly* class was associated with an increase of 0.35. The results for opioids found a positive association for both K6 (b = 0.07; SE = 0.008, p <0.001) and class allocation (b = 2.23; SE = 0.126, p <0.001). Nicotine (K6: b = 0.03, SE

= 0.002; class: b = 0.79, SE = 0.068), cannabis (K6: b = 0.05, SE = 0.002; class: b = 0.71, SE = 0.068), cocaine (K6: b = 0.03, SE = 0.006; class: b = 1.74, SE = 0.112), stimulants (K6: b = 0.07, SE = 0.005; class: b = 1.33, SE = 0.101), inhalants (K6: b = 0.04, SE = 0.009; class: b = 2.32, SE = 0.138), sedatives (K6: b = 0.09, SE = 0.058; class: b = 1.56, SE = 0.108) and hallucinogens (K6: b = 0.04, SE = 0.005; class: b = 1.58, SE = 0.100) all had positive, significant (p <0.001) associations with class allocation and K6 scores to varying degrees . While methamphetamine also had positive associations with both class allocation (b = 3.94, SE = 0.226, p <0.001) and K6 scores (b = 0.04, SE = 0.177, p = 0.026), class allocation had a larger association and heightened level of significance.

***Verbal/Discrimination* Latent Class**

Looking first at alcohol (K6: b = 0.001, SE = 0.002, p = 0.782; class: b = 0.24, SE = 0.041, p <0.001), while there was a positive, significant association between drinking alcohol and class allocation, there was no significant association with alcohol consumption and K6 scores. Binge drinking 1-10 episodes (K6: b = 0.01, SE = 0.002, p = 0.004; class: b = 0.13, SE = 0.040, p = 0.002) had a significant association with both K6 scores and class allocation; whereas binge drinking $\geq$10 times (K6: b = 0.10, SE = 0.020, p <0.001; class: b = 0.46, SE = 0.335, p = 0.173) had a significant association with K6 scores but not class allocation. Not binge drinking (K6: b = -0.02, SE = 0.002, p <0.001; class: b = 0.05, SE = 0.043, p = 0.294) also demonstrated a significant association with K6 scores but not class allocation.

Nicotine (K6: b = 0.03, SE = 0.002; class: b = 0.34, SE = 0.041), cannabis (K6: b = 0.05, SE = 0.002; class: b = 0.30, SE = 0.040), cocaine (K6: b = 0.04, SE = 0.006;

class: b = 0.44, SE = 0.103), stimulants (K6: b = 0.07, SE = 0.005; class: b = 0.31, SE = 0.085), and hallucinogens (K6: b = 0.05, SE = 0.005; class: b = 0.36, SE = 0.089) all had positive, significant (p <0.001) associations with class allocation and K6 scores to varying degrees. Opioids (K6: b = 0.09, SE = 0.008, p <0.001; class: b = 0.39, SE = 0.138, p = 0.005), methamphetamine (K6: b = 0.12, SE = 0.017, p <0.001; class: b = -0.69, SE = 0.425, p = 0.102), inhalants (K6: b = 0.06, SE = 0.009, p = 0.001; class: b = 0.47, SE = 0.150, p = 0.002), and sedatives (K6: b = 0.11, SE = 0.006, p <0.001; class: b = 0.21, SE = 0.103, p = 0.041) all had significant, positive associations with K6 scores. Class allocation was significant for all substance outcomes, save for methamphetamine.

***Sexual/Discrimination* Latent Class**

For alcohol (K6: b = -0.002, SE = 0.002, p = 0.248; class: b = 0.89, SE = 0.055, p <0.001), there was a positive, significant association between drinking alcohol and class allocation. However, there was no significant association with alcohol consumption and K6 scores. Binge drinking 1-10 times (K6: b = 0.003, SE = 0.002, p = 0.244; class: b = 0.68, SE = 0.043, p <0.001) had a significant association with class allocation but not K6 scores; whereas binge drinking $\geq$10 times (K6: b = 0.10, SE = 0.020, p <0.001; class: b = 0.66, SE = 0.348, p = 0.059) had a significant association with K6 scores but not class allocation. Not binge drinking (K6: b = -0.02, SE = 0.002, p <0.001; class: b = 0.11, SE = 0.049, p = 0.03) also demonstrated a significant association with K6 scores but not class allocation.

Nicotine (K6: b = 0.03, SE = 0.002; class: b = 0.55, SE = 0.045), cannabis (K6: b = 0.04, SE = 0.002; class: b = 0.92, SE = 0.043), cocaine (K6: b = 0.04, SE = 0.006;

class: b = 0.69, SE = 0.107), stimulants (K6: b = 0.07, SE = 0.005; class: b = 0.75, SE = 0.083), inhalants (K6: b = 0.06, SE = 0.009; class: b = 0.68, SE = 0.156), sedatives (K6: b = 0.10, SE = 0.006; class: b = 0.63, SE = 0.101, p <0.001), and hallucinogens (K6: b = 0.05, SE = 0.005; class: b = 0.81, SE = 0.089) all had positive, significant (p <0.001) associations with class allocation and K6 scores to varying degrees. Opioids (K6: b = 0.01, SE = 0.008, p <0.001; class: b = 0.34, SE = 0.157, p = 0.028) also had a significant, positive association with K6 scores and class allocation, but with class allocation being slightly less significant. Alternatively, methamphetamine (K6: b = 0.11, SE = 0.017, p <0.001; class: b = -0.38, SE = 0.425, p = 0.375), was significantly associated with K6 scores, but not class allocation.

Low/No Latent Class

When it comes to *low/no* class allocation, alcohol (K6: b = -0.01, SE = 0.002, p <0.001; class: b = -0.58, SE = 0.032, p <0.001), had a negative, significant association with both K6 scores and class allocation. Binge drinking 1-10 times (K6: b = -0.002, SE = 0.002, p = 0.323; class: b = -0.49, SE = 0.029, p <0.001) had a significant association with class allocation but not K6 scores; whereas binge drinking ≥10 times (K6: b = 0.07, SE = 0.021, p <0.001; class: b = -1.29, SE = 0.259, p <0.001) had a significant association with K6 scores and class allocation. Not binge drinking (K6: b = -0.02, SE = 0.002, p <0.001; class: b = 0.02, SE = 0.033, p = 0.644) also demonstrated a significant association with K6 scores but not class allocation.

Opioids (K6: b = 0.06, SE = 0.009; class: b = -1.32, SE = 0.102), nicotine (K6: b = 0.02, SE = 0.002; class: b = -0.63, SE = 0.031), cannabis (K6: b = 0.04, SE = 0.002;

class: b = -0.75, SE = 0.030), stimulants (K6: b = 0.05, SE = 0.005; class: b = -0.95, SE = 0.061), methamphetamine (K6: b = 0.06, SE = 0.018; class: b = -2.27, SE = 0.239), sedatives (K6: b = 0.09, SE = 0.006; class: b = -0.94, SE = 0.073), and hallucinogens (K6: b = 0.03, SE = 0.005; class: b = -1.07, SE = 0.064), all had significant (<0.001) positive associations with K6 scores and significant (<0.001) negative associations with class allocation. Cocaine (K6: b = 0.02, SE = 0.007, *p* = 0.003 class: b = -1.15, SE = 0.076) and inhalants (K6: b = 0.03, SE = 0.010, *p* = 0.002; class: b = -1.53, SE = 0.112) also had the same findings as the other substance outcomes, only with slight differences in *p* values.

Mediation Analyses

Finally, the third part of analysis, using causal mediation, was conducted. This part of the analysis was coded to examine whether psychological distress mediated the relationship between class allocation and each type of substance use (see Appendix A). Statistically significant results follow below, using the average causal mediation effect (ACME). Other effects (i.e., average direct effect, proportion mediated, and total effect) and ACME confidence intervals can be found in Tables 14-26. However, it is important to note that when one of the indirect pathways has an association that is positive and the other is negative (i.e., victimization → psychological distress positive, psychological distress → substance use negative *or* victimization → psychological distress negative, psychological distress → substance use positive), *R* averages the two during computation, resulting in a negative total effect being mediated – which is uninterpretable (see tables 14-26 for select uninterpretable values).

High/Poly Latent Class

Looking first at binge drinking (1-10 times), results show that the ACME is statistically significant (b = 0.01, p <0.001), indicating that psychological distress partially mediates the relationship between class and binge drinking. Specifically, the proportion of the total effect mediated was 4.69%, which was statistically significant (p <0.001). These findings suggest that psychological distress plays a small, but significant, role in the relationship between latent class membership and *1-10 binge episodes*. Similarly, ≥10 binge drinking episodes generated an ACME that is statistically significant (b = 0.002, p <0.001), with the proportion of the total effect that was mediated being 20%. No binge drinking also generated a significant ACME (b = -0.01, p <0.001), with the proportion of the total effect mediated being 22%.

Opioids (b = 0.08), nicotine (b = 0.03), cannabis (b = 0.04), cocaine (b = 0.01), stimulants (b = 0.02), inhalants (b = 0.01), sedatives (b = 0.02), and hallucinogens (b = 0.01) all had an ACME that is statistically significant (p <0.001) – with the proportion of the total effect being mediated being around 14%, 14%, 22%, 8%, 19%, and 12%, respectively. Methamphetamine (b = 0.005, p = 0.08), on the other hand, did not have a significant ACME. General alcohol consumption (b = 0.001, p = 0.66) also did not produce a significant ACME.

Verbal/Discrimination *Latent Class*

Binge drinking (1-10 times) results show that the ACME is statistically significant (b = 0.004, p <0.001), indicating that psychological distress partially mediates the relationship between class and binge drinking around 13%. Similarly, ≥10 binge drinking episodes generated an ACME that is statistically significant (b = 0.001, *p* <0.001), with the proportion of the total effect that was mediated being 35%. No binge drinking also generated a significant ACME (b = -0.01, *p* <0.001), with the proportion of the total effect mediated being 74%.

Opioids (b = 0.003), nicotine (b = 0.02), cannabis (b = 0.03), cocaine (b = 0.003), stimulants (b = 0.01), inhalants (b = 0.002), sedatives (b = 0.01), and hallucinogens (b = 0.01) all had an ACME that is statistically significant (*p* <0.001) – with the proportion of the total effect being mediated being around 38%, 20%, 30%, 20%, 38%, 26%, 58%, and 28%, respectively. Alternatively, methamphetamine (b = 0.001, *p* <0.001) did have a significant ACME, but not a significant proportion mediated (*p* = 0.36). General alcohol consumption (b = 0.0004, *p* = 0.76) did not produce a significant ACME.

Sexual/Discrimination **Latent Class**

Binge drinking (1-10 times) results show that the ACME was not statistically significant (b = 0.002, *p* = 0.28), indicating that psychological distress does not, statistically, mediate the relationship between class and binge drinking. Binge drinking with ≥10 episodes, however, did generate an ACME that is statistically significant (b = 0.0004, *p* <0.001), with the proportion of the total effect mediated being 30%. No binge drinking also generated a significant ACME (b = -0.01, *p* <0.001), with the proportion of the total effect mediated being uninterpretable.

Opioids (b = 0.004), nicotine (b = 0.02), cannabis (b = 0.03), cocaine (b = 0.004), stimulants (b = 0.01), inhalants (b = 0.002), sedatives (b = 0.01), and hallucinogens (b = 0.01) all had an ACME that is statistically significant (p <0.001) – with the proportion of the total effect being mediated being around 45%, 14%, 12%, 15%, 22%, 21%, 32% and 16%, respectively. Methamphetamine (b = 0.001, p <0.001) did have a significant ACME, but not a significant proportion mediated (p = 0.98). General alcohol consumption (b = -0.001, *p* = 0.3) did not produce a significant ACME.

***Low/No* Latent Class**

Binge drinking (1-10 times) results show that the ACME was not statistically significant (b = 0.002, *p* = 0.3), indicating that psychological distress does not, statistically, mediate the relationship between class and binge drinking. Binge drinking with ≥10 episodes, however, did generate an ACME that is statistically significant (b = -0.001, *p* = 0.02), with the proportion of the total effect that was mediated being 19%. No binge drinking also generated a significant ACME (b = 0.01, *p* <0.001), but the proportion of the total effect mediated was not significant (0.08).

Opioids (b = -0.004), nicotine (b = -0.015), cannabis (b = 0.025), cocaine (b = -0.02), stimulants (b = -0.01), methamphetamine (b = -0.001), inhalants (b = -0.002), sedatives (b = -0.01), and hallucinogens (b = -0.005) all had an ACME that is statistically significant (p <0.001) – with the proportion of the total effect being mediated being around 15%, 11%, 14%, 6%, 17%, 11%, 7%, 25%, and 11%, respectively. General alcohol consumption (b = 0.01, *p* <0.001) did produce a significant ACME, with the proportion of the total effect mediated being uninterpretable.

Demographic	High/Poly Class 1 *n* (%)	Diff*	Verbal/Discrimination Class 2 *n* (%)	Diff*	Sexual/Discrimination Class 3 *n* (%)	Diff*	Low/No Class 4 *n* (%)	Diff*
Race/Ethnicity								
Black	89 (10)	N/A	337 (11)	[3,4]	201 (8)	[2]	2348 (8)	[2]
White	452 (49)	[3]	1615 (50)	[3,4]	1404 (59)	[1,2,4]	16760 (56)	[2,3]
Hispanic	133 (14)	[3]	470 (15)	[3]	232 (10)	[1,2,4]	4139 (14)	[3]
Asian	77 (8)	[4]	299 (9)	[3,4]	155 (6)	[2,4]	3336 (11)	[1,2,3]
Bi/Multi	157 (17)	[2,4]	413 (13)	[1,3,4]	364 (15)	[2,4]	2807 (9)	[1,2,3]
Other	23 (2)	[4]	69 (2)	[4]	35 (1)	N/A	377 (1)	[1,2]
Total	**931**		**3203**		**2391**		**29767**	
Gender Identity								
Female	689 (73)	[2,3,4]	1902 (58)	[1,3,4]	2021 (84)	[1,2,4]	18567 (62)	[1,2,3]
Male	215 (23)	[2,3,4]	1229 (38)	[1,3]	275 (11)	[1,2,4]	11108 (37)	[1,3]
Nonbinary	11 (1)	[4]	43 (1)	[3,4]	49 (2)	[2,4]	150 (<1)	[1,2,3]
Transgender	7 (1)	[4]	25 (1)	[4]	13 (1)	[4]	65 (<1)	[1,2,3]
Other	24 (3)	[4]	59 (2)	[4]	62 (3)	[4]	217 (1)	[1,2,3]
Total	**946**		**3258**		**2420**		**30107**	
Sexual Orientation								
Straight	625 (66)	[2,3,4]	2452 (76)	[1,3,4]	1485 (61)	[1,2,4]	25478 (85)	[1,2,3]
Bisexual	171 (18)	[2,4]	410 (13)	[1,3,4]	468 (19)	[2,4]	2205 (7)	[1,2,3]
Gay/Lesbian	42 (4)	[4]	158 (5)	[4]	129 (5)	[4]	882 (3)	[1,2,3]
Other	105 (11)	[2,3,4]	226 (7)	[1,3,4]	334 (14)	[1,2,4]	1462 (5)	[1,2,3]
Total	**943**		**3246**		**2416**		**30027**	
Year in College								
1st Year	232 (25)	[3]	739 (23)	N/A	498 (21)	[1,4]	6937 (23)	[3]
2nd to 5th Year	589 (63)	[2,4]	1836 (57)	[1,3]	1479 (62)	[2,4]	16449 (55)	[1,3]
Graduate	120 (13)	[2,3,4]	635 (20)	[1,3]	417 (17)	[1,2,4]	6280 (21)	[1,3]
Total	**941**		**3210**		**2394**		**29666**	
Enrollment Status								
Fulltime	836 (89)	[3,4]	2905 (89)	[3,4]	2220 (92)	[1,2]	27337 (91)	[1,2]
Parttime	104 (11)	[3]	351 (11)	[3,4]	193 (8)	[1,2]	2731 (9)	[2]

Total	**940**		**3256**		**2413**		**30068**	
Residence								
On-Campus	338 (37)	[3]	1171 (36)	[3,4]	978 (41)	[1,2]	11585 (39)	[2]
Off-Campus	574 (63)	[3]	2038 (64)	[3,4]	1397 (59)	[1,2]	17997 (61)	[2]
Total	**912**		**3209**		**2375**		**29582**	
Athletics								
Athlete	195 (20)	N/A	683 (21)	[4]	466 (19)	[4]	6991 (23)	[2,3]
Non-athlete	759 (80)	N/A	2584 (79)	[4]	1960(81)	[4]	23180 (77)	[2,3]
Total	**954**		**3267**		**2426**		**30171**	
Disability								
Disability	300 (31)	[2,3,4]	754 (23)	[1,3,4]	634 (26)	[1,2,4]	4242 (14)	[1,2,3]
No Disability	654 (69)	[2,3,4]	2513 (77)	[1,3,4]	1792 (73)	[1,2,4]	25929 (86)	[1,2,3]
Total	**954**		**3267**		**2426**		**30171**	
Greek-letter Organization								
GLO Affiliate	109 (11)	[2,4]	286 (9)	[1,3]	264 (11)	[2,4]	2394 (8)	[1,3]
Non-GLO Affiliate	839 (89)	[2,4]	2974 (91)	[1,3]	2157 (89)	[2,4]	27701 (92)	[1,3]
Total	**948**		**3260**		**2421**		**30095**	
Age (mean)	21.8	[2,4]	23.1	[1,3,4]	21.7	[2,4]	22.5	[1,2,3]

Table 9. Demographic Makeup and Proportional Differences of Latent Classes
Note: Age reported as class mean and t-test proportional difference. GLO = Greek-letter organization.
* = Chi-square proportional difference between classes; Diff = significant differences.

Class and Substance	Logit	SE	OR	*p* value	CI
High/Poly (Class 1)					
Opioids	2.52	0.12	12.39	<.001	[9.74, 15.61]
Nicotine	0.93	0.07	2.52	<.001	[2.21, 2.88]
Cannabis	0.90	0.07	2.46	<.001	[2016, 2.80]
Cocaine	1.88	0.12	6.56	<.001	[5.29, 8.07]
Stimulant	1.61	0.09	5.00	<.001	[4.12, 6.04]
Methamphetamine	4.12	0.21	61.31	<.001	[40.69, 93.46]
Inhalants	2.49	0.13	12.02	<.001	[9.25, 15.46]
Sedatives	1.96	0.10	7.13	<.001	[5.80, 8.69]
Hallucinogens	1.77	0.10	5.86	<.001	[4.83, 7.07]
Alcohol	0.36	0.07	1.43	<.001	[1.24, 1.66]
No Binge	-0.38	0.08	0.68	<.001	[0.58, 0.80]
Binge 1-10	0.49	0.07	1.63	<.001	[1.42, 1.86]
Binge >10	2.14	0.32	8.49	<.001	[4.32, 15.36]

Table 10. *High/Poly* Logistic Regression Outcomes
Note: SE = standard error; OR = odds ratio; CI = confidence interval.

Class and Substance	Logit	SE	OR	*p* value	CI
Verbal/Discrimination (Class 2)					
Opioids	0.62	0.14	1.87	<.001	[1.42, 2.42]
Nicotine	0.42	0.04	1.53	<.001	[1.41, 1.65]
Cannabis	0.42	0.04	1.52	<.001	[1.41, 1.64]
Cocaine	0.56	0.10	1.74	<.001	[1.42, 2.12]
Stimulant	0.51	0.08	1.66	<.001	[1.41, 1.95]
Methamphetamine	-0.37	0.42	0.69	0.375	[0.27, 1.44]
Inhalants	0.64	0.15	1.89	<.001	[1.40, 2.51]
Sedatives	0.49	0.10	1.64	<.001	[1.34, 1.99]
Hallucinogens	0.51	0.09	1.66	<.001	[1.40, 1.97]
Alcohol	0.24	0.04	1.27	<.001	[1.18, 1.38]
No Binge	-0.01	0.04	0.99	0.812	[0.91, 1.08]
Binge 1-10	0.14	0.04	1.15	<.001	[1.07, 1.25]
Binge >10	0.73	0.33	2.07	0.028	[1.02, 3.80]

Table 11. *Verbal/Discrimination* Logistic Regression Outcomes
Note: SE = standard error; OR = odds ratio; CI = confidence interval.

Class and Substance	Logit	SE	OR	*p* value	CI
Sexual/Discrimination (Class 3)					
Opioids	0.60	0.15	1.82	<.001	[1.32, 2.43]
Nicotine	0.64	0.04	1.90	<.001	[1.74, 2.07]
Cannabis	1.04	0.04	2.82	<.001	[2.59, 3.06]
Cocaine	0.81	0.11	2.24	<.001	[1.81, 2.74]
Stimulant	0.94	0.08	2.56	<.001	[2.18, 3.00]
Methamphetamine	-0.05	0.42	0.95	0.902	[0.37, 1.99]
Inhalants	0.85	0.15	2.35	<.001	[1.72, 3.14]
Sedatives	0.91	0.10	2.49	<.001	[2.04, 3.01]
Hallucinogens	0.95	0.09	2.60	<.001	[2.19, 3.06]
Alcohol	0.88	0.05	2.42	<.001	[2.18, 2.70]
No Binge	0.05	0.05	1.05	0.329	[0.95, 1.15]
Binge 1-10	0.69	0.04	1.99	<.001	[1.83, 2.17]
Binge >10	0.94	0.34	2.55	0.006	[1.22, 4.78]

Table 12. *Sexual/Discrimination* Logistic Regression Outcomes
Note: SE = standard error; OR = odds ratio; CI = confidence interval.

Class and Substance	Logit	SE	OR	*p* value	CI
Low/No (Class 4)					
Opioids	-1.53	0.10	0.22	<.001	[0.18, 0.26]
Nicotine	-0.70	0.03	0.49	<.001	[0.47, 0.52]
Cannabis	-0.87	0.03	0.42	<.001	[0.40, 0.44]
Cocaine	-1.21	0.07	0.30	<.001	[0.26, 0.34]
Stimulant	-1.14	0.06	0.32	<.001	[0.29, 0.36]
Methamphetamine	-2.49	0.23	0.08	<.001	[0.05, 0.13]
Inhalants	-1.63	0.11	0.20	<.001	[0.16, 0.24]
Sedatives	-1.24	0.07	0.29	<.001	[0.25, 0.33]
Hallucinogens	-1.19	0.06	0.30	<.001	[0.27, 0.34]
Alcohol	-0.55	0.03	0.58	<.001	[0.54, 0.61]
No Binge	0.06	0.03	1.06	0.080	[0.99, 1.12]
Binge 1-10	-0.49	0.03	0.62	<.001	[0.58, 0.65]
Binge >10	-1.55	0.25	0.21	<.001	[0.13, 0.34]

Table 13. *Low/No* Logistic Regression Outcomes
Note: SE = standard error; OR = odds ratio; CI = confidence interval.

Class and Pathway	Estimate	SE	OR	95% LCI	95% UCI	*p* value
High/Poly Class						
Indirect Pathway A						
Intercept	7.612	0.028	N/A	N/A	N/A	<0.001
Class	4.349	0.172	N/A	N/A	N/A	<0.001
Indirect Pathway B						
Intercept	-5.244	0.97	0.01	N/A	N/A	<0.001
K6	0.065	0.008	1.07	N/A	N/A	<0.001
Class	2.231	0.126	9.31	N/A	N/A	<0.001
Mediation						
Total Effect	0.094	N/A	N/A	0.073	0.12	<0.001
ACME	0.013	N/A	N/A	0.018	0.02	<0.001
ADE	0.081	N/A	N/A	0.062	0.11	<0.001
Proportion Mediated	0.142	N/A	N/A	0.100	0.18	<0.001
Verbal/Discrimination Class						
Pathway A						
Intercept	7.487	0.029	N/A	N/A	N/A	<0.001
Class	2.695	0.096	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-5.290	0.983	0.01	N/A	N/A	<0.001
K6	0.087	0.008	1.09	N/A	N/A	<0.001
Class	0.385	0.138	1.47	N/A	N/A	0.005
Mediation						
Total Effect	0.010	N/A	N/A	0.005	0.01	<0.001
ACME	0.003	N/A	N/A	0.003	0.00	<0.001
ADE	0.005	N/A	N/A	0.001	0.01	<0.001
Proportion Mediated	0.386	N/A	N/A	0.249	0.67	<0.001
Sexual/Discrimination Class						
Pathway A						
Intercept	7.533	0.028	N/A	N/A	N/A	<0.001
Class	2.919	0.110	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-5.280	0.098	0.01	N/A	N/A	<0.001
K6	0.088	0.008	1.09	N/A	N/A	<0.001

Class	0.344	0.157	1.41	N/A	N/A	0.028
Mediation						
Total Effect	0.009	N/A	N/A	0.005	0.01	<0.001
ACME	0.004	N/A	N/A	0.003	0.00	<0.001
ADE	0.005	N/A	N/A	0.001	0.01	0.04
Proportion Mediated	0.450	N/A	N/A	0.279	0.74	<0.001
Low/No Class						
Pathway A						
Intercept	10.526	0.062	N/A	N/A	N/A	<0.001
Class	-3.434	0.069	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-4.118	0.127	0.02	N/A	N/A	<0.001
K6	0.061	0.009	1.06	N/A	N/A	<0.001
Class	-1.317	0.102	0.27	N/A	N/A	<0.001
Mediation						
Total Effect	-0.024	N/A	N/A	-0.028	-0.02	<0.001
ACME	-0.004	N/A	N/A	-0.005	0.00	<0.001
ADE	-0.020	N/A	N/A	-0.024	-0.02	<0.001
Proportion Mediated	0.155	N/A	N/A	0.110	0.19	<0.001

Table 14. Mediation of Opioids

Note: SE = standard error; OR = odds ratio, UCI = upper confidence interval; LCI = lower confidence interval.; K6 = Kessler 6 Distress Scale; ACME = average causal mediated effect; ADE = average direct effects.

Class and Pathway	Estimate	SE	OR	95% LCI	95% UCI	*p* value
High/Poly Class						
Indirect Pathway A						
Intercept	7.612	0.028	N/A	N/A	N/A	<0.001
Class	4.349	0.172	N/A	N/A	N/A	<0.001
Indirect Pathway B						
Intercept	-1.524	0.023	0.22	N/A	N/A	<0.001
K6	0.031	0.002	1.03	N/A	N/A	<0.001
Class	0.794	0.068	2.21	N/A	N/A	<0.001
Mediation						
Total Effect	0.199	N/A	N/A	0.172	0.23	<0.001
ACME	0.029	N/A	N/A	0.024	0.03	<0.001
ADE	0.171	N/A	N/A	0.141	0.20	<0.001
Proportion Mediated	0.141	N/A	N/A	0.114	0.18	<0.001
Verbal/Discrimination Class						
Pathway A						
Intercept	7.487	0.029	N/A	N/A	N/A	<0.001
Class	2.695	0.096	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-1.539	0.023	0.21	N/A	N/A	<0.001
K6	0.032	0.002	1.03	N/A	N/A	<0.001
Class	0.338	0.041	1.40	N/A	N/A	<0.001
Mediation						
Total Effect	0.081	N/A	N/A	0.06	0.09	<0.001
ACME	0.016	N/A	N/A	0.014	0.02	<0.001
ADE	0.064	N/A	N/A	0.051	0.08	<0.001
Proportion Mediated	0.203	N/A	N/A	0.159	0.26	<0.001
Sexual/Discrimination Class						
Pathway A						
Intercept	7.533	0.028	N/A	N/A	N/A	<0.001
Class	2.919	0.110	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-1.540	0.023	0.21	N/A	N/A	<0.001
K6	0.031	0.002	1.03	N/A	N/A	<0.001
Class	0.554	0.045	1.74	N/A	N/A	<0.001
Mediation						
Total Effect	0.126	N/A	N/A	0.109	0.15	<0.001

ACME	0.018	N/A	N/A	0.015	0.02	<0.001
ADE	0.108	N/A	N/A	0.091	0.13	<0.001
Proportion Mediated	0.141	N/A	N/A	0.117	0.17	<0.001
Low/No Class						
Pathway A						
Intercept	10.526	0.062	N/A	N/A	N/A	<0.001
Class	-3.434	0.069	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-0.938	0.036	0.39	N/A	N/A	<0.001
K6	0.023	0.002	1.02	N/A	N/A	<0.001
Class	-0.627	0.031	0.53	N/A	N/A	<0.001
Mediation						
Total Effect	-0.136	N/A	N/A	-0.148	-0.12	<0.001
ACME	-0.015	N/A	N/A	-0.018	-0.01	<0.001
ADE	-0.121	N/A	N/A	-0.133	-0.11	<0.001
Proportion Mediated	0.107	N/A	N/A	0.084	0.13	<0.001

Table 15. Mediation of Nicotine

Note: SE = standard error; OR = odds ratio, UCI = upper confidence interval; LCI = lower confidence interval.; K6 = Kessler 6 Distress Scale; ACME = average causal mediated effect; ADE = average direct effect.

Class and Pathway	Estimate	SE	OR	95% LCI	95% UCI	*p* value
High/Poly Class						
Indirect Pathway A						
Intercept	7.612	0.028	N/A	N/A	N/A	<0.001
Class	4.349	0.172	N/A	N/A	N/A	<0.001
Indirect Pathway B						
Intercept	-1.516	0.022	0.22	N/A	N/A	<0.001
K6	0.047	0.002	1.05	N/A	N/A	<0.001
Class	0.707	0.068	2.03	N/A	N/A	<0.001
Mediation						
Total Effect	0.199	N/A	N/A	0.172	0.23	<0.001
ACME	0.044	N/A	N/A	0.039	0.05	<0.001
ADE	0.155	N/A	N/A	0.125	0.19	<0.001
Proportion Mediated	0.223	N/A	N/A	0.182	0.27	<0.001
Verbal/Discrimination Class						
Pathway A						
Intercept	7.487	0.029	N/A	N/A	N/A	<0.001
Class	2.695	0.096	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-1.529	0.022	0.22	N/A	N/A	<0.001
K6	0.048	0.002	1.05	N/A	N/A	<0.001
Class	0.296	0.040	1.34	N/A	N/A	<0.001
Mediation						
Total Effect	0.085	N/A	N/A	0.068	0.10	<0.001
ACME	0.025	N/A	N/A	0.022	0.03	<0.001
ADE	0.059	N/A	N/A	0.043	0.07	<0.001
Proportion Mediated	0.298	N/A	N/A	0.250	0.37	<0.001
Sexual/Discrimination Class						
Pathway A						
Intercept	7.533	0.028	N/A	N/A	N/A	<0.001
Class	2.919	0.110	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-1.544	0.022	0.01	N/A	N/A	<0.001
K6	0.044	0.002	1.09	N/A	N/A	<0.001
Class	0.919	0.043	1.41	N/A	N/A	<0.001
Mediation						
Total Effect	0.229	N/A	N/A	0.209	0.25	<0.001

ACME	0.028	N/A	N/A	0.024	0.03	<0.001
ADE	0.200	N/A	N/A	0.181	0.22	<0.001
Proportion Mediated	0.121	N/A	N/A	0.106	0.14	<0.001
Low/No Class						
Pathway A						
Intercept	10.526	0.062	N/A	N/A	N/A	<0.001
Class	-3.434	0.069	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-0.813	0.035	0.44	N/A	N/A	<0.001
K6	0.036	0.002	1.04	N/A	N/A	<0.001
Class	-0.752	0.030	0.47	N/A	N/A	<0.001
Mediation						
Total Effect	-0.179	N/A	N/A	-0.189	-0.17	<0.001
ACME	-0.025	N/A	N/A	-0.028	-0.02	<0.001
ADE	-0.154	N/A	N/A	-0.166	-0.14	<0.001
Proportion Mediated	0.138	N/A	N/A	0.117	0.16	<0.001

Table 16. Mediation of Cannabis

Note: SE = standard error; OR = odds ratio, UCI = upper confidence interval; LCI = lower confidence interval.; K6 = Kessler 6 Distress Scale; ACME = average causal mediated effect; ADE = average direct effect.

Class and Pathway	Estimate	SE	OR	95% LCI	95% UCI	*p* value
High/Poly Class						
Indirect Pathway A						
Intercept	7.612	0.028	N/A	N/A	N/A	<0.001
Class	4.349	0.172	N/A	N/A	N/A	<0.001
Indirect Pathway B						
Intercept	-4.155	0.066	0.02	N/A	N/A	<0.001
K6	0.031	0.006	1.03	N/A	N/A	<0.001
Class	1.747	0.112	5.74	N/A	N/A	<0.001
Mediation						
Total Effect	0.097	N/A	N/A	0.076	0.12	<0.001
ACME	0.008	N/A	N/A	0.016	0.01	<0.001
ADE	0.089	N/A	N/A	0.070	0.11	<0.001
Proportion Mediated	0.082	N/A	N/A	0.054	0.11	<0.001
Verbal/Discrimination Class						
Pathway A						
Intercept	7.487	0.029	N/A	N/A	N/A	<0.001
Class	2.695	0.096	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-4.188	0.066	0.02	N/A	N/A	<0.001
K6	0.042	0.006	1.04	N/A	N/A	<0.001
Class	0.442	0.103	1.56	N/A	N/A	<0.001
Mediation						
Total Effect	0.015	N/A	N/A	0.009	0.02	<0.001
ACME	0.003	N/A	N/A	0.002	0.00	<0.001
ADE	0.012	N/A	N/A	0.006	0.02	<0.001
Proportion Mediated	0.200	N/A	N/A	0.133	0.38	<0.001
Sexual/Discrimination Class						
Pathway A						
Intercept	7.533	0.028	N/A	N/A	N/A	<0.001
Class	2.919	0.110	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-4.191	0.067	0.01	N/A	N/A	<0.001
K6	0.041	0.006	1.09	N/A	N/A	<0.001
Class	0.689	0.107	1.41	N/A	N/A	<0.001
Mediation						
Total Effect	0.025	N/A	N/A	0.017	0.03	<0.001

ACME	0.004	N/A	N/A	0.002	0.00	<0.001
ADE	0.021	N/A	N/A	0.014	0.03	<0.001
Proportion Mediated	0.146	N/A	N/A	0.099	0.21	<0.001
Low/No Class						
Pathway A						
Intercept	10.526	0.062	N/A	N/A	N/A	<0.001
Class	-3.434	0.069	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-3.139	0.091	0.04	N/A	N/A	<0.001
K6	0.020	0.007	1.02	N/A	N/A	0.003
Class	-1.146	0.076	0.32	N/A	N/A	<0.001
Mediation						
Total Effect	-0.035	N/A	N/A	-0.041	-0.03	<0.001
ACME	-0.002	N/A	N/A	-0.004	0.00	<0.001
ADE	-0.033	N/A	N/A	-0.039	-0.03	<0.001
Proportion Mediated	0..064	N/A	N/A	0.030	0.10	<0.001

Table 17. Mediation of Cocaine

Note: SE = standard error; OR = odds ratio, UCI = upper confidence interval; LCI = lower confidence interval.; K6 = Kessler 6 Distress Scale; ACME = average causal mediated effect; ADE = average direct effect.

Class and Pathway	Estimate	SE	OR	95% LCI	95% UCI	*p* value
High/Poly Class						
Indirect Pathway A						
Intercept	7.612	0.028	N/A	N/A	N/A	<0.001
Class	4.349	0.172	N/A	N/A	N/A	<0.001
Indirect Pathway B						
Intercept	-3.971	0.055	0.02	N/A	N/A	<0.001
K6	0.066	0.005	1.07	N/A	N/A	<0.001
Class	1.327	0.101	3.77	N/A	N/A	<0.001
Mediation						
Total Effect	0.108	N/A	N/A	0.087	0.13	<0.001
ACME	0.020	N/A	N/A	0.016	0.02	<0.001
ADE	0.088	N/A	N/A	0.070	0.11	<0.001
Proportion Mediated	0.188	N/A	N/A	0.159	0.22	<0.001
Verbal/Discrimination Class						
Pathway A						
Intercept	7.487	0.029	N/A	N/A	N/A	<0.001
Class	2.695	0.096	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-3.997	0.056	0.02	N/A	N/A	<0.001
K6	0.073	0.005	1.08	N/A	N/A	<0.001
Class	0.313	0.085	1.37	N/A	N/A	<0.001
Mediation						
Total Effect	0.021	N/A	N/A	0.012	0.03	<0.001
ACME	0.018	N/A	N/A	0.007	0.01	<0.001
ADE	0.013	N/A	N/A	0.005	0.02	<0.001
Proportion Mediated	0.383	N/A	N/A	0.276	0.60	<0.001
Sexual/Discrimination Class						
Pathway A						
Intercept	7.533	0.028	N/A	N/A	N/A	<0.001
Class	2.919	0.110	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-4.010	0.056	0.01	N/A	N/A	<0.001
K6	0.070	0.005	1.09	N/A	N/A	<0.001
Class	0.746	0.083	1.41	N/A	N/A	<0.001
Mediation						
Total Effect	0.046	N/A	N/A	0.038	0.06	<0.001

ACME	0.010	N/A	N/A	0.008	0.01	<0.001
ADE	0.036	N/A	N/A	0.028	0.05	<0.001
Proportion Mediated	0.220	N/A	N/A	0.177	0.27	<0.001
Low/No Class						
Pathway A						
Intercept	10.526	0.062	N/A	N/A	N/A	<0.001
Class	-3.434	0.069	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-3.122	0.077	0.04	N/A	N/A	<0.001
K6	0.055	0.005	1.06	N/A	N/A	<0.001
Class	-0.949	0.061	0.39	N/A	N/A	<0.001
Mediation						
Total Effect	-0.050	N/A	N/A	-0.056	-0.04	<0.001
ACME	-0.009	N/A	N/A	-0.010	-0.01	<0.001
ADE	-0.041	N/A	N/A	-0.047	-0.04	<0.001
Proportion Mediated	0.174	N/A	N/A	0.133	0.20	<0.001

Table 18. Mediation of Stimulants

Note: SE = standard error; OR = odds ratio, UCI = upper confidence interval; LCI = lower confidence interval.; K6 = Kessler 6 Distress Scale; ACME = average causal mediated effect; ADE = average direct effect.

Class and Pathway	Estimate	SE	OR	95% LCI	95% UCI	*p* value
High/Poly Class						
Indirect Pathway A						
Intercept	7.612	0.028	N/A	N/A	N/A	<0.001
Class	4.349	0.172	N/A	N/A	N/A	<0.001
Indirect Pathway B						
Intercept	-7.174	0.224	7.66	N/A	N/A	<0.001
K6	0.039	0.176	1.04	N/A	N/A	0.026
Class	3.942	0.226	5.15	N/A	N/A	<0.001
Mediation						
Total Effect	0.006	N/A	N/A	0.004	0.08	<0.001
ACME	0.004	N/A	N/A	-0.008	0.01	0.08
ADE	0.005	N/A	N/A	0.004	0.07	<0.001
Proportion Mediated	0.007	N/A	N/A	-0.001	0.13	0.08
Verbal/Discrimination Class						
Pathway A						
Intercept	7.487	0.029	N/A	N/A	N/A	<0.001
Class	2.695	0.096	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-7.009	0.215	0.00	N/A	N/A	<0.001
K6	0.117	0.017	1.12	N/A	N/A	<0.001
Class	-0.695	0.425	0.50	N/A	N/A	0.102
Mediation						
Total Effect	-0.0007	N/A	N/A	-0.002	0.00	0.36
ACME	0.0007	N/A	N/A	0.0005	0.00	<0.001
ADE	-0.001	N/A	N/A	-0.003	0.00	0.16
Proportion Mediated	0.553	N/A	N/A	-6.224	4.14	0.36
Sexual/Discrimination Class						
Pathway A						
Intercept	7.533	0.028	N/A	N/A	N/A	<0.001
Class	2.919	0.110	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-7.019	0.215	0.00	N/A	N/A	<0.001
K6	0.115	0.017	1.12	N/A	N/A	<0.001
Class	-0.377	0.425	0.69	N/A	N/A	0.375
Mediation						
Total Effect	0.0002	N/A	N/A	-0.002	0.0	0.98

ACME	0.001	N/A	N/A	0.0004	0.0	<0.001
ADE	-0.007	N/A	N/A	-0.002	0.0	0.42
Proportion Mediated	*	N/A	N/A	*	*	0.98
Low/No Class						
Pathway A						
Intercept	10.526	0.062	N/A	N/A	N/A	<0.001
Class	-3.434	0.069	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-5.284	0.253	0.01	N/A	N/A	<0.001
K6	0.062	0.018	1.06	N/A	N/A	<0.001
Class	-2.266	0.240	0.10	N/A	N/A	<0.001
Mediation						
Total Effect	-0.009	N/A	N/A	-0.012	-0.01	<0.001
ACME	-0.001	N/A	N/A	-0.012	0.00	<0.001
ADE	-0.008	N/A	N/A	-0.011	-0.01	<0.001
Proportion Mediated	0.113	N/A	N/A	0.046	0.19	<0.001

Table 19. Mediation of Methamphetamine
Note: SE = standard error; OR = odds ratio, UCI = upper confidence interval; LCI = lower confidence interval.; K6 = Kessler 6 Distress Scale; ACME = average causal mediated effect; ADE = average direct effect.
* = value not interpretable; proportion mediated negative due to direct and indirect effects having opposite direction.

Class and Pathway	Estimate	SE	OR	95% LCI	95% UCI	*p* value
High/Poly Class						
Indirect Pathway A						
Intercept	7.612	0.028	N/A	N/A	N/A	<0.001
Class	4.349	0.172	N/A	N/A	N/A	<0.001
Indirect Pathway B						
Intercept	-5.175	0.102	0.01	N/A	N/A	<0.001
K6	0.038	0.009	1.04	N/A	N/A	<0.001
Class	2.318	0.138	10.16	N/A	N/A	<0.001
Mediation						
Total Effect	0.077	N/A	N/A	0.064	0.09	<0.001
ACME	0.018	N/A	N/A	0.005	0.01	<0.001
ADE	0.070	N/A	N/A	0.059	0.09	<0.001
Proportion Mediated	0.091	N/A	N/A	0.056	0.13	<0.001
Verbal/Discrimination Class						
Pathway A						
Intercept	7.487	0.029	N/A	N/A	N/A	<0.001
Class	2.695	0.096	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-5.217	0.103	0.01	N/A	N/A	0.001
K6	0.061	0.009	1.06	N/A	N/A	0.001
Class	0.472	0.150	1.60	N/A	N/A	0.002
Mediation						
Total Effect	0.008	N/A	N/A	0.005	0.01	0.001
ACME	0.002	N/A	N/A	0.001	0.00	0.001
ADE	0.006	N/A	N/A	0.003	0.01	0.001
Proportion Mediated	0.257	N/A	N/A	0.155	0.46	0.001
Sexual/Discrimination Class						
Pathway A						
Intercept	7.533	0.028	N/A	N/A	N/A	<0.001
Class	2.919	0.110	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-5.218	0.103	0.01	N/A	N/A	<0.001
K6	0.060	0.009	1.09	N/A	N/A	<0.001
Class	0.680	0.156	1.41	N/A	N/A	<0.001
Mediation						
Total Effect	0.012	N/A	N/A	0.006	0.02	<0.001

ACME	0.002	N/A	N/A	0.006	0.00	<0.001
ADE	0.009	N/A	N/A	0.004	0.01	<0.001
Proportion Mediated	0.213	N/A	N/A	0.132	0.36	<0.001
Low/No Class						
Pathway A						
Intercept	10.526	0.062	N/A	N/A	N/A	<0.001
Class	-3.434	0.069	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-3.879	0.133	0.02	N/A	N/A	<0.001
K6	0.029	0.001	1.03	N/A	N/A	0.002
Class	-1.526	0.112	0.22	N/A	N/A	<0.001
Mediation						
Total Effect	-0.022	N/A	N/A	-0.026	-0.02	<0.001
ACME	-0.002	N/A	N/A	-0.003	0.00	<0.001
ADE	-0.021	N/A	N/A	-0.024	-0.02	<0.001
Proportion Mediated	0.074	N/A	N/A	0.024	0.12	<0.001

Table 20. Mediation of Inhalants

Note: SE = standard error; OR = odds ratio, UCI = upper confidence interval; LCI = lower confidence interval.; K6 = Kessler 6 Distress Scale; ACME = average causal mediated effect; ADE = average direct effect.

Class and Pathway	Estimate	SE	OR	95% LCI	95% UCI	*p* value
High/Poly Class						
Indirect Pathway A						
Intercept	7.612	0.028	N/A	N/A	N/A	<0.001
Class	4.349	0.172	N/A	N/A	N/A	<0.001
Indirect Pathway B						
Intercept	-4.705	0.071	0.01	N/A	N/A	<0.001
K6	0.094	0.006	1.10	N/A	N/A	<0.001
Class	1.564	0.108	4.78	N/A	N/A	<0.001
Mediation						
Total Effect	0.108	N/A	N/A	0.088	0.13	<0.001
ACME	0.024	N/A	N/A	0.021	0.03	<0.001
ADE	0.084	N/A	N/A	0.065	0.10	<0.001
Proportion Mediated	0.223	N/A	N/A	0.190	0.25	<0.001
Verbal/Discrimination Class						
Pathway A						
Intercept	7.487	0.029	N/A	N/A	N/A	<0.001
Class	2.695	0.096	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-4.734	0.072	0.01	N/A	N/A	<0.001
K6	0.105	0.006	1.11	N/A	N/A	<0.001
Class	0.211	0.103	1.23	N/A	N/A	0.041
Mediation						
Total Effect	0.014	N/A	N/A	0.0099	0.02	<0.001
ACME	0.008	N/A	N/A	0.006	0.01	<0.001
ADE	0.006	N/A	N/A	0.001	0.01	0.02
Proportion Mediated	0.575	N/A	N/A	0.403	0.88	<0.001
Sexual/Discrimination Class						
Pathway A						
Intercept	7.533	0.028	N/A	N/A	N/A	<0.001
Class	2.919	0.110	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-4.748	0.072	0.01	N/A	N/A	<0.001
K6	0.102	0.006	1.09	N/A	N/A	<0.001

Class	0.628	0.101	1.41	N/A	N/A	<0.001
Mediation						
Total Effect	0.031	N/A	N/A	0.022	0.04	<0.001
ACME	0.010	N/A	N/A	0.008	0.01	<0.001
ADE	0.021	N/A	N/A	0.014	0.03	<0.001
Proportion Mediated	0.320	N/A	N/A	0.259	0.41	<0.001
Low/No Class						
Pathway A						
Intercept	10.526	0.062	N/A	N/A	N/A	<0.001
Class	-3.434	0.069	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-3.879	0.095	0.02	N/A	N/A	<0.001
K6	0.087	0.006	1.09	N/A	N/A	<0.001
Class	-0.939	0.073	0.39	N/A	N/A	<0.001
Mediation						
Total Effect	-0.037	N/A	N/A	-0.043	-0.03	<0.001
ACME	-0.009	N/A	N/A	-0.010	-0.01	<0.001
ADE	-0.028	N/A	N/A	-0.033	-0.02	<0.001
Proportion Mediated	0.249	N/A	N/A	0.219	0.29	<0.001

Table 21. Mediation of Sedatives

Note: SE = standard error; OR = odds ratio, UCI = upper confidence interval; LCI = lower confidence interval.; K6 = Kessler 6 Distress Scale; ACME = average causal mediated effect; ADE = average direct effect.

Class and Pathway	Estimate	SE	OR	95% LCI	95% UCI	*p* value
High/Poly Class						
Indirect Pathway A						
Intercept	7.612	0.028	N/A	N/A	N/A	<0.001
Class	4.349	0.172	N/A	N/A	N/A	<0.001
Indirect Pathway B						
Intercept	-3.901	0.057	0.02	N/A	N/A	<0.001
K6	0.044	0.005	1.05	N/A	N/A	<0.001
Class	1.576	0.100	4.83	N/A	N/A	<0.001
Mediation						
Total Effect	0.116	N/A	N/A	0.094	0.13	<0.001
ACME	0.014	N/A	N/A	0.012	0.02	<0.001
ADE	0.102	N/A	N/A	0.182	0.12	<0.001
Proportion Mediated	0.123	N/A	N/A	0.098	0.16	<0.001
Verbal/Discrimination Class						
Pathway A						
Intercept	7.487	0.029	N/A	N/A	N/A	<0.001
Class	2.695	0.096	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-3.930	0.057	0.02	N/A	N/A	<0.001
K6	0.054	0.005	1.06	N/A	N/A	<0.001
Class	0.362	0.089	1.44	N/A	N/A	<0.001
Mediation						
Total Effect	0.019	N/A	N/A	0.011	0.03	<0.001
ACME	0.005	N/A	N/A	0.005	0.01	<0.001
ADE	0.014	N/A	N/A	0.016	0.02	<0.001
Proportion Mediated	0.279	N/A	N/A	0.204	0.45	<0.001
Sexual/Discrimination Class						
Pathway A						
Intercept	7.533	0.028	N/A	N/A	N/A	<0.001
Class	2.919	0.110	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-3.942	0.057	0.01	N/A	N/A	<0.001
K6	0.050	0.005	1.09	N/A	N/A	<0.001
Class	0.811	0.089	1.41	N/A	N/A	<0.001
Mediation						
Total Effect	0.042	N/A	N/A	0.034	0.05	<0.001

ACME	0.007	N/A	N/A	0.005	0.01	<0.001
ADE	0.035	N/A	N/A	0.028	0.05	<0.001
Proportion Mediated	0.160	N/A	N/A	0.123	0.20	<0.001
Low/No Class						
Pathway A						
Intercept	10.526	0.062	N/A	N/A	N/A	<0.001
Class	-3.434	0.069	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-2.944	0.079	0.05	N/A	N/A	<0.001
K6	0.033	0.005	1.03	N/A	N/A	<0.001
Class	-1.075	0.064	0.34	N/A	N/A	<0.001
Mediation						
Total Effect	-0.048	N/A	N/A	-0.053	-0.04	<0.001
ACME	-0.005	N/A	N/A	-0.006	0.00	<0.001
ADE	-0.043	N/A	N/A	-0.049	-0.004	<0.001
Proportion Mediated	0.107	N/A	N/A	0.074	0.13	<0.001

Table 22. Mediation of Hallucinogens

Note: SE = standard error; OR = odds ratio, UCI = upper confidence interval; LCI = lower confidence interval.; K6 = Kessler 6 Distress Scale; ACME = average causal mediated effect; ADE = average direct effect.

Class and Pathway	Estimate	SE	OR	95% LCI	95% UCI	*p* value
High/Poly Class						
Indirect Pathway A						
Intercept	7.612	0.028	N/A	N/A	N/A	<0.001
Class	4.349	0.172	N/A	N/A	N/A	<0.001
Indirect Pathway B						
Intercept	0.696	0.020	2.01	N/A	N/A	<0.001
K6	0.001	0.002	1.00	N/A	N/A	0.604
Class	0.353	0.080	1.42	N/A	N/A	<0.001
Mediation						
Total Effect	0.080	N/A	N/A	0.049	0.10	<0.001
ACME	0.001	N/A	N/A	-0.002	0.00	0.66
ADE	0.075	N/A	N/A	0.050	0.10	<0.001
Proportion Mediated	0.013	N/A	N/A	-0.032	0.06	0.66
Verbal/Discrimination Class						
Pathway A						
Intercept	7.487	0.029	N/A	N/A	N/A	<0.001
Class	2.695	0.096	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	0.688	0.200	1.99	N/A	N/A	<0.001
K6	0.001	0.002	1.00	N/A	N/A	0.782
Class	0.241	0.041	1.27	N/A	N/A	<0.001
Mediation						
Total Effect	0.053	N/A	N/A	0.037	0.07	<0.001
ACME	0.0004	N/A	N/A	-0.002	0.00	0.76
ADE	0.052	N/A	N/A	0.035	0.07	<0.001
Proportion Mediated	0.011	N/A	N/A	-0.050	0.06	0.76
Sexual/Discrimination Class						
Pathway A						
Intercept	7.533	0.028	N/A	N/A	N/A	<0.001
Class	2.919	0.110	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	0.683	0.020	0.01	N/A	N/A	<0.001
K6	-0.002	0.002	1.09	N/A	N/A	0.248
Class	0.892	0.055	1.41	N/A	N/A	<0.001
Mediation						
Total Effect	0.164	N/A	N/A	0.148	0.18	<0.001

ACME	-0.001	N/A	N/A	-0.003	0.00	0.3
ADE	0.166	N/A	N/A	0.150	0.18	<0.001
Proportion Mediated	*	N/A	N/A	*	*	0.3
Low/No Class						
Pathway A						
Intercept	10.526	0.062	N/A	N/A	N/A	<0.001
Class	-3.434	0.069	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	1.250	0.037	3.49	N/A	N/A	<0.001
K6	-0.008	0.002	0.99	N/A	N/A	<0.001
Class	-0.575	0.032	0.56	N/A	N/A	<0.001
Mediation						
Total Effect	-0.112	N/A	N/A	-0.126	-0.10	<0.001
ACME	0.005	N/A	N/A	0.002	0.01	<0.001
ADE	-0.118	N/A	N/A	-0.131	-0.11	<0.001
Proportion Mediated	*	N/A	N/A	*	*	<0.001

Table 23. Mediation of Alcohol

Note: SE = standard error; OR = odds ratio, UCI = upper confidence interval; LCI = lower confidence interval.; K6 = Kessler 6 Distress Scale; ACME = average causal mediated effect; ADE = average direct effect.

* = value not interpretable; proportion mediated negative due to direct and indirect effects having opposite direction.

Class and Pathway	Estimate	SE	OR	95% LCI	95% UCI	*p* value
High/Poly Class						
Indirect Pathway A						
Intercept	7.612	0.028	N/A	N/A	N/A	<0.001
Class	4.349	0.172	N/A	N/A	N/A	<0.001
Indirect Pathway B						
Intercept	-0.980	0.020	0.38	N/A	N/A	<0.001
K6	0.005	0.002	1.01	N/A	N/A	0.014
Class	0.463	0.068	1.59	N/A	N/A	<0.001
Mediation						
Total Effect	0.110	N/A	N/A	0.079	0.14	<0.001
ACME	0.005	N/A	N/A	0.009	0.01	<0.001
ADE	0.105	N/A	N/A	0.074	0.13	<0.001
Proportion Mediated	0.047	N/A	N/A	0.010	0.08	<0.001
Verbal/Discrimination Class						
Pathway A						
Intercept	7.487	0.029	N/A	N/A	N/A	<0.001
Class	2.695	0.096	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-0.985	0.021	0.37	N/A	N/A	<0.001
K6	0.006	0.002	1.01	N/A	N/A	0.004
Class	0.126	0.040	1.13	N/A	N/A	0.002
Mediation						
Total Effect	0.030	N/A	N/A	0.013	0.04	<0.001
ACME	0.004	N/A	N/A	0.002	0.01	<0.001
ADE	0.026	N/A	N/A	0.018	0.04	<0.001
Proportion Mediated	0.129	N/A	N/A	0.044	0.33	<0.001
Sexual/Discrimination Class						
Pathway A						
Intercept	7.533	0.028	N/A	N/A	N/A	<0.001
Class	2.919	0.110	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-0.995	0.02	0.37	N/A	N/A	<0.001
K6	0.003	0.00	1.00	N/A	N/A	0.244
Class	0.682	0.04	1.98	N/A	N/A	<0.001
Mediation						

Total Effect	0.155	N/A	N/A	0.140	0.17	<0.001
ACME	0.002	N/A	N/A	-0.010	0.00	0.28
ADE	0.154	N/A	N/A	0.138	0.17	<0.001
Proportion Mediated	0.009	N/A	N/A	-0.011	0.03	0.28
Low/No Class						
Pathway A						
Intercept	10.526	0.062	N/A	N/A	N/A	<0.001
Class	-3.434	0.069	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-0.512	0.035	0.60	N/A	N/A	<0.001
K6	-0.002	0.002	1.00	N/A	N/A	0.323
Class	-0.493	0.029	0.61	N/A	N/A	<0.001
Mediation						
Total Effect	-0.105	N/A	N/A	-0.117	-0.09	<0.001
ACME	0.002	N/A	N/A	-0.001	0.01	0.3
ADE	-0.106	N/A	N/A	-0.120	-0.09	<0.001
Proportion Mediated	*	N/A	N/A	*	*	0.3

Table 24. Mediation of 1-10 Binge Drinking Episodes

Note: SE = standard error; OR = odds ratio, UCI = upper confidence interval; LCI = lower confidence interval.; K6 = Kessler 6 Distress Scale; ACME = average causal mediated effect; ADE = average direct effect.

* = value not interpretable; proportion mediated negative due to direct and indirect effects having opposite direction.

Class and Pathway	Estimate	SE	OR	95% LCI	95% UCI	*p* value
High/Poly Class						
Indirect Pathway A						
Intercept	7.612	0.028	N/A	N/A	N/A	<0.001
Class	4.349	0.172	N/A	N/A	N/A	<0.001
Indirect Pathway B						
Intercept	-7.242	0.251	0.00	N/A	N/A	<0.001
K6	0.083	0.021	1.09	N/A	N/A	<0.001
Class	1.753	0.336	5.77	N/A	N/A	<0.001
Mediation						
Total Effect	0.011	N/A	N/A	0.005	0.02	<0.001
ACME	0.002	N/A	N/A	0.001	0.00	<0.001
ADE	0.009	N/A	N/A	0.004	0.02	<0.001
Proportion Mediated	0.202	N/A	N/A	0.107	0.32	<0.001
Verbal/Discrimination Class						
Pathway A						
Intercept	7.487	0.029	N/A	N/A	N/A	<0.001
Class	2.695	0.096	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-7.300	0.255	0.00	N/A	N/A	<0.001
K6	0.098	0.020	1.10	N/A	N/A	<0.001
Class	0.457	0.335	1.58	N/A	N/A	0.173
Mediation						
Total Effect	0.002	N/A	N/A	0.0002	0.01	0.04
ACME	0.001	N/A	N/A	0.0003	0.00	<0.001
ADE	0.001	N/A	N/A	-0.0003	0.00	0.12
Proportion Mediated	0.350	N/A	N/A	0.131	1.26	0.04
Sexual/Discrimination Class						
Pathway A						
Intercept	7.533	0.028	N/A	N/A	N/A	<0.001
Class	2.919	0.110	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-7.303	0.256	0.01	N/A	N/A	<0.001
K6	0.658	0.020	1.09	N/A	N/A	<0.001

Class	0.658	0.348	1.41	N/A	N/A	0.059
Mediation						
Total Effect	0.003	N/A	N/A	0.0003	0.01	<0.001
ACME	0.0008	N/A	N/A	0.0004	0.00	<0.001
ADE	0.001	N/A	N/A	-0.0003	0.01	0.18
Proportion Mediated	0.302	N/A	N/A	0.165	1.93	<0.001
Low/No Class						
Pathway A						
Intercept	10.526	0.062	N/A	N/A	N/A	<0.001
Class	-3.434	0.069	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-6.152	0.324	0.00	N/A	N/A	<0.001
K6	0.073	0.021	1.08	N/A	N/A	<0.001
Class	-1.290	0.259	0.28	N/A	N/A	<0.001
Mediation						
Total Effect	-0.004	N/A	N/A	-0.006	0.18	<0.001
ACME	-0.001	N/A	N/A	-0.001	0.00	0.02
ADE	-0.003	N/A	N/A	-0.005	0.00	<0.001
Proportion Mediated	0.187	N/A	N/A	0.082	0.30	0.02

Table 25. Mediation of ≥10 Binge Drinking Episodes

Note: SE = standard error; OR = odds ratio, UCI = upper confidence interval; LCI = lower confidence interval.; K6 = Kessler 6 Distress Scale; ACME = average causal mediated effect; ADE = average direct effect.

Class and Pathway	Estimate	SE	OR	95% LCI	95% UCI	*p* value
High/Poly Class						
Indirect Pathway A						
Intercept	7.612	0.028	N/A	N/A	N/A	<0.001
Class	4.349	0.172	N/A	N/A	N/A	<0.001
Indirect Pathway B						
Intercept	-0.969	0.021	0.38	N/A	N/A	<0.001
K6	-0.019	0.002	0.98	N/A	N/A	<0.001
Class	-0.298	0.085	0.74	N/A	N/A	<0.001
Mediation						
Total Effect	-0.064	N/A	N/A	-0.084	-0.04	<0.001
ACME	-0.014	N/A	N/A	-0.017	-0.01	<0.001
ADE	-0.050	N/A	N/A	-0.072	-0.02	<0.001
Proportion Mediated	0.219	N/A	N/A	0.138	0.38	<0.001
Verbal/Discrimination Class						
Pathway A						
Intercept	7.487	0.029	N/A	N/A	N/A	<0.001
Class	2.695	0.096	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-0.969	0.021	0.38	N/A	N/A	<0.001
K6	-0.021	0.002	0.98	N/A	N/A	<0.001
Class	0.045	0.043	1.05	N/A	N/A	0.294
Mediation						
Total Effect	-0.001	N/A	N/A	-0.018	0.01	0.86
ACME	-0.010	N/A	N/A	-0.013	-0.01	<0.001
ADE	0.009	N/A	N/A	-0.008	0.02	0.24
Proportion Mediated	0.741	N/A	N/A	-24.382	22.24	0.86
Sexual/Discrimination Class						
Pathway A						
Intercept	7.533	0.028	N/A	N/A	N/A	<0.001
Class	2.919	0.110	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-0.970	0.021	0.01	N/A	N/A	<0.001
K6	-0.021	0.002	1.09	N/A	N/A	<0.001
Class	0.109	0.049	1.41	N/A	N/A	0.026
Mediation						
Total Effect	0.009	N/A	N/A	-0.006	0.03	0.28

ACME	-0.012	N/A	N/A	-0.014	-0.01	<0.001
ADE	0.021	N/A	N/A	0.005	0.04	0.02
Proportion Mediated	*	N/A	N/A	*	*	0.28
Low/No Class						
Pathway A						
Intercept	10.526	0.062	N/A	N/A	N/A	<0.001
Class	-3.434	0.069	N/A	N/A	N/A	<0.001
Pathway B						
Intercept	-0.953	0.038	0.39	N/A	N/A	<0.001
K6	-0.021	0.002	0.98	N/A	N/A	<0.001
Class	-0.015	0.033	0.99	N/A	N/A	0.644
Mediation						
Total Effect	0.011	N/A	N/A	-0.001	0.02	0.08
ACME	0.013	N/A	N/A	0.010	0.02	<0.001
ADE	-0.002	N/A	N/A	-0.014	0.01	0.76
Proportion Mediated	1.113	N/A	N/A	-4.794	5.44	0.08

Table 26. Mediation of No Binge Drinking Episodes

Note: SE = standard error; OR = odds ratio, UCI = upper confidence interval; LCI = lower confidence interval.; K6 = Kessler 6 Distress Scale; ACME = average causal mediated effect; ADE = average direct effect.

* = value not interpretable; proportion mediated negative due to direct and indirect effects having opposite direction.

Chapter 5. Discussion and Recommendations

The specific aims of this study were threefold: 1) identify typologies of victimization experience among college students; 2) determine which typologies of victimization are associated with risk of substance use; and 3) examine if psychological distress functions as a mechanism (i.e., mediator) through which typologies of victimization may contribute to substance use. Results from this study support the hypothesis that there may be differences in substance use based on types of victimization endorsed – with psychological distress partially mediating, albeit to varying degrees, the relationship between latent class membership and substance use.

In meeting the first specific aim of this dissertation study, a four-class model was identified through LCA. This four-class model was comprised of four notable classes: *high/poly, verbal/discrimination, sexual/discrimination,* and *low/no*. The *high/poly* class was comprised primarily of students that were a sexual and gender minority, a racial and ethnic minority, enrolled parttime, associated with a Greek-letter organization, and/or diagnosed with a disability. Students in the *high/poly* class were also found to have a higher endorsement probability for all types of victimization examined.

The *verbal/discrimination* class, on the other hand, was comprised mostly of male, parttime students of color. The highest victimization endorsement probabilities for this class revolved around *non-intimate partner verbal* and *general discrimination* types of victimization. The third identified class, the *sexual/discrimination* class, had a larger proportion of students identifying as a sexual or gender minority. A large proportion of these students also reported residing on-campus, being enrolled fulltime, being at the graduate level, and being White or Hispanic. Endorsement probabilities were the highest in this class for *non-intimate partner sexual*, *general sexual*, and *general discrimination*. Finally, the *low/no* class was comprised of students with low or no endorsement probabilities for all types of victimization examined. This class was predominantly made up of students who were not in a minority group, who resided on-campus, do not have a disability, and are not athletes.

While not conclusive, these identified classes do suggest that polyvictimization is commonplace in the collegiate setting – at least with this sample. When examining the selected four-class model, several latent classes included victimization endorsement probabilities for more than one type of victimization – resulting in multiple latent classes being polyvictimization classes by definition. While these latent classes had fairly distinct differences in endorsement probabilities for the different types of victimization examined, as summarized above, three of these classes are explicitly polyvictimization classes. However, it is important to note that a majority of students in this sample were allocated to the *low/no* latent class. For those students who were allocated to a class other than *low/no*, polyvictimization appears to be more commonplace than singular victimization. Similarly, it appears that students who are members of a minority group are exceptionally vulnerable to allocation to a latent class other than *low/no*.

Regarding the second aim of this dissertation, analyses embedded into this study indicate that there may be some association between victimization exposure (i.e., as established by latent class membership) and use of specific substances – and that different exposures are related to different odds of substance use engagement. The *high/poly* latent class had the highest odds of containing students who used all substances in the past three months – with heightened ORs calculated across all substances. Specifically, the *high/poly* latent class demonstrated strong, positive associations with opioid, methamphetamine, and inhalant use. The *verbal/discrimination* class also had significant, positive associations with all substances – save for methamphetamine – with the strongest associations revolving around opioids, inhalants, and cocaine.

Similarly, the *sexual/discrimination* class had significant positive associations for all substances, except for methamphetamine. The strongest associations in this class revolved around cannabis, hallucinogens, and stimulants. Finally, the *low/no* class was examined. This was the largest class identified, containing 81.6% of the entire sample. This class had significant negative associations across all substances, except for consumption of alcohol – which had an OR of 1.06.

Binge drinking results were examined slightly differently as they were broken up into three separate outcomes (i.e., *1-10 binge episodes, ≥10 binge episodes,* and *no binge episodes*). Binge drinking, at both 1-10 and ≥10 episodes in a two week period, was positively associated with latent class membership across all classes except *low/no*; whereas not binge drinking was negatively associated with latent class membership in all classes except *low/no*. The inverse of this was true for the *low/no* class, as being in the *low/no* class had a positive association with no binge drinking and a negative association with binge drinking, both 1-10 and ≥10 times in two weeks.

These findings reinforce the importance of investigating substances that are more "uncommon" among college students. As discussed previously, substance use outcomes in collegiate studies tend to revolve around alcohol, cannabis, and nicotine as these are the most commonly used substances in this population. Some studies do examine general substance use (e.g., "use" versus "nonuse"), but fail to capture different substances. Inclusion of more uncommon substances can help to further the collective understanding of substance use following polyvictimization. These findings, while preliminary, correspond with the general hypothesis guiding this dissertation – that as the number of victimization experiences increase in some fashion, so too does substance use engagement. However, it is important to remember that for all of these outcomes, it is not that students in a certain latent class are more or less likely to use the substances with a positive/negative association to a class, rather that students who use these substances are more or less likely to be allocated to that class.

Regarding the third aim of this dissertation, psychological distress was inserted as a mediator for a series of causal mediation analyses. The results of these analyses indicate that psychological distress does partially mediate the relationship between victimization and substance use, for a majority of substances – however, not to a large extent. It is likely that other variables (e.g., a psychopathological disorder, access to substances, prior victimization, student resiliency, ability to cope) help to explain more of the association between victimization and substance use. Further, while the calculated K6 score differed depending on latent class membership – all latent class scores, and the score of the original sample, were categorized as being *moderate.* Being that college students already are at risk for elevated psychological distress, it could be possible that these scores originate from stressors outside of the victimization realm.

Together, these findings bring into question the current prevention and intervention efforts targeting substance use among college students – suggesting that current prevention and intervention efforts targeting collegiate substance use may need to be re-evaluated and revised. While the findings of this dissertation cannot be widely generalized to the entire collegiate populace, they do reveal some potentially vulnerable student groups that should receive attention. Types of victimization and substance use reported also varied across student groups and latent classes. This highlights the importance of tailoring prevention and intervention efforts to the specific needs of the college students being targeted.

Using the findings of this study as an example, interventions targeting students within a group like the *high/poly* class may need to focus more on reducing the use of more "uncommon" substances like opioids, methamphetamine, or inhalants. Similarly, interventions targeting groups like the *high/poly* class may need to be tailored to target specific student demographics (e.g., female, first year undergraduate, enrolled parttime) or victimization combinations (e.g., *intimate partner victimization* and *general victimization*). Alternatively, interventions targeting the *low/no* latent class may need to focus on reinforcing the already existing low levels of substance use in some fashion, rather than address high-risk substance use behaviors. For students falling into a group like *verbal/discrimination*, prevention and intervention efforts may need to be tailored to address use of substances such as opioids, inhalants, or cocaine. Similarly, students falling into a group like *sexual/discrimination* may be better served by prevention and intervention efforts geared towards cannabis, hallucinogens, and stimulants.

Recommendations for Research

Polyvictimization is a growing concern among college students – as it has the potential to contribute to increased rates of substance use in this population. Findings of this dissertation highlight the need for further polyvictimization research for those enrolled in college. Future studies should give attention to college students who are in a minority group, who have a disability, who reside off-campus, who are enrolled parttime, who are affiliated with a Greek-letter organization, and who are undergraduate students beyond their freshman year. Differences in polyvictimization among students of differing majors and minors should also be considered. Future work should focus on differences in polyvictimization among college students in varying postsecondary environments (e.g., public/private, urban/rural, two/four year, state political orientation, research activity). Postsecondary institutions which are online only, single-gender (e.g., all-male, all-female), historically Black, military-affiliated, or faith-based should also be explored.

It will be important for future studies to consider the effects of various combinations of victimization on substance use outcomes. Combinations of polyvictimization should be explored for differences in substance use outcomes, to further what is known about substance use in students with differing victimization exposures – especially victimization types not captured by this LCA. Substance use outcomes should also be expanded upon – with more focus on substance use latency, frequency, quantity, severity, duration, and route of administration – rather than just use versus nonuse. The findings of this dissertation are limited by exploration of substance use within the last three months (two weeks for binge drinking) and student victimization occurring within the last 12 months. Unfortunately, data was not available to examine directionality or latency of associations between substance use and victimization. Future research should seek to close this gap, examining whether victimization occurs before substance use and duration of time between experiencing victimization and engaging in substance use.

In this study, data analyzed was collected during the Fall of 2019 – which contains the red zone. However, since the ACHA-NCHA III survey only inquired about victimization in the past 12 months, it is unknown if this victimization occurred during the Fall 2019 semester, the previous Fall 2018 semester, or during a non-fall semester. Thus, this study is unable to explore the role the red zone played in reported sexual types of victimization – in any of the latent classes. Future work should take a closer look at the red zone, and examine if any differences manifest (e.g., different identified latent classes) based on semester of enrollment or semester of victimization.

In the literature, collegiate substance use routinely revolves around alcohol, cannabis, and nicotine. As this dissertation revealed, there may be value in studies examining substances not widely seen in collegiate settings. While the use of substances other than alcohol, cannabis, and nicotine (e.g., opioids, methamphetamine, and inhalants) are statistically lower, those students who did engage in use of these substances were overwhelming allocated to the *high/poly* latent class – indicating that future research efforts should seek to expand the number of substances examined in students who have experienced high rates of victimization.

Regarding psychological distress, future research efforts should attempt to connect different forms of substance use to psychological distress symptoms – to explore if select substances are being used to alleviate specific symptoms that are distressing (i.e., the SMH). While not possible using this ACHA-NCHA III dataset (as data analyzed only contained the final, cumulative K6 scores of students), value could come from looking at the different types of psychological distress symptoms endorsed. While this study was not able to directly test the SMH in this way, findings suggest that the presence of more psychological distress (i.e., through higher K6 scores) may contribute to use of substances to cope to some degree. Beyond this dissertation study, the next steps are to examine LCA differences across different semesters, as well as build a stronger foundation for future studies that look at specific psychological distress symptoms and substances used.

Several other variables, outside of psychological distress, may also help to explain the relationship between victimization and substance use. Thus, future research should explore other potential mediators, such as: age, gender identity, sexual orientation, race/ethnicity, social support, self-esteem, substance availability, psychopathology, substance use expectancies, familial substance use, socioeconomic status, coping strategies, peer pressure, access to health services, religious affiliation, cultural practices, societal norms, personality traits, resiliency, disability, academic workload, and medical conditions. Consideration should also be given to analyze these variables as moderators – to see if these variables potentially affect the strength or direction of the relationship between victimization and substance use. Future work may also consider branching out to explore stress response and pathological changes in the body following victimization (e.g., hypothalamus-pituitary-adrenal axis adaptation).

Recommendations for Practice

Individuals experiencing victimization, especially violent victimization leading to injury, often seek medical care without prior interaction with police or disclosure that they have been victimized (Rahmqvist et al., 2019). In these situations, healthcare providers are often the first to identify, witness, or hear of subjected victimization. In this regard, healthcare providers are pivotal in the prevention of substance use among college students who have experienced victimization – in any form, number, or context.

For healthcare providers working in conjunction with college-associated medical centers, student health clinics, campus-based sexual assault centers, or healthcare facilities neighboring postsecondary institutions – the chances of interacting with a victimized college student are high. While no explicit prevalence rates have been reported for number of college students seeking medical or psychiatric care following victimization, a systematic review regarding campus health service utilization among sexually victimized female college students found that up to 42% of survivors utilized university-based resources and care following victimization (Stoner & Cramer, 2017). It is important to note, however, that this percentage does not include students who may have sought care from an off-campus facility.

Due to the risk of harm arising from all forms of victimization, especially polyvictimization, it is likely that health care services are utilized by college students experiencing other forms and combinations of victimization as well – highlighting the dire need for healthcare providers trained to care for those affected by polyvictimization. Specifically, healthcare providers should be educated to recognize the signs of, and screen for, polyvictimization in college students. Per the United States Preventative Services Task Force (USPST), intimate partner victimization screenings are recommended for women of reproductive age and other vulnerable adults (Feltner et al., 2018). Unhealthy alcohol and illicit drug use screenings are also recommended for adults above the age of 18 in the clinical practice setting (United States Preventive Services Task Force [USPST] et al., 2018). However, the USPST falls short – missing several forms of victimization in their screening recommendation. Increased screening for victimization and substance use should be encouraged for all healthcare providers, especially those working with college students. Collegiate polyvictimization screening tools should also be developed, as current screening tools (e.g., ACEs Questionnaire) may not fully capture collegiate polyvictimization or may only capture polyvictimization-related symptoms and not victimization experience counts.

Further, the USPST states that healthcare providers should provide brief behavioral counseling interventions for those who screen positive for either intimate partner victimization or substance use (Feltner et al., 2018; USPST et al., 2018). Thus, it is imperative that healthcare providers treating collegiate populations receive training in brief behavioral counseling, trauma-informed care, substance misuse and abuse, and holistic care of students following victimization. Early identification of students who have experienced victimization in any form, number, or context is critical – as prevention or early intervention could help to decrease the risk of victimization-related harm and outcomes. Additional efforts should be made to test the findings of this dissertation and translate corroborated findings into healthcare practice and health care policy.

As aforementioned, this dissertation focused on identifying victimization typologies and associated substance use through previously unidentified latent classes. Through this, was the discovery that there may be college students who have experienced victimization in several forms, number, and contexts – with differing levels of substance use and psychological distress as a result. Additionally, the findings of this dissertation suggest that substance use may be associated with combinations of victimization seen with latent class allocation – bringing to light the need for clinical services geared towards addiction medicine, trauma, and general psychiatry for victimized students in the collegiate setting.

Strengths and Limitations

While this study has several strengths, it is not without limitations. As detailed in Chapter 3 of this dissertation, this study is limited through use of cross-sectional data – thereby preventing analysis of potential longitudinal associations that may be present between victimization and substance use. Additionally, due to a low percentage of responses for certain demographic items, some important minority groups have been compressed into single categories – which did not allow for deeper exploration of select minority groups that may be particularly at-risk. Similarly, some demographic groups were relatively small, and comprised only a small portion of a latent class, making proportional differences challenging to confidently determine. Lastly, this LCA is subject to naming fallacy. The classes originating from the selected four-class model were aptly named based on the highest victimization endorsement probabilities – but the names alone do not capture every endorsed probability, which is a common naming fallacy.

Despite these limitations, this study was adequately powered and had a majority of outputs indicating significance with a p value <0.001. While not completely generalizable to the entire collegiate populace, this study did include participants from 58 U.S. colleges and universities, not a single site or state – allowing for greater generalizability of findings. Further, this dissertation was able to examine 13 different substance use outcomes across four latent classes results – the first known study to do so.

While this study was not able to strongly demonstrate that psychological distress acts as a primary mediator (as it explained a small amount of variance in a majority of models), the findings of this study do showcase that there are other covariates that may explain the associations between substance use and victimization configurations. This is a strength, as this study shows that there is merit in further exploration of these topics with other variables (e.g., psychopathology, latency to use, prior use, access to substances). It is imperative to note, however, that the opinions, findings, and conclusions reported in this dissertation are those of the author and are in no way meant to represent the corporate opinions, views, or policies of the ACHA. The ACHA does not warrant nor assume any liability or responsibility for the accuracy, completeness, or usefulness of any information presented in this dissertation.

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Appendix A. *R* Code and Syntax

```
############################## project set up ################################
##set working directory and connect to R drive

setwd("//research/Shared/Melnyk/Holod.1")

############################### load packages
####################################

library(tidyverse)
library(lubridate)
library(corrr)
library(naniar)
library(DataExplorer)
library(GGally)
library(haven)
library(psych)
library(naniar)
library(mice)
library(visdat)
library(ggplot2)
library(poLCA)
library(gdata)
library(dplyr)
library(tidyr)
library(sjPlot)
library(lme4)

############################ load whole data set #############################
##using updated K6 code per ACHA

polyvic <- read_csv("ACHA NCHA III Dataset.csv")

########################## examine format of data ############################

summary(polyvic)
head(polyvic, 10) #showing first 10 lines of data
```

```
str(polyvic)
dplyr::glimpse(polyvic)

########################## examine missing data ###########################
##recall embedded survey skip function
#missingness for whole dataset

missing <- miss_var_summary(polyvic)

######################## separate four study waves ##########################
##turn STUDY into a factor variable

polyvic$STUDY <- as.factor(polyvic$STUDY)
summary(polyvic)

##see number of participants in each wave
table(polyvic$STUDY)

##40 = Fall 2019 --> "wave_1"
##41 = Spring 2020 --> "wave_2"
##42 = Fall 2020 --> "wave_3"
##43 = Spring 2021  --> "wave_4"

##total number in each wave
##40    41    42    43
##38679 50307 13373 96489

##construct a new variable "wave"
polyvic <- polyvic %>%
  mutate(wave = case_when(
    STUDY == "40" ~ 1,
    STUDY == "41" ~ 2,
    STUDY == "42" ~ 3,
    STUDY == "43" ~ 4,
  ))

##since ACHA-NCHA III does not include respondent ID
##assign a new ID variable to each row:
polyvic <- polyvic %>%
  mutate(ID = row_number())

##split data into four sets; one for each wave
wave_1 <- polyvic %>%
  filter(wave==1)
```

```
wave_2 <- polyvic %>%
  filter(wave==2)

wave_3 <- polyvic %>%
  filter(wave==3)

wave_4 <- polyvic %>%
  filter(wave==4)

############### determine completeness for victimization and K6 ################
##K6 = psychological distress

############## wave one victimization and K6 completeness ####################

  K6vic1 <- wave_1 %>%
    dplyr::select(c("ID", "N3Q19A", "N3Q19B", "N3Q19C", "N3Q19D", "N3Q19E",
"N3Q20A", "N3Q20B", "N3Q20C", "N3Q20D",
           "N3Q20E", "N3Q20F", "N3Q20G", "N3Q47A13", "N3Q47A14", "N3Q47A15",
"N3Q47A16", "N3Q47A17", "N3Q47A18",
           "N3Q44A", "N3Q44B", "N3Q44C", "N3Q44D", "N3Q44E", "N3Q44F",
"N3Q75A1", "N3Q75A2", "N3Q75A3", "N3Q75A4",
           "N3Q75A5", "N3Q75A6", "N3Q75A7", "N3Q75A8", "N3Q67C", "N3Q68",
"N3Q69", "N3Q72", "N3Q73", "N3Q77A", "N3Q77B",
           "N3Q78", "N3Q81A", "N3Q81B", "N3Q81C","N3Q82A","N3Q82B",
"N3Q82C", "N3Q82D","N3Q82E","N3Q82F", "N3Q82G",
           "N3Q22A1", "N3Q22A2", "N3Q22A3", "N3Q22A4", "N3Q22A5",
"N3Q22A6","N3Q22A7","N3Q22A8","N3Q22A9",
           "N3Q22A10","N3Q22A11", "N3Q22B1", "N3Q28", "N3Q22B2" , "N3Q22B3" ,
"N3Q22B4", "N3Q22B5", "N3Q22B6", "N3Q22B7",
           "N3Q22B8", "N3Q22B9", "N3Q22B10", "N3Q22B11", "N3Q22B12"))

  wave_1_sample_K6vic <- K6vic1 %>%
    rowwise() %>%
    mutate(int_part = sum(N3Q19A, N3Q19B, N3Q19C, N3Q19D, N3Q19E),
          non_int_part = sum(N3Q20A, N3Q20B, N3Q20C, N3Q20D, N3Q20E, N3Q20F,
N3Q20G),
          K6 = sum(N3Q44A, N3Q44B, N3Q44C, N3Q44D, N3Q44E, N3Q44F),
          general = sum(N3Q47A13, N3Q47A14, N3Q47A15, N3Q47A16, N3Q47A17,
N3Q47A18)) %>%
    mutate(K6victotal = sum(int_part, non_int_part, general, K6)) %>%
    filter(!is.na(K6victotal))

##original wave one sample = 38,679
```

```
##number of respondents with all answers completed = 36,986

################## final total completeness and missingness ######################

##want missingness to be ~5% or less
##wave 1 = 95.6% of items fully completed

############################ variable reductions ##############################

##included demographic variables:
##race/ethnicity (N3Q75A), gender identity (N3Q67C), sexual orientation (N3Q68),
Greek-letter affiliate (N3Q77A),
##enrollment status (N3Q73), disability status (N3Q82A-G), college athlete (N3Q81A-
C), year in school (N3Q72),
##residence (N3Q78), age (N3Q69)

############################## code race/ethnicity #############################
##looking at each race variable and number reporting from each wave
## 0 = not selected; 1 = selected
##note: bi/multiracial an item option, but respondents could select more than one

################################ wave one race ###############################

wave_1_test <- wave_1 %>%
  mutate(sum_race = N3Q75A1 + N3Q75A2 + N3Q75A3 + N3Q75A4 + N3Q75A5 +
N3Q75A6 + N3Q75A7) %>% # include all race variables except multiracial in this sum
  mutate(multi = case_when(
    sum_race >= 2 ~ "1", ##for multiple race responses
    N3Q75A8 == 1 ~ "1",
    TRUE ~ "0"
  ))

wave_1_test$multi <- as.numeric(wave_1_test$multi) ##change from categorical
variable back to numeric variable

one <- wave_1_test%>% ##multirace
  filter(multi == 1)

two <- wave_1_test%>% ##single race
  filter(multi == 0)

two <- two%>%
  mutate(other_race = N3Q75A1 + N3Q75A5 + N3Q75A6) %>%  ##combine groups into
temporary variables
```

```
  mutate(                                    ##create dummy codes for each level
    white = ifelse(N3Q75A7 == 1, 1, 0),
    black = ifelse(N3Q75A3 == 1, 1, 0),
    asian = ifelse(N3Q75A2 == 1, 1, 0),
    hispanic = ifelse(N3Q75A4 == 1, 1, 0),
    other = ifelse(other_race >= 1, 1, 0)
  )

one$other_race <- 0
one$white <- 0
one$black <- 0
one$asian <- 0
one$hispanic <- 0
one$other <- 0

wave_one_recode <- bind_rows(one, two)

test <- wave_one_recode %>%
  arrange(ID)

##turn multiple groups into dummy variables
##making binary with 1 = yes; 0 = no

########################## code enrollment status ############################
##parttime and other = 0; fulltime = 1

######################### wave one enrollment status #########################
wave_1 <- wave_1 %>%
    mutate(fulltime = ifelse(N3Q73 == 1, 1, 0))

##example of code to get table for wave one
table(wave_1$fulltime)

############################### code residence ###############################
##1 = on campus, 0 = not on campus (includes parent home, friend home, homeless)

############################# wave one residence #########################

wave_1 <- wave_1 %>%
  mutate(campus = ifelse(N3Q78 == 1, 1, 0))

##example code for table for wave one
table(wave_1$campus)
```

```
############################ code year in school ############################

############################## wave one year ##############################

wave_1 <- wave_1 %>%
  mutate(firstyear = ifelse(N3Q72 == 1, 1, 0)) %>%
  mutate(undergrad = case_when(
       N3Q72 == 1 ~ 0, ##first year
       N3Q72 == 2 ~ 1, ##second year
       N3Q72 == 3 ~ 1, ##third year
       N3Q72 == 4 ~ 1, ##fourth year
       N3Q72 == 5 ~ 1, ##fifth year
       N3Q72 == 6 ~ 0, ##masters
       N3Q72 == 7 ~ 0, ##doctorate
       N3Q72 == 8 ~ 0, ##non-degree
       N3Q72 == 9 ~ 0  ##other
      )) %>%
 mutate(grad = case_when(
      N3Q72 == 1 ~ 0,
      N3Q72 == 2 ~ 0,
      N3Q72 == 3 ~ 0,
      N3Q72 == 4 ~ 0,
      N3Q72 == 5 ~ 0,
      N3Q72 == 6 ~ 1,
      N3Q72 == 7 ~ 1,
      N3Q72 == 8 ~ 0,
      N3Q72 == 9 ~ 0
     ))

wave_1 <- wave_1 %>%
 arrange(ID)

############################ code gender identity ############################

############################# wave one gender ##############################

wave_1 <- wave_1 %>%
 mutate(female = ifelse(N3Q67C == 1, 1, 0)) %>%
 mutate(male = ifelse(N3Q67C == 2, 1, 0)) %>%
 mutate(nonbinary = ifelse(N3Q67C == 9, 1, 0)) %>%
 mutate(trans = case_when(
   N3Q67C == 1 ~ 0, ##woman/female
   N3Q67C == 2 ~ 0, ##man/male
   N3Q67C == 3 ~ 1, ##trans woman
```

```
    N3Q67C == 4 ~ 1, ##trans man
    N3Q67C == 5 ~ 0, ##genderqueer
    N3Q67C == 6 ~ 0, ##other
    N3Q67C == 7 ~ 0, ##agender
    N3Q67C == 8 ~ 0, ##genderfluid
    N3Q67C == 9 ~ 0,  ##non-binary
    N3Q67C == 10 ~ 0 ##intersex
  )) %>%
mutate(othergen = case_when(
  N3Q67C == 1 ~ 0, ##woman/female
  N3Q67C == 2 ~ 0, ##man/male
  N3Q67C == 3 ~ 0, ##trans woman
  N3Q67C == 4 ~ 0, ##trans man
  N3Q67C == 5 ~ 1, ##genderqueer
  N3Q67C == 6 ~ 1, ##other
  N3Q67C == 7 ~ 1, ##agender
  N3Q67C == 8 ~ 1, ##genderfluid
  N3Q67C == 9 ~ 0,  ##non-binary
  N3Q67C == 10 ~ 1 ##intersex
))

wave_1 <- wave_1 %>%
  arrange(ID)

############################ code sexual orientation ########################
##note from codebook: Students selecting “my identity is not listed above” (10) and
specifying Asexual, Ace,
##or Aces in N3Q68TEXT are recoded Asexual (1) for N3Q68.
##Students selecting “my identity is not listed above” (10) and specifying “straight” in
##N3Q68TEXT are recoded Straight/Heterosexual (9) for N3Q68.
##Students who indicate more than one sexual orientation in N3Q68TEXT are NOT
recoded.
##No additional recoding is done for N3Q68.
##condensing into straight, bisexual, gay/lesbian, and other

############################ wave one sexual orient ########################

wave_1 <- wave_1 %>%
  mutate(straight = ifelse(N3Q68 == 9, 1, 0)) %>%
  mutate(bisexual = ifelse(N3Q68 == 2, 1, 0)) %>%
  mutate(gaylesbian = case_when(
    N3Q68 == 1 ~ 0, ##asexual
    N3Q68 == 2 ~ 0, ##bisexual
    N3Q68 == 3 ~ 1, ##gay
```

```
    N3Q68 == 4 ~ 1, ##lesbian
    N3Q68 == 5 ~ 0, ##pansexual
    N3Q68 == 6 ~ 0, ##queer
    N3Q68 == 7 ~ 0, ##questioning
    N3Q68 == 9 ~ 0, ##straight
    N3Q68 == 10 ~ 0 ##other
  )) %>%
mutate(othersex = case_when(
  N3Q68 == 1 ~ 1, ##asexual
  N3Q68 == 2 ~ 0, ##bisexual
  N3Q68 == 3 ~ 0, ##gay
  N3Q68 == 4 ~ 0, ##lesbian
  N3Q68 == 5 ~ 1, ##pansexual
  N3Q68 == 6 ~ 1, ##queer
  N3Q68 == 7 ~ 1, ##questioning
  N3Q68 == 9 ~ 0, ##straight
  N3Q68 == 10 ~ 1 ##other
))

wave_1 <- wave_1 %>%
  arrange(ID)

######################## code Greek-letter affiliation ########################

################################ wave one GLO ############################

wave_1 <- wave_1 %>%
  mutate(greek = ifelse(N3Q77A == 2, 1, 0))

################################ code athletics ##############################

############################### wave one athlete ############################

wave_1 <- wave_1 %>%
  mutate(athlete = case_when(
  N3Q81A == 2 ~ 1, ##varsity
  N3Q81B == 2 ~ 1, ##club sports
  N3Q81C == 2 ~ 1, ##intramurals
  TRUE ~ 0
))

########################### code disability status
#############################
```

```
############################## wave one disable
##################################

wave_1 <- wave_1 %>%
  mutate(disabled = case_when(
    N3Q82A == 2 ~ 1, ##ADHD
    N3Q82B == 2 ~ 1, ##autism
    N3Q82C == 2 ~ 1, ##deaf/HoH
    N3Q82D == 2 ~ 1, ##learning disability
    N3Q82E == 2 ~ 1, ##mobility/dexterity disability
    N3Q82F == 2 ~ 1, ##blind/low vision
    N3Q82G == 2 ~ 1, ##speech/language disorder
    TRUE ~ 0
  ))

###################### compress substance use variables ####################
##create substance use variables
##Use question one from ASSIST --> N3Q22A1-11
##Note: did not include N3Q22A12 (other specify text)
##Use in last three months --> N3Q22B (rows endorsed in N3Q22A drop down)

########################## recode each substance ##########################

############################ wave one substance ###########################
  wave_1 <- wave_1 %>%
    mutate(opioid = case_when (
    N3Q22B10 >= 2 ~ 1,
    N3Q22B11 >= 2 ~ 1,
    TRUE ~ 0 )) %>%
    mutate(nicotine = case_when (
    N3Q22B1 >= 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(alcohol = case_when (
    N3Q22B2 >= 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(THC = case_when (
    N3Q22B3 >= 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(cocaine = case_when (
    N3Q22B4 >= 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(stimulant = case_when (
    N3Q22B5 >= 2 ~ 1,
    TRUE ~ 0 )) %>%
```

```
  mutate(meth = case_when (
    N3Q22B6 >= 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(inhale = case_when (
    N3Q22B7 >= 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(sed = case_when (
    N3Q22B8 >= 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(hall = case_when (
    N3Q22B9 >= 2 ~ 1,
    TRUE ~ 0 ))

######################### code binge drinking frequency #####################
##no episodes, 1-10 episodes, and >10 episodes.

wave_1 <- wave_1 %>%
  mutate(nobinge = case_when (
    N3Q28 == 1 ~ 1,
    N3Q28 >= 2 ~ 0,
    TRUE ~ 0 )) %>%
  mutate(binge = case_when (
    N3Q28 == 1 ~ 0,
    N3Q28 >= 2 | N3Q28 <= 10 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(bingeplus = case_when (
   N3Q28 == 11 ~ 1,
   TRUE ~ 0 ))

######################## variable name change ##############################

##get rid of these variable names and retain new variable names
wave_1 <- wave_1 %>%
  dplyr::select(-c("N3Q75A1", "N3Q75A2", "N3Q75A3", "N3Q75A4", "N3Q75A5",
"N3Q75A6", "N3Q75A7", "N3Q75A8",
        "N3Q67C",   "N3Q68", "N3Q72", "N3Q73", "N3Q77A", "N3Q77B","N3Q78",
"N3Q81A", "N3Q81B", "N3Q81C", "N3Q28",
        "N3Q22A1", "N3Q22A2", "N3Q22A3", "N3Q22A4", "N3Q22A5",
"N3Q22A6","N3Q22A7","N3Q22A8","N3Q22A9",
        "N3Q22A10","N3Q22A11", "N3Q22B1", "N3Q22B2" , "N3Q22B3" ,
"N3Q22B4", "N3Q22B5", "N3Q22B6", "N3Q22B7",
        "N3Q22B8", "N3Q22B9", "N3Q22B10", "N3Q22B11", "N3Q22B12"))

######################### create variables for LCA ##########################
```

```
lca <- wave_1 %>%
  mutate(ipvphysical = case_when (  ##intimate partner
    N3Q19C == 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(ipvpsych = case_when (
    N3Q19A == 2 ~ 1,
    N3Q19B == 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(ipvsexual = case_when (
    N3Q19D == 2 ~ 1,
    N3Q19E == 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(nipvphysical = case_when ( ##nonintimate parter
    N3Q20B == 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(nipvverbal = case_when (
    N3Q20C == 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(nipvsexual = case_when (
    N3Q20D == 2 ~ 1,
    N3Q20E == 2 ~ 1,
    N3Q20F == 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(nipvstalk = case_when (
    N3Q20G == 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(gbully = case_when (  ##general victimization
    N3Q47A13 == 2 ~ 1,
    N3Q47A14 == 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(ghazing = case_when (
    N3Q47A15 == 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(gdiscrim = case_when (
    N3Q47A16 == 2 ~ 1,
    N3Q47A18 == 2 ~ 1,
    TRUE ~ 0 )) %>%
  mutate(gsexual = case_when (
    N3Q47A17 == 2 ~ 1,
    TRUE ~ 0 )) %>%
dplyr::select(c("ID", "K6", "ipvphysical", "ipvpsych", "ipvsexual","nipvphysical",
"nipvverbal", "nipvsexual", "nipvstalk",
        "gbully", "ghazing", "gdiscrim", "gsexual"))
```

```
##turn into categorical variables

factors <- c("ipvphysical", "ipvpsych", "ipvsexual","nipvphysical", "nipvverbal",
"nipvsexual", "nipvstalk",
            "gbully", "ghazing", "gdiscrim", "gsexual")
lca[factors] <- lapply(lca[factors], factor)

######################## generate latent classes ############################

f <- cbind(ipvphysical, ipvpsych, ipvsexual,nipvphysical, nipvverbal, nipvsexual,
nipvstalk,
          gbully, ghazing, gdiscrim, gsexual) ~ 1

############################ one class model ###############################
##for comparing ##null model

lca1 <- poLCA(f, lca, nclass = 1, maxiter = 10000) ##1 class model ##maxiter =
maximum iterations 10,000

##turn poLCA entropy to relative entropy for reporting
###### from https://stackoverflow.com/questions/33000511/entropy-measure-polca-
mplus
##RELATIVE ENTROPY
##Numerator:
nume.E <- -sum(lca1$posterior * log(lca1$posterior))
##Denominator (n*log(K)): ## n is a sample size, and K is a number of class
deno.E <- 36986*log(1)
##Relative Entropy
Entro <- 1-(nume.E/deno.E)
##entropy = N/A
Entro

############################ two class model ##############################
lca2 <- poLCA(f, lca, nclass = 2, maxiter = 10000) ##2 class model

###other best fit statistics
poLCA.entropy(lca2)  ##get poLCA entropy

##turn poLCA entropy to relative entropy for reporting
###### from https://stackoverflow.com/questions/33000511/entropy-measure-polca-
mplus
##RELATIVE ENTROPY
##Numerator:
```

```
nume.E <- -sum(lca2$posterior * log(lca2$posterior))
##Denominator (n*log(K)): ## n is a sample size, and K is a number of class
deno.E <- 36986*log(2)
##Relative Entropy
Entro <- 1-(nume.E/deno.E)
Entro
  ##entropy = 0.82

############################ three class model ###########################

lca3 <- poLCA(f, lca, nclass = 3, maxiter = 10000) ##3 class model

##entropy
nume.E <- -sum(lca3$posterior * log(lca3$posterior))
##Denominator (n*log(K)): ## n is a sample size, and K is a number of class
deno.E <- 36986*log(3)
##Relative Entropy
Entro <- 1-(nume.E/deno.E)
Entro

#################### compare two class to three class #######################

# load packages/install if needed
library(poLCA)
library(tidyLPA)

# store values baseline model
n <- lca2$Nobs #number of observations (should be equal in both models)
null_ll <- lca2$llik #log-likelihood ratio
null_param <- lca2$npar # number of parameters
null_classes <- length(lca2$P) # number of classes

# store values alternative model
alt_ll <- lca3$llik #log-likelihood
alt_param <- lca3$npar # number of parameters
alt_classes <- length(lca3$P) # number of classes

# use calc_lrt from tidyLPA package
calc_lrt(n, null_ll, null_param, null_classes, alt_ll, alt_param, alt_classes)

##new model better than previous, d/t p being significant
##LR = 2583.617, LMR LR (df = 12) = 2504.255, p < 0.001

########################### four class model ############################
```

```
lca4 <- poLCA(f, lca, nclass = 4, maxiter = 10000) ##4 class model

##entropy
nume.E <- -sum(lca4$posterior * log(lca4$posterior))
##Denominator (n*log(K)): ## n is a sample size, and K is a number of class
deno.E <- 36986*log(4)
##Relative Entropy
Entro <- 1-(nume.E/deno.E)
Entro

#################### compare three class to four class ########################

# store values baseline model
n <- lca3$Nobs #number of observations (should be equal in both models)
null_ll <- lca3$llik #log-likelihood ratio
null_param <- lca3$npar # number of parameters
null_classes <- length(lca3$P) # number of classes

# store values alternative model
alt_ll <- lca4$llik #log-likelihood
alt_param <- lca4$npar # number of parameters
alt_classes <- length(lca4$P) # number of classes

# use calc_lrt from tidyLPA package
calc_lrt(n, null_ll, null_param, null_classes, alt_ll, alt_param, alt_classes)

############################# five class model ##############################

lca5 <- poLCA(f, lca, nclass = 5, maxiter = 10000) ##5 class model

##entropy
nume.E <- -sum(lca5$posterior * log(lca5$posterior))
##Denominator (n*log(K)): ## n is a sample size, and K is a number of class
deno.E <- 36986*log(5)
##Relative Entropy
Entro <- 1-(nume.E/deno.E)
Entro

###################### compare four class to five class #######################

# store values baseline model
n <- lca4$Nobs #number of observations (should be equal in both models)
null_ll <- lca4$llik #log-likelihood ratio
```

```
null_param <- lca4$npar # number of parameters
null_classes <- length(lca4$P) # number of classes

# store values alternative model
alt_ll <- lca5$llik #log-likelihood
alt_param <- lca5$npar # number of parameters
alt_classes <- length(lca5$P) # number of classes

# use calc_lrt from tidyLPA package
calc_lrt(n, null_ll, null_param, null_classes, alt_ll, alt_param, alt_classes)

############################## six class model #############################

lca6 <- poLCA(f, lca, nclass = 6, maxiter = 10000) ##6 class model

##entropy
nume.E <- -sum(lca6$posterior * log(lca6$posterior))
##Denominator (n*log(K)): ## n is a sample size, and K is a number of class
deno.E <- 36986*log(6)
##Relative Entropy
Entro <- 1-(nume.E/deno.E)
Entro

###################### compare five class to six class ########################

# store values baseline model
n <- lca5$Nobs #number of observations (should be equal in both models)
null_ll <- lca5$llik #log-likelihood ratio
null_param <- lca5$npar # number of parameters
null_classes <- length(lca5$P) # number of classes

# store values alternative model
alt_ll <- lca6$llik #log-likelihood
alt_param <- lca6$npar # number of parameters
alt_classes <- length(lca6$P) # number of classes

# use calc_lrt from tidyLPA package
calc_lrt(n, null_ll, null_param, null_classes, alt_ll, alt_param, alt_classes)

############################# seven class model ############################

lca7 <- poLCA(f, lca, nclass = 7, maxiter = 10000) ##7 class model

##entropy
```

```
nume.E <- -sum(lca7$posterior * log(lca7$posterior))
##Denominator (n*log(K)): ## n is a sample size, and K is a number of class
deno.E <- 36986*log(7)
##Relative Entropy
Entro <- 1-(nume.E/deno.E)
Entro

##################### compare six class to seven class ######################

# store values baseline model
n <- lca6$Nobs #number of observations (should be equal in both models)
null_ll <- lca6$llik #log-likelihood ratio
null_param <- lca6$npar # number of parameters
null_classes <- length(lca6$P) # number of classes

# store values alternative model
alt_ll <- lca7$llik #log-likelihood
alt_param <- lca7$npar # number of parameters
alt_classes <- length(lca7$P) # number of classes

# use calc_lrt from tidyLPA package
calc_lrt(n, null_ll, null_param, null_classes, alt_ll, alt_param, alt_classes)

############################ eight class model ###########################

lca8 <- poLCA(f, lca, nclass = 8, maxiter = 10000) ##8 class model

##entropy
nume.E <- -sum(lca8$posterior * log(lca8$posterior))
##Denominator (n*log(K)): ## n is a sample size, and K is a number of class
deno.E <- 36986*log(8)
##Relative Entropy
Entro <- 1-(nume.E/deno.E)
Entro

#################### compare seven class to eight class #####################

# store values baseline model
n <- lca7$Nobs #number of observations (should be equal in both models)
null_ll <- lca7$llik #log-likelihood ratio
null_param <- lca7$npar # number of parameters
null_classes <- length(lca7$P) # number of classes

# store values alternative model
```

```
alt_ll <- lca8$llik #log-likelihood
alt_param <- lca8$npar # number of parameters
alt_classes <- length(lca8$P) # number of classes

# use calc_lrt from tidyLPA package
calc_lrt(n, null_ll, null_param, null_classes, alt_ll, alt_param, alt_classes)

############################### nine class model ##############################

lca9 <- poLCA(f, lca, nclass = 9, maxiter = 10000) ##9 class model

##entropy
nume.E <- -sum(lca9$posterior * log(lca9$posterior))
##Denominator (n*log(K)): ## n is a sample size, and K is a number of class
deno.E <- 36986*log(9)
##Relative Entropy
Entro <- 1-(nume.E/deno.E)
Entro

###################### compare eight class to nine class ######################

# store values baseline model
n <- lca8$Nobs #number of observations (should be equal in both models)
null_ll <- lca8$llik #log-likelihood ratio
null_param <- lca8$npar # number of parameters
null_classes <- length(lca8$P) # number of classes

# store values alternative model
alt_ll <- lca9$llik #log-likelihood
alt_param <- lca9$npar # number of parameters
alt_classes <- length(lca9$P) # number of classes

# use calc_lrt from tidyLPA package
calc_lrt(n, null_ll, null_param, null_classes, alt_ll, alt_param, alt_classes)

############################### demographics ################################

##rename classes
temp1 <- as.data.frame(round(lca4$posterior))
temp1$lca4_1 <- temp1$V1
temp1$lca4_2 <- temp1$V2
temp1$lca4_3 <- temp1$V3
temp1$lca4_4 <- temp1$V4
```

```
temp1 <- temp1 %>%
  dplyr::select(-c("V1", "V2", "V3", "V4"))

lcanew <- bind_cols(lca, temp1)

temp2<- as.data.frame(round(lca5$posterior))
temp2$lca5_1 <- temp2$V1
temp2$lca5_2 <- temp2$V2
temp2$lca5_3 <- temp2$V3
temp2$lca5_4 <- temp2$V4
temp2$lca5_5 <- temp2$V5

temp2 <- temp2 %>%
  dplyr::select(-c("V1", "V2", "V3", "V4", "V5"))

lcanew <- bind_cols(lcanew, temp2)

wave1lca <- wave_1 %>%
  left_join(lcanew, by= "ID")

###################### number students in each class #######################
summary <- wave1lca %>%
  mutate(class1 = sum(lca4_1)/36986)

str(wave1lca$lca4_1)

sum(wave1lca$lca4_1) ##954
sum(wave1lca$lca4_2) ##3267
sum(wave1lca$lca4_3) ##2426
sum(wave1lca$lca4_4) ##30171 (no/low)

##class one (model 4)
954/36986  ##0.02579354 = 2.6% #was class 3 AKA high

##class two
3267/36986 ##0.08833072 = 8.8% verbal/discrim

##class three
2426/36986 ## 0.06559239 = 6.5% #was 4 = sexual/discrim

##class four
30171/36986 #0.8157411 = 81.6% ##was 1 aka low/no

##################### class one demographics (high/poly) ###################
```

```
##use 1:1 answer for having both the variable and being in the class

##race/ethnicity
table(wave1lca$lca4_1, wave1lca$black) ##who is in class 1 and is black
table(wave1lca$lca4_1, wave1lca$white)
table(wave1lca$lca4_1, wave1lca$hispanic)
table(wave1lca$lca4_1, wave1lca$asian)
table(wave1lca$lca4_1, wave1lca$other)
table(wave1lca$lca4_1, wave1lca$multi)

##gender
table(wave1lca$lca4_1, wave1lca$female)
table(wave1lca$lca4_1, wave1lca$male)
table(wave1lca$lca4_1, wave1lca$trans)
table(wave1lca$lca4_1, wave1lca$nonbinary)
table(wave1lca$lca4_1, wave1lca$othergen)

##sexual orientation
table(wave1lca$lca4_1, wave1lca$straight)
table(wave1lca$lca4_1, wave1lca$bisexual)
table(wave1lca$lca4_1, wave1lca$gaylesbian)
table(wave1lca$lca4_1, wave1lca$othersex)

##GLO affiliation
table(wave1lca$lca4_1, wave1lca$greek)

##athletics
table(wave1lca$lca4_1, wave1lca$athlete)

##disability
table(wave1lca$lca4_1, wave1lca$disabled)

##residence
table(wave1lca$lca4_1, wave1lca$campus)

##enrollment status
table(wave1lca$lca4_1, wave1lca$fulltime)

##year in school
table(wave1lca$lca4_1, wave1lca$firstyear)
table(wave1lca$lca4_1, wave1lca$undergrad)
table(wave1lca$lca4_1, wave1lca$grad)

################### class two demographics (verbal/discrim) #################
```

```
##race/ethnicity
table(wave1lca$lca4_2, wave1lca$black) ##who is in class 2 and is black
table(wave1lca$lca4_2, wave1lca$white)
table(wave1lca$lca4_2, wave1lca$hispanic)
table(wave1lca$lca4_2, wave1lca$asian)
table(wave1lca$lca4_2, wave1lca$other)
table(wave1lca$lca4_2, wave1lca$multi)

##gender
table(wave1lca$lca4_2, wave1lca$female)
table(wave1lca$lca4_2, wave1lca$male)
table(wave1lca$lca4_2, wave1lca$trans)
table(wave1lca$lca4_2, wave1lca$nonbinary)
table(wave1lca$lca4_2, wave1lca$othergen)

##sexual orientation
table(wave1lca$lca4_2, wave1lca$straight)
table(wave1lca$lca4_2, wave1lca$bisexual)
table(wave1lca$lca4_2, wave1lca$gaylesbian)
table(wave1lca$lca4_2, wave1lca$othersex)

##GLO affiliation
table(wave1lca$lca4_2, wave1lca$greek)

##athletics
table(wave1lca$lca4_2, wave1lca$athlete)

##disability
table(wave1lca$lca4_2, wave1lca$disabled)

##residence
table(wave1lca$lca4_2, wave1lca$campus)

##enrollment status
table(wave1lca$lca4_2, wave1lca$fulltime)

##year in school
table(wave1lca$lca4_2, wave1lca$firstyear)
table(wave1lca$lca4_2, wave1lca$undergrad)
table(wave1lca$lca4_2, wave1lca$grad)

##RECALL: top/horizontal part of the output represents the second argument (so
demographic variable)
```

```
##vertical part corresponds to first argument (so class)

#################### class three demographics (sexual/discrim ) ################

##race/ethnicity
table(wave1lca$lca4_3, wave1lca$black)
table(wave1lca$lca4_3, wave1lca$white)
table(wave1lca$lca4_3, wave1lca$hispanic)
table(wave1lca$lca4_3, wave1lca$asian)
table(wave1lca$lca4_3, wave1lca$other)
table(wave1lca$lca4_3, wave1lca$multi)

##gender
table(wave1lca$lca4_3, wave1lca$female)
table(wave1lca$lca4_3, wave1lca$male)
table(wave1lca$lca4_3, wave1lca$trans)
table(wave1lca$lca4_3, wave1lca$nonbinary)
table(wave1lca$lca4_3, wave1lca$othergen)

##sexual orientation
table(wave1lca$lca4_3, wave1lca$straight)
table(wave1lca$lca4_3, wave1lca$bisexual)
table(wave1lca$lca4_3, wave1lca$gaylesbian)
table(wave1lca$lca4_3, wave1lca$othersex)

##GLO affiliation
table(wave1lca$lca4_3, wave1lca$greek)

##athletics
table(wave1lca$lca4_3, wave1lca$athlete)

##disability
table(wave1lca$lca4_3, wave1lca$disabled)

##residence
table(wave1lca$lca4_3, wave1lca$campus)

##enrollment status
table(wave1lca$lca4_3, wave1lca$fulltime)

##year in school
table(wave1lca$lca4_3, wave1lca$firstyear)
table(wave1lca$lca4_3, wave1lca$undergrad)
table(wave1lca$lca4_3, wave1lca$grad)
```

```
###################### class four demographics (low/no) ####################

##race/ethnicity
table(wave1lca$lca4_4, wave1lca$black)
table(wave1lca$lca4_4, wave1lca$white)
table(wave1lca$lca4_4, wave1lca$hispanic)
table(wave1lca$lca4_4, wave1lca$asian)
table(wave1lca$lca4_4, wave1lca$other)
table(wave1lca$lca4_4, wave1lca$multi)

##gender
table(wave1lca$lca4_4, wave1lca$female)
table(wave1lca$lca4_4, wave1lca$male)
table(wave1lca$lca4_4, wave1lca$trans)
table(wave1lca$lca4_4, wave1lca$nonbinary)
table(wave1lca$lca4_4, wave1lca$othergen)

##sexual orientation
table(wave1lca$lca4_4, wave1lca$straight)
table(wave1lca$lca4_4, wave1lca$bisexual)
table(wave1lca$lca4_4, wave1lca$gaylesbian)
table(wave1lca$lca4_4, wave1lca$othersex)

##GLO affiliation
table(wave1lca$lca4_4, wave1lca$greek)

##athletics
table(wave1lca$lca4_4, wave1lca$athlete)

##disability
table(wave1lca$lca4_4, wave1lca$disabled)

##residence
table(wave1lca$lca4_4, wave1lca$campus)

##enrollment status
table(wave1lca$lca4_4, wave1lca$fulltime)

##year in school
table(wave1lca$lca4_4, wave1lca$firstyear)
table(wave1lca$lca4_4, wave1lca$undergrad)
table(wave1lca$lca4_4, wave1lca$grad)
```

```
########################### t test for age variable ############################

class1 <- wave1lca %>%
  filter(lca4_1 == 1)

class2 <- wave1lca %>%
  filter(lca4_2 == 1)

class3 <- wave1lca %>%
  filter(lca4_3 == 1)

class4 <- wave1lca %>%
  filter(lca4_4 == 1)

t.test(class1$N3Q69, class2$N3Q69)
## class1 mean age = 21.77385l; class2 mean age = 23.11012
##significant that age is different = 21 vs 23 (p value)

t.test(class1$N3Q69, class3$N3Q69)
## 21.77385  21.67552 (not significant) ONLY ONE

t.test(class1$N3Q69, class4$N3Q69)
## 21.77385  22.53761 (sig)

t.test(class2$N3Q69, class3$N3Q69)
## class2 = 23.11012  class3 = 21.67552
##significant age difference (p = < 2.2e-16)

t.test(class2$N3Q69, class4$N3Q69)
##23.11012  22.53761 (sig)

t.test(class3$N3Q69, class4$N3Q69)
## 21.67552  22.53761 (sig)

################################## code K6 ##################################

wave1lca <- wave1lca %>%
  mutate(K6 = N3Q44A + N3Q44B + N3Q44C + N3Q44D + N3Q44E +N3Q44F)

################### chi square value for class differences #####################

##black
black12 <- prop.test(x = c(89, 337), n = c(954, 3267)) #black between class 1 and 2
black12 ##need this portion to get answer
```

```
black13 <- prop.test(x = c(89, 201), n = c(954, 2426)) #black between class 1 and 3
black13
black14 <- prop.test(x = c(89, 2348), n = c(954, 30171)) #black between class 1 and 4
black14
black23 <- prop.test(x = c(337, 201), n = c(3267, 2426)) #black between class 2 and 3
black23
black24 <- prop.test(x = c(337, 2348), n = c(3267, 30171)) #black between class 2 and 4
black24
black34 <- prop.test(x = c(201, 2348), n = c(2426, 30171)) #black between class 3 and 4
black34

##white
white12 <- prop.test(x = c(452, 1615), n = c(954, 3267)) #white between class 1 and 2
white12
white13 <- prop.test(x = c(452, 1404), n = c(954, 2426))
white13
white14 <- prop.test(x = c(452, 16760), n = c(954, 30171))
black14
white23 <- prop.test(x = c(1615, 1404), n = c(3267, 2426))
white23
white24 <- prop.test(x = c(1615, 16760), n = c(3267, 30171))
white24
white34 <- prop.test(x = c(1404, 16760), n = c(2426, 30171))
white34

##hispanic
hispanic12 <- prop.test(x = c(133, 470), n = c(954, 3267))
hispanic12
hispanic13 <- prop.test(x = c(133, 232), n = c(954, 2426))
hispanic13
hispanic14 <- prop.test(x = c(133, 4139), n = c(954, 30171))
hispanic14
hispanic23 <- prop.test(x = c(470, 232), n = c(3267, 2426))
hispanic23
hispanic24 <- prop.test(x = c(470, 4139), n = c(3267, 30171))
hispanic24
hispanic34 <- prop.test(x = c(232, 4139), n = c(2426, 30171))
hispanic34

##asian
asian12 <- prop.test(x = c(77, 299), n = c(954, 3267))
asian12
asian13 <- prop.test(x = c(77, 155), n = c(954, 2426))
```

```
asian13
asian14 <- prop.test(x = c(77, 3336), n = c(954, 30171))
asian14
asian23 <- prop.test(x = c(299, 155), n = c(3267, 2426))
asian23
asian24 <- prop.test(x = c(299, 3336), n = c(3267, 30171))
asian24
asian34 <- prop.test(x = c(155, 3336), n = c(2426, 30171))
asian34

##multi
multi12 <- prop.test(x = c(157, 413), n = c(954, 3267))
multi12
multi13 <- prop.test(x = c(157, 364), n = c(954, 2426))
multi13
multi14 <- prop.test(x = c(157, 2807), n = c(954, 30171))
multi14
multi23 <- prop.test(x = c(413, 364), n = c(3267, 2426))
multi23
multi24 <- prop.test(x = c(413, 2807), n = c(3267, 30171))
multi24
multi34 <- prop.test(x = c(364, 2807), n = c(2426, 30171))
multi34

##other
other12 <- prop.test(x = c(23, 69), n = c(954, 3267))
other12
other13 <- prop.test(x = c(23, 35), n = c(954, 2426))
other13
other14 <- prop.test(x = c(23, 377), n = c(954, 30171))
other14
other23 <- prop.test(x = c(69, 35), n = c(3267, 2426))
other23
other24 <- prop.test(x = c(69, 377), n = c(3267, 30171))
other24
other34 <- prop.test(x = c(35, 377), n = c(2426, 30171))
other34

##female
female12 <- prop.test(x = c(689, 1902), n = c(954, 3267))
female12
female13 <- prop.test(x = c(689, 2021), n = c(954, 2426))
female13
```

```
female14 <- prop.test(x = c(689, 18567), n = c(954, 30171))
female14
female23 <- prop.test(x = c(1902, 2021), n = c(3267, 2426))
female23
female24 <- prop.test(x = c(1902, 18567), n = c(3267, 30171))
female24
female34 <- prop.test(x = c(2021, 18567), n = c(2426, 30171))
female34

##male
male12 <- prop.test(x = c(215, 1229), n = c(954, 3267))
male12
male13 <- prop.test(x = c(215, 275), n = c(954, 2426))
male13
male14 <- prop.test(x = c(215, 11108), n = c(954, 30171))
male14
male23 <- prop.test(x = c(1229, 275), n = c(3267, 2426))
male23
male24 <- prop.test(x = c(1229, 11108), n = c(3267, 30171))
male24
male34 <- prop.test(x = c(275, 11108), n = c(2426, 30171))
male34

##trans
trans12 <- prop.test(x = c(7, 25), n = c(954, 3267))
trans12
trans13 <- prop.test(x = c(7, 13), n = c(954, 2426))
trans13
trans14 <- prop.test(x = c(7, 65), n = c(954, 30171))
trans14
trans23 <- prop.test(x = c(25, 13), n = c(3267, 2426))
trans23
trans24 <- prop.test(x = c(25, 65), n = c(3267, 30171))
trans24
trans34 <- prop.test(x = c(13, 65), n = c(2426, 30171))
trans34

##nonbinary
nonbinary12 <- prop.test(x = c(11, 43), n = c(954, 3267))
nonbinary12
nonbinary13 <- prop.test(x = c(11, 49), n = c(954, 2426))
nonbinary13
nonbinary14 <- prop.test(x = c(11, 150), n = c(954, 30171))
nonbinary14
```

```
nonbinary23 <- prop.test(x = c(43, 49), n = c(3267, 2426))
nonbinary23
nonbinary24 <- prop.test(x = c(43, 150), n = c(3267, 30171))
nonbinary24
nonbinary34 <- prop.test(x = c(49, 150), n = c(2426, 30171))
nonbinary34

##othergen
othergen12 <- prop.test(x = c(24, 59), n = c(954, 3267))
othergen12
othergen13 <- prop.test(x = c(24, 62), n = c(954, 2426))
othergen13
othergen14 <- prop.test(x = c(24, 217), n = c(954, 30171))
othergen14
othergen23 <- prop.test(x = c(59, 62), n = c(3267, 2426))
othergen23
othergen24 <- prop.test(x = c(59, 217), n = c(3267, 30171))
othergen24
othergen34 <- prop.test(x = c(62, 217), n = c(2426, 30171))
othergen34

##straight
straight12 <- prop.test(x = c(625, 2452), n = c(954, 3267))
straight12
straight13 <- prop.test(x = c(625, 1485), n = c(954, 2426))
straight13
straight14 <- prop.test(x = c(625, 25478), n = c(954, 30171))
straight14
straight23 <- prop.test(x = c(2452, 1485), n = c(3267, 2426))
straight23
straight24 <- prop.test(x = c(2452, 25478), n = c(3267, 30171))
straight24
straight34 <- prop.test(x = c(1485, 25478), n = c(2426, 30171))
straight34

##bisexual
bisexual12 <- prop.test(x = c(171, 410), n = c(954, 3267))
bisexual12
bisexual13 <- prop.test(x = c(171, 468), n = c(954, 2426))
bisexual13
bisexual14 <- prop.test(x = c(171, 2205), n = c(954, 30171))
bisexual14
bisexual23 <- prop.test(x = c(410, 468), n = c(3267, 2426))
bisexual23
```

```
bisexual24 <- prop.test(x = c(410, 2205), n = c(3267, 30171))
bisexual24
bisexual34 <- prop.test(x = c(468, 2205), n = c(2426, 30171))
bisexual34

##gaylesbian
gaylesbian12 <- prop.test(x = c(42, 158), n = c(954, 3267))
gaylesbian12
gaylesbian13 <- prop.test(x = c(42, 129), n = c(954, 2426))
gaylesbian13
gaylesbian14 <- prop.test(x = c(42, 882), n = c(954, 30171))
gaylesbian14
gaylesbian23 <- prop.test(x = c(158, 129), n = c(3267, 2426))
gaylesbian23
gaylesbian24 <- prop.test(x = c(158, 882), n = c(3267, 30171))
gaylesbian24
gaylesbian34 <- prop.test(x = c(129, 882), n = c(2426, 30171))
gaylesbian34

##othersex
othersex12 <- prop.test(x = c(105, 226), n = c(954, 3267))
othersex12
othersex13 <- prop.test(x = c(105, 334), n = c(954, 2426))
othersex13
othersex14 <- prop.test(x = c(105, 1462), n = c(954, 30171))
othersex14
othersex23 <- prop.test(x = c(226, 334), n = c(3267, 2426))
othersex23
othersex24 <- prop.test(x = c(226, 1462), n = c(3267, 30171))
othersex24
othersex34 <- prop.test(x = c(334, 1462), n = c(2426, 30171))
othersex34

##greek
greek12 <- prop.test(x = c(109, 286), n = c(954, 3267))
greek12
greek13 <- prop.test(x = c(109, 264), n = c(954, 2426))
greek13
greek14 <- prop.test(x = c(109, 2394), n = c(954, 30171))
greek14
greek23 <- prop.test(x = c(286, 264), n = c(3267, 2426))
greek23
greek24 <- prop.test(x = c(286, 2394), n = c(3267, 30171))
greek24
```

```
greek34 <- prop.test(x = c(264, 2394), n = c(2426, 30171))
greek34

##athlete
athlete12 <- prop.test(x = c(195, 683), n = c(954, 3267))  ##redo this one
athlete12
athlete13 <- prop.test(x = c(195, 466), n = c(954, 2426))
athlete13
athlete14 <- prop.test(x = c(195, 6991), n = c(954, 30171))
athlete14
athlete23 <- prop.test(x = c(683, 466), n = c(3267, 2426))
athlete23
athlete24 <- prop.test(x = c(683, 6991), n = c(3267, 30171))
athlete24
athlete34 <- prop.test(x = c(466, 6991), n = c(2426, 30171))
athlete34

##disabled
disabled12 <- prop.test(x = c(300, 754), n = c(954, 3267))
disabled12
disabled13 <- prop.test(x = c(300, 634), n = c(954, 2426))
disabled13
disabled14 <- prop.test(x = c(300, 4242), n = c(954, 30171))
disabled14
disabled23 <- prop.test(x = c(754, 634), n = c(3267, 2426))
disabled23
disabled24 <- prop.test(x = c(754, 4242), n = c(3267, 30171))
disabled24
disabled34 <- prop.test(x = c(634, 4242), n = c(2426, 30171))
disabled34

##campus
campus12 <- prop.test(x = c(338, 1171), n = c(954, 3267))
campus12
campus13 <- prop.test(x = c(338, 978), n = c(954, 2426))
campus13
campus14 <- prop.test(x = c(338, 11585), n = c(954, 30171))
campus14
campus23 <- prop.test(x = c(1171, 978), n = c(3267, 2426))
campus23
campus24 <- prop.test(x = c(1171, 11585), n = c(3267, 30171))
campus24
campus34 <- prop.test(x = c(978, 11585), n = c(2426, 30171))
campus34
```

```
##fulltime
fulltime12 <- prop.test(x = c(836, 2905), n = c(954, 3267))
fulltime12
fulltime13 <- prop.test(x = c(836, 2220), n = c(954, 2426))
fulltime13
fulltime14 <- prop.test(x = c(836, 27337), n = c(954, 30171))
fulltime14
fulltime23 <- prop.test(x = c(2905, 2220), n = c(3267, 2426))
fulltime23
fulltime24 <- prop.test(x = c(2905, 27337), n = c(3267, 30171))
fulltime24
fulltime34 <- prop.test(x = c(2220, 27337), n = c(2426, 30171))
fulltime34

##firstyear
firstyear12 <- prop.test(x = c(232, 739), n = c(954, 3267))
firstyear12
firstyear13 <- prop.test(x = c(232, 498), n = c(954, 2426))
firstyear13
firstyear14 <- prop.test(x = c(232, 6937), n = c(954, 30171))
firstyear14
firstyear23 <- prop.test(x = c(739, 498), n = c(3267, 2426))
firstyear23
firstyear24 <- prop.test(x = c(739, 6937), n = c(3267, 30171))
firstyear24
firstyear34 <- prop.test(x = c(498, 6937), n = c(2426, 30171))
firstyear34

##undergrad
undergrad12 <- prop.test(x = c(589, 1836), n = c(954, 3267))
undergrad12
undergrad13 <- prop.test(x = c(589, 1479), n = c(954, 2426))
undergrad13
undergrad14 <- prop.test(x = c(589, 16449), n = c(954, 30171))
undergrad14
undergrad23 <- prop.test(x = c(1836, 1479), n = c(3267, 2426))
undergrad23
undergrad24 <- prop.test(x = c(1836, 16449), n = c(3267, 30171))
undergrad24
undergrad34 <- prop.test(x = c(1479, 16449), n = c(2426, 30171))
undergrad34

##grad
```

```
grad12 <- prop.test(x = c(120, 635), n = c(954, 3267))
grad12
grad13 <- prop.test(x = c(120, 417), n = c(954, 2426))
grad13
grad14 <- prop.test(x = c(120, 6280), n = c(954, 30171))
grad14
grad23 <- prop.test(x = c(635, 417), n = c(3267, 2426))
grad23
grad24 <- prop.test(x = c(635, 6280), n = c(3267, 30171))
grad24
grad34 <- prop.test(x = c(417, 6280), n = c(2426, 30171))
grad34


##nondisabled
nondisabled12 <- prop.test(x = c(654, 2513), n = c(954, 3267))
nondisabled12
nondisabled13 <- prop.test(x = c(654, 1792), n = c(954, 2426))
nondisabled13
nondisabled14 <- prop.test(x = c(654, 25929), n = c(954, 30171))
nondisabled14
nondisabled23 <- prop.test(x = c(2513, 1792), n = c(3267, 2426))
nondisabled23
nondisabled24 <- prop.test(x = c(2513, 25929), n = c(3267, 30171))
nondisabled24
nondisabled34 <- prop.test(x = c(1792, 25929), n = c(2426, 30171))
nondisabled34

##nongreek
nongreek12 <- prop.test(x = c(839, 2974), n = c(954, 3267))
nongreek12
nongreek13 <- prop.test(x = c(839, 2157), n = c(954, 2426))
nongreek13
nongreek14 <- prop.test(x = c(839, 27701), n = c(954, 30171))
nongreek14
nongreek23 <- prop.test(x = c(2974, 2157), n = c(3267, 2426))
nongreek23
nongreek24 <- prop.test(x = c(2974, 27701), n = c(3267, 30171))
nongreek24
nongreek34 <- prop.test(x = c(2157, 27701), n = c(2426, 30171))
nongreek34

##nonathlete
nonathlete12 <- prop.test(x = c(759, 2584), n = c(954, 3267))
```

```
nonathlete12
nonathlete13 <- prop.test(x = c(759, 1960), n = c(954, 2426))
nonathlete13
nonathlete14 <- prop.test(x = c(759, 23180), n = c(954, 30171))
nonathlete14
nonathlete23 <- prop.test(x = c(2584, 1960), n = c(3267, 2426))
nonathlete23
nonathlete24 <- prop.test(x = c(2584, 23180), n = c(3267, 30171))
nonathlete24
nonathlete34 <- prop.test(x = c(1960, 23180), n = c(2426, 30171))
nonathlete34

##offcampus
offcampus12 <- prop.test(x = c(574, 2038), n = c(954, 3267))
offcampus12
offcampus13 <- prop.test(x = c(574, 1397), n = c(954, 2426))
offcampus13
offcampus14 <- prop.test(x = c(574, 17997), n = c(954, 30171))
offcampus14
offcampus23 <- prop.test(x = c(2038, 1397), n = c(3267, 2426))
offcampus23
offcampus24 <- prop.test(x = c(2038, 17997), n = c(3267, 30171))
offcampus24
offcampus34 <- prop.test(x = c(1397, 17997), n = c(2426, 30171))
offcampus34

##parttime
parttime12 <- prop.test(x = c(104, 351), n = c(954, 3267))
parttime12
parttime13 <- prop.test(x = c(104, 193), n = c(954, 2426))
parttime13
parttime14 <- prop.test(x = c(104, 2731), n = c(954, 30171))
parttime14
parttime23 <- prop.test(x = c(351, 193), n = c(3267, 2426))
parttime23
parttime24 <- prop.test(x = c(351, 2731), n = c(3267, 30171))
parttime24
parttime34 <- prop.test(x = c(193, 2731), n = c(2426, 30171))
parttime34

########################### logistic regression ##############################
##REMEMBER SUBSTANCE OUTCOMES:
##opioid, nicotine, alcohol, THC, cocaine, stimulant, meth, inhale, sed, hall <- use yes/no
##binge, nobinge, bingeplus
```

```
temp <- as.data.frame(round(lca4$posterior))  ##using four-class model
lca4lr <- bind_cols(lca4, temp)

############################## class one LR ##############################

##binge drinking
mod1 <- glm(binge ~ lca4_1, data = wave1lca, family = binomial(link = "logit"))
summary(mod1) # display results
#confint(mod1) # 95% CI for the coefficients
exp(coef(mod1)) # exponentiated coefficients
exp(confint(mod1)) # 95% CI for exponentiated coefficients
##predict(mod1, type="response") # predicted values (to find percent)  ##don't do going
forward
##residuals(mod1, type="deviance") # residuals
exp(coef(mod1))/(1+exp(coef(mod1))) # probability associated with lca4_1; being in lca4
associated with 62% more likely to engage in
##binge drinking compared to other groups

## OR =  1.6262626
##logit = 0.48628
##standard error =  0.06744
## p value = <.001
#CI 1.4239767 1.8550250

tab_model(mod1) ##to see summary as a table in viewer

##alcohol
mod2 <- glm(alcohol ~ lca4_1, data = wave1lca, family = binomial(link = "logit"))
##change name of model not to overwrite?
summary(mod2) # display results
#confint(mod2) # 95% CI for the coefficients
exp(coef(mod2)) # exponentiated coefficients
exp(confint(mod2)) # 95% CI for exponentiated coefficients
##predict(mod2, type="response") # predicted values
##residuals(mod2, type="deviance") # residuals
exp(coef(mod2))/(1+exp(coef(mod2)))

## OR =   1.430616
##logit = 0.35811
##standard error = 0.07495
## p value = <.001
#CI = 1.237155 1.659882
```

```
tab_model(mod2)

##opioid
mod3 <- glm(opioid ~ lca4_1, data = wave1lca, family = binomial(link = "logit"))
summary(mod3) # display results
confint(mod3) # 95% CI for the coefficients
exp(coef(mod3)) # exponentiated coefficients
exp(confint(mod3)) # 95% CI for exponentiated coefficients
##predict(mod3, type="response") # predicted values
##residuals(mod3, type="deviance") # residuals
exp(coef(mod3))/(1+exp(coef(mod3)))

tab_model(mod3)

##nicotine
mod4 <- glm(nicotine ~ lca4_1, data = wave1lca, family = binomial(link = "logit"))
summary(mod4) # display results
confint(mod4) # 95% CI for the coefficients
exp(coef(mod4)) # exponentiated coefficients
exp(confint(mod4)) # 95% CI for exponentiated coefficients
##predict(mod4, type="response") # predicted values
##residuals(mod4, type="deviance") # residuals
exp(coef(mod4))/(1+exp(coef(mod4)))

tab_model(mod4)

##THC
mod5 <- glm(THC ~ lca4_1, data = wave1lca, family = binomial(link = "logit"))
summary(mod5) # display results
confint(mod5) # 95% CI for the coefficients
exp(coef(mod5)) # exponentiated coefficients
exp(confint(mod5)) # 95% CI for exponentiated coefficients
##predict(mod5, type="response") # predicted values
##residuals(mod5, type="deviance") # residuals
exp(coef(mod5))/(1+exp(coef(mod5)))

tab_model(mod5)

##cocaine
mod6 <- glm(cocaine ~ lca4_1, data = wave1lca, family = binomial(link = "logit"))
summary(mod6) # display results
confint(mod6) # 95% CI for the coefficients
exp(coef(mod6)) # exponentiated coefficients
exp(confint(mod6)) # 95% CI for exponentiated coefficients
```

```
##predict(mod6, type="response") # predicted values
##residuals(mod6, type="deviance") # residuals
exp(coef(mod6))/(1+exp(coef(mod6)))

tab_model(mod6)

##stimulant
mod7 <- glm(stimulant ~ lca4_1, data = wave1lca, family = binomial(link = "logit"))
summary(mod7) # display results
confint(mod7) # 95% CI for the coefficients
exp(coef(mod7)) # exponentiated coefficients
exp(confint(mod7)) # 95% CI for exponentiated coefficients
##predict(mod7, type="response") # predicted values
##residuals(mod7, type="deviance") # residuals
exp(coef(mod7))/(1+exp(coef(mod7)))

tab_model(mod7)

##meth
mod8 <- glm(meth ~ lca4_1, data = wave1lca, family = binomial(link = "logit"))
summary(mod8) # display results
confint(mod8) # 95% CI for the coefficients
exp(coef(mod8)) # exponentiated coefficients
exp(confint(mod8)) # 95% CI for exponentiated coefficients
##predict(mod8, type="response") # predicted values
##residuals(mod8, type="deviance") # residuals
exp(coef(mod8))/(1+exp(coef(mod8)))

tab_model(mod8)

##inhale
mod9 <- glm(inhale ~ lca4_1, data = wave1lca, family = binomial(link = "logit"))
summary(mod9) # display results
confint(mod9) # 95% CI for the coefficients
exp(coef(mod9)) # exponentiated coefficients
exp(confint(mod9)) # 95% CI for exponentiated coefficients
##predict(mod9, type="response") # predicted values
##residuals(mod9, type="deviance") # residuals
exp(coef(mod9))/(1+exp(coef(mod9)))

tab_model(mod9)

##sed
mod10 <- glm(sed ~ lca4_1, data = wave1lca, family = binomial(link = "logit"))
```

```
summary(mod10) # display results
confint(mod10) # 95% CI for the coefficients
exp(coef(mod10)) # exponentiated coefficients
exp(confint(mod10)) # 95% CI for exponentiated coefficients
##predict(mod10, type="response") # predicted values
##residuals(mod10, type="deviance") # residuals
exp(coef(mod10))/(1+exp(coef(mod10)))

tab_model(mod10)

##hall
mod11 <- glm(hall ~ lca4_1, data = wave1lca, family = binomial(link = "logit"))
summary(mod11) # display results
confint(mod11) # 95% CI for the coefficients
exp(coef(mod11)) # exponentiated coefficients
exp(confint(mod11)) # 95% CI for exponentiated coefficients
##predict(mod11, type="response") # predicted values
##residuals(mod11, type="deviance") # residuals
exp(coef(mod11))/(1+exp(coef(mod11)))

tab_model(mod11)

##bingeplus
mod12 <- glm(bingeplus ~ lca4_1, data = wave1lca, family = binomial(link = "logit"))
summary(mod12) # display results
confint(mod12) # 95% CI for the coefficients
exp(coef(mod12)) # exponentiated coefficients
exp(confint(mod12)) # 95% CI for exponentiated coefficients
##predict(mod12, type="response") # predicted values
##residuals(mod12, type="deviance") # residuals
exp(coef(mod12))/(1+exp(coef(mod12)))

tab_model(mod12)

##nobinge
mod13 <- glm(nobinge ~ lca4_1, data = wave1lca, family = binomial(link = "logit"))
summary(mod13) # display results
confint(mod13) # 95% CI for the coefficients
exp(coef(mod13)) # exponentiated coefficients
exp(confint(mod13)) # 95% CI for exponentiated coefficients
##predict(mod13, type="response") # predicted values
##residuals(mod13, type="deviance") # residuals
exp(coef(mod13))/(1+exp(coef(mod12)))
```

```
tab_model(mod13)

################################ class two LR ############################

##binge drinking
mod1_2 <- glm(binge ~ lca4_2, data = wave1lca, family = binomial(link = "logit"))
summary(mod1_2) # display results
confint(mod1_2) # 95% CI for the coefficients
exp(coef(mod1_2)) # exponentiated coefficients
exp(confint(mod1_2)) # 95% CI for exponentiated coefficients
##predict(mod1_2, type="response") # predicted values (to find percent)  ##don't do
going forward
##residuals(mod_2, type="deviance") # residuals
exp(coef(mod1_2))/(1+exp(coef(mod1_2))) # probability

tab_model(mod1_2)

##alcohol
mod2_2 <- glm(alcohol ~ lca4_2, data = wave1lca, family = binomial(link = "logit"))
##change name of model not to overwrite?
summary(mod2_2) # display results
confint(mod2_2) # 95% CI for the coefficients
exp(coef(mod2_2)) # exponentiated coefficients
exp(confint(mod2_2)) # 95% CI for exponentiated coefficients
##predict(mod2_2, type="response") # predicted values
##residuals(mod2_2, type="deviance") # residuals
exp(coef(mod2_2))/(1+exp(coef(mod2_2)))

tab_model(mod2_2)

##opioid
mod3_2 <- glm(opioid ~ lca4_2, data = wave1lca, family = binomial(link = "logit"))
summary(mod3_2) # display results
confint(mod3_2) # 95% CI for the coefficients
exp(coef(mod3_2)) # exponentiated coefficients
exp(confint(mod3_2)) # 95% CI for exponentiated coefficients
##predict(mod3_2, type="response") # predicted values
##residuals(mod3_2, type="deviance") # residuals
exp(coef(mod3_2))/(1+exp(coef(mod3_2)))

tab_model(mod3_2)

##nicotine
mod4_2 <- glm(nicotine ~ lca4_2, data = wave1lca, family = binomial(link = "logit"))
```

```
summary(mod4_2) # display results
confint(mod4_2) # 95% CI for the coefficients
exp(coef(mod4_2)) # exponentiated coefficients
exp(confint(mod4_2)) # 95% CI for exponentiated coefficients
##predict(mod4_2, type="response") # predicted values
##residuals(mod4_2, type="deviance") # residuals
exp(coef(mod4_2))/(1+exp(coef(mod4_2)))

tab_model(mod4_2)

##THC
mod5_2 <- glm(THC ~ lca4_2, data = wave1lca, family = binomial(link = "logit"))
summary(mod5_2) # display results
confint(mod5_2) # 95% CI for the coefficients
exp(coef(mod5_2)) # exponentiated coefficients
exp(confint(mod5_2)) # 95% CI for exponentiated coefficients
##predict(mod5_2, type="response") # predicted values
##residuals(mod5_2, type="deviance") # residuals
exp(coef(mod5_2))/(1+exp(coef(mod5_2)))

tab_model(mod5_2)

##cocaine
mod6_2 <- glm(cocaine ~ lca4_2, data = wave1lca, family = binomial(link = "logit"))
summary(mod6_2) # display results
confint(mod6_2) # 95% CI for the coefficients
exp(coef(mod6_2)) # exponentiated coefficients
exp(confint(mod6_2)) # 95% CI for exponentiated coefficients
##predict(mod6_2, type="response") # predicted values
##residuals(mod6_2, type="deviance") # residuals
exp(coef(mod6_2))/(1+exp(coef(mod6_2)))

tab_model(mod6_2)

##stimulant
mod7_2 <- glm(stimulant ~ lca4_2, data = wave1lca, family = binomial(link = "logit"))
summary(mod7_2) # display results
confint(mod7_2) # 95% CI for the coefficients
exp(coef(mod7_2)) # exponentiated coefficients
exp(confint(mod7_2)) # 95% CI for exponentiated coefficients
##predict(mod7_2, type="response") # predicted values
##residuals(mod7_2, type="deviance") # residuals
exp(coef(mod7_2))/(1+exp(coef(mod7_2)))
```

```
tab_model(mod7_2)

##meth
mod8_2 <- glm(meth ~ lca4_2, data = wave1lca, family = binomial(link = "logit"))
summary(mod8_2) # display results
confint(mod8_2) # 95% CI for the coefficients
exp(coef(mod8_2)) # exponentiated coefficients
exp(confint(mod8_2)) # 95% CI for exponentiated coefficients
##predict(mod8_2, type="response") # predicted values
##residuals(mod8_2, type="deviance") # residuals
exp(coef(mod8_2))/(1+exp(coef(mod8_2)))

tab_model(mod8_2)

##inhale
mod9_2 <- glm(inhale ~ lca4_2, data = wave1lca, family = binomial(link = "logit"))
summary(mod9_2) # display results
confint(mod9_2) # 95% CI for the coefficients
exp(coef(mod9_2)) # exponentiated coefficients
exp(confint(mod9_2)) # 95% CI for exponentiated coefficients
##predict(mod9_2, type="response") # predicted values
##residuals(mod9_2, type="deviance") # residuals
exp(coef(mod9_2))/(1+exp(coef(mod9_2)))

tab_model(mod9_2)

##sed
mod10_2 <- glm(sed ~ lca4_2, data = wave1lca, family = binomial(link = "logit"))
summary(mod10_2) # display results
confint(mod10_2) # 95% CI for the coefficients
exp(coef(mod10_2)) # exponentiated coefficients
exp(confint(mod10_2)) # 95% CI for exponentiated coefficients
##predict(mod10_2, type="response") # predicted values
##residuals(mod10_2, type="deviance") # residuals
exp(coef(mod10_2))/(1+exp(coef(mod10_2)))

tab_model(mod10_2)

##hall
mod11_2 <- glm(hall ~ lca4_2, data = wave1lca, family = binomial(link = "logit"))
summary(mod11_2) # display results
confint(mod11_2) # 95% CI for the coefficients
exp(coef(mod11_2)) # exponentiated coefficients
exp(confint(mod11_2)) # 95% CI for exponentiated coefficients
```

```
##predict(mod11_2, type="response") # predicted values
##residuals(mod11_2, type="deviance") # residuals
exp(coef(mod11_2))/(1+exp(coef(mod11_2)))

tab_model(mod11_2)

##bingeplus
mod12_2 <- glm(bingeplus ~ lca4_2, data = wave1lca, family = binomial(link = "logit"))
summary(mod12_2) # display results
confint(mod12_2) # 95% CI for the coefficients
exp(coef(mod12_2)) # exponentiated coefficients
exp(confint(mod12_2)) # 95% CI for exponentiated coefficients
##predict(mod12_2, type="response") # predicted values
##residuals(mod12_2, type="deviance") # residuals
exp(coef(mod12_2))/(1+exp(coef(mod12_2)))

tab_model(mod12_2)

##nobinge
mod13_2 <- glm(nobinge ~ lca4_2, data = wave1lca, family = binomial(link = "logit"))
summary(mod13_2) # display results
confint(mod13_2) # 95% CI for the coefficients
exp(coef(mod13_2)) # exponentiated coefficients
exp(confint(mod13_2)) # 95% CI for exponentiated coefficients
##predict(mod13_2, type="response") # predicted values
##residuals(mod13_2, type="deviance") # residuals
exp(coef(mod13_2))/(1+exp(coef(mod12_2)))

tab_model(mod13_2)

############################## class three LR ###############################

##binge drinking
mod1_3 <- glm(binge ~ lca4_3, data = wave1lca, family = binomial(link = "logit"))
summary(mod1_3) # display results
confint(mod1_3) # 95% CI for the coefficients
exp(coef(mod1_3)) # exponentiated coefficients
exp(confint(mod1_3)) # 95% CI for exponentiated coefficients
##predict(mod1_3, type="response") # predicted values (to find percent)  ##don't do
going forward
##residuals(mod_3, type="deviance") # residuals
exp(coef(mod1_3))/(1+exp(coef(mod1_3))) # probability

tab_model(mod1_3)
```

```
##alcohol
mod2_3 <- glm(alcohol ~ lca4_3, data = wave1lca, family = binomial(link = "logit"))
##change name of model not to overwrite?
summary(mod2_3) # display results
confint(mod2_3) # 95% CI for the coefficients
exp(coef(mod2_3)) # exponentiated coefficients
exp(confint(mod2_3)) # 95% CI for exponentiated coefficients
##predict(mod2_3, type="response") # predicted values
##residuals(mod2_3, type="deviance") # residuals
exp(coef(mod2_3))/(1+exp(coef(mod2_3)))

tab_model(mod2_3)

##opioid
mod3_3 <- glm(opioid ~ lca4_3, data = wave1lca, family = binomial(link = "logit"))
summary(mod3_3) # display results
confint(mod3_3) # 95% CI for the coefficients
exp(coef(mod3_3)) # exponentiated coefficients
exp(confint(mod3_3)) # 95% CI for exponentiated coefficients
##predict(mod3_3, type="response") # predicted values
##residuals(mod3_3, type="deviance") # residuals
exp(coef(mod3_3))/(1+exp(coef(mod3_3)))

tab_model(mod3_3)

##nicotine
mod4_3 <- glm(nicotine ~ lca4_3, data = wave1lca, family = binomial(link = "logit"))
summary(mod4_3) # display results
confint(mod4_3) # 95% CI for the coefficients
exp(coef(mod4_3)) # exponentiated coefficients
exp(confint(mod4_3)) # 95% CI for exponentiated coefficients
##predict(mod4_3, type="response") # predicted values
##residuals(mod4_3, type="deviance") # residuals
exp(coef(mod4_3))/(1+exp(coef(mod4_3)))

tab_model(mod4_3)

##THC
mod5_3 <- glm(THC ~ lca4_3, data = wave1lca, family = binomial(link = "logit"))
summary(mod5_3) # display results
confint(mod5_3) # 95% CI for the coefficients
exp(coef(mod5_3)) # exponentiated coefficients
exp(confint(mod5_3)) # 95% CI for exponentiated coefficients
```

```
##predict(mod5_3, type="response") # predicted values
##residuals(mod5_3, type="deviance") # residuals
exp(coef(mod5_3))/(1+exp(coef(mod5_3)))

tab_model(mod5_3)

##cocaine
mod6_3 <- glm(cocaine ~ lca4_3, data = wave1lca, family = binomial(link = "logit"))
summary(mod6_3) # display results
confint(mod6_3) # 95% CI for the coefficients
exp(coef(mod6_3)) # exponentiated coefficients
exp(confint(mod6_3)) # 95% CI for exponentiated coefficients
##predict(mod6_3, type="response") # predicted values
##residuals(mod6_3, type="deviance") # residuals
exp(coef(mod6_3))/(1+exp(coef(mod6_3)))

tab_model(mod6_3)

##stimulant
mod7_3 <- glm(stimulant ~ lca4_3, data = wave1lca, family = binomial(link = "logit"))
summary(mod7_3) # display results
confint(mod7_3) # 95% CI for the coefficients
exp(coef(mod7_3)) # exponentiated coefficients
exp(confint(mod7_3)) # 95% CI for exponentiated coefficients
##predict(mod7_3, type="response") # predicted values
##residuals(mod7_3, type="deviance") # residuals
exp(coef(mod7_3))/(1+exp(coef(mod7_3)))

tab_model(mod7_3)

##meth
mod8_3 <- glm(meth ~ lca4_3, data = wave1lca, family = binomial(link = "logit"))
summary(mod8_3) # display results
confint(mod8_3) # 95% CI for the coefficients
exp(coef(mod8_3)) # exponentiated coefficients
exp(confint(mod8_3)) # 95% CI for exponentiated coefficients
##predict(mod8_3, type="response") # predicted values
##residuals(mod8_3, type="deviance") # residuals
exp(coef(mod8_3))/(1+exp(coef(mod8_3)))

tab_model(mod8_3)

##inhale
mod9_3 <- glm(inhale ~ lca4_3, data = wave1lca, family = binomial(link = "logit"))
```

```
summary(mod9_3) # display results
confint(mod9_3) # 95% CI for the coefficients
exp(coef(mod9_3)) # exponentiated coefficients
exp(confint(mod9_3)) # 95% CI for exponentiated coefficients
##predict(mod9_3, type="response") # predicted values
##residuals(mod9_3, type="deviance") # residuals
exp(coef(mod9_3))/(1+exp(coef(mod9_3)))

tab_model(mod9_3)

##sed
mod10_3 <- glm(sed ~ lca4_3, data = wave1lca, family = binomial(link = "logit"))
summary(mod10_3) # display results
confint(mod10_3) # 95% CI for the coefficients
exp(coef(mod10_3)) # exponentiated coefficients
exp(confint(mod10_3)) # 95% CI for exponentiated coefficients
##predict(mod10_3, type="response") # predicted values
##residuals(mod10_3, type="deviance") # residuals
exp(coef(mod10_3))/(1+exp(coef(mod10_3)))

tab_model(mod10_3)

##hall
mod11_3 <- glm(hall ~ lca4_3, data = wave1lca, family = binomial(link = "logit"))
summary(mod11_3) # display results
confint(mod11_3) # 95% CI for the coefficients
exp(coef(mod11_3)) # exponentiated coefficients
exp(confint(mod11_3)) # 95% CI for exponentiated coefficients
##predict(mod11_3, type="response") # predicted values
##residuals(mod11_3, type="deviance") # residuals
exp(coef(mod11_3))/(1+exp(coef(mod11_3)))

tab_model(mod11_3)

##bingeplus
mod12_3 <- glm(bingeplus ~ lca4_3, data = wave1lca, family = binomial(link = "logit"))
summary(mod12_3) # display results
confint(mod12_3) # 95% CI for the coefficients
exp(coef(mod12_3)) # exponentiated coefficients
exp(confint(mod12_3)) # 95% CI for exponentiated coefficients
##predict(mod12_3, type="response") # predicted values
##residuals(mod12_3, type="deviance") # residuals
exp(coef(mod12_3))/(1+exp(coef(mod12_3)))
```

```
tab_model(mod12_3)

##nobinge
mod13_3 <- glm(nobinge ~ lca4_3, data = wave1lca, family = binomial(link = "logit"))
summary(mod13_3) # display results
confint(mod13_3) # 95% CI for the coefficients
exp(coef(mod13_3)) # exponentiated coefficients
exp(confint(mod13_3)) # 95% CI for exponentiated coefficients
##predict(mod13_3, type="response") # predicted values
##residuals(mod13_3, type="deviance") # residuals
exp(coef(mod13_3))/(1+exp(coef(mod12_3)))

tab_model(mod13_3)

############################### class four LR ###############################

##binge drinking
mod1_4 <- glm(binge ~ lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(mod1_4) # display results
confint(mod1_4) # 95% CI for the coefficients
exp(coef(mod1_4)) # exponentiated coefficients
exp(confint(mod1_4)) # 95% CI for exponentiated coefficients
##predict(mod1_4, type="response") # predicted values (to find percent)  ##don't do
going forward
##residuals(mod_4, type="deviance") # residuals
exp(coef(mod1_4))/(1+exp(coef(mod1_4))) # probability

tab_model(mod1_4)

##alcohol
mod2_4 <- glm(alcohol ~ lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(mod2_4) # display results
#confint(mod2_4) # 95% CI for the coefficients
exp(coef(mod2_4)) # exponentiated coefficients
exp(confint(mod2_4)) # 95% CI for exponentiated coefficients
##predict(mod2_4, type="response") # predicted values
##residuals(mod2_4, type="deviance") # residuals
exp(coef(mod2_4))/(1+exp(coef(mod2_4)))

tab_model(mod2_4)

##opioid
mod3_4 <- glm(opioid ~ lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(mod3_4) # display results
```

```
confint(mod3_4) # 95% CI for the coefficients
exp(coef(mod3_4)) # exponentiated coefficients
exp(confint(mod3_4)) # 95% CI for exponentiated coefficients
##predict(mod3_4, type="response") # predicted values
##residuals(mod3_4, type="deviance") # residuals
exp(coef(mod3_4))/(1+exp(coef(mod3_4)))

tab_model(mod3_4)

##nicotine
mod4_4 <- glm(nicotine ~ lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(mod4_4) # display results
confint(mod4_4) # 95% CI for the coefficients
exp(coef(mod4_4)) # exponentiated coefficients
exp(confint(mod4_4)) # 95% CI for exponentiated coefficients
##predict(mod4_4, type="response") # predicted values
##residuals(mod4_4, type="deviance") # residuals
exp(coef(mod4_4))/(1+exp(coef(mod4_4)))

tab_model(mod4_4)

##THC
mod5_4 <- glm(THC ~ lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(mod5_4) # display results
confint(mod5_4) # 95% CI for the coefficients
exp(coef(mod5_4)) # exponentiated coefficients
exp(confint(mod5_4)) # 95% CI for exponentiated coefficients
##predict(mod5_4, type="response") # predicted values
##residuals(mod5_4, type="deviance") # residuals
exp(coef(mod5_4))/(1+exp(coef(mod5_4)))

tab_model(mod5_4)

##cocaine
mod6_4 <- glm(cocaine ~ lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(mod6_4) # display results
confint(mod6_4) # 95% CI for the coefficients
exp(coef(mod6_4)) # exponentiated coefficients
exp(confint(mod6_4)) # 95% CI for exponentiated coefficients
##predict(mod6_4, type="response") # predicted values
##residuals(mod6_4, type="deviance") # residuals
exp(coef(mod6_4))/(1+exp(coef(mod6_4)))

tab_model(mod6_4)
```

```
##stimulant
mod7_4 <- glm(stimulant ~ lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(mod7_4) # display results
confint(mod7_4) # 95% CI for the coefficients
exp(coef(mod7_4)) # exponentiated coefficients
exp(confint(mod7_4)) # 95% CI for exponentiated coefficients
##predict(mod7_4, type="response") # predicted values
##residuals(mod7_4, type="deviance") # residuals
exp(coef(mod7_4))/(1+exp(coef(mod7_4)))

tab_model(mod7_4)

##meth
mod8_4 <- glm(meth ~ lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(mod8_4) # display results
confint(mod8_4) # 95% CI for the coefficients
exp(coef(mod8_4)) # exponentiated coefficients
exp(confint(mod8_4)) # 95% CI for exponentiated coefficients
##predict(mod8_4, type="response") # predicted values
##residuals(mod8_4, type="deviance") # residuals
exp(coef(mod8_4))/(1+exp(coef(mod8_4)))

tab_model(mod8_4)

##inhale
mod9_4 <- glm(inhale ~ lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(mod9_4) # display results
confint(mod9_4) # 95% CI for the coefficients
exp(coef(mod9_4)) # exponentiated coefficients
exp(confint(mod9_4)) # 95% CI for exponentiated coefficients
##predict(mod9_4, type="response") # predicted values
##residuals(mod9_4, type="deviance") # residuals
exp(coef(mod9_4))/(1+exp(coef(mod9_4)))

tab_model(mod9_4)

##sed
mod10_4 <- glm(sed ~ lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(mod10_4) # display results
confint(mod10_4) # 95% CI for the coefficients
exp(coef(mod10_4)) # exponentiated coefficients
exp(confint(mod10_4)) # 95% CI for exponentiated coefficients
##predict(mod10_4, type="response") # predicted values
```

```
##residuals(mod10_4, type="deviance") # residuals
exp(coef(mod10_4))/(1+exp(coef(mod10_4)))

tab_model(mod10_4)

##hall
mod11_4 <- glm(hall ~ lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(mod11_4) # display results
confint(mod11_4) # 95% CI for the coefficients
exp(coef(mod11_4)) # exponentiated coefficients
exp(confint(mod11_4)) # 95% CI for exponentiated coefficients
##predict(mod11_4, type="response") # predicted values
##residuals(mod11_4, type="deviance") # residuals
exp(coef(mod11_4))/(1+exp(coef(mod11_4)))

tab_model(mod11_4)

##bingeplus
mod12_4 <- glm(bingeplus ~ lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(mod12_4) # display results
confint(mod12_4) # 95% CI for the coefficients
exp(coef(mod12_4)) # exponentiated coefficients
exp(confint(mod12_4)) # 95% CI for exponentiated coefficients
##predict(mod12_4, type="response") # predicted values
##residuals(mod12_4, type="deviance") # residuals
exp(coef(mod12_4))/(1+exp(coef(mod12_4)))

tab_model(mod12_4)

##nobinge
mod13_4 <- glm(nobinge ~ lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(mod13_4) # display results
confint(mod13_4) # 95% CI for the coefficients
exp(coef(mod13_4)) # exponentiated coefficients
exp(confint(mod13_4)) # 95% CI for exponentiated coefficients
##predict(mod13_4, type="response") # predicted values
##residuals(mod13_4, type="deviance") # residuals
exp(coef(mod13_4))/(1+exp(coef(mod13_4)))

tab_model(mod13_4)

############################### LR mediation ############################

library(mediation)
```

```
######################## class one a' pathway #############################

model1 <- lm(K6 ~ lca4_1, data = wave1lca)
summary(model1)  ##a' pathway

######################## class one b' pathway #############################

##binge
model1.1 <- glm(binge ~ K6 + lca4_1, data = wave1lca, family = binomial(link =
"logit"))
summary(model1.1) ##b' pathway
exp(coef(model1.1))  ##for odds ratio
med1.1.out <- mediate(model1, model1.1, treat = "lca4_1", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med1.1.out)
##estimate = 7.61240
##a pathway estimate = 4.34882  SE = 0.17198 p = <2e-16 ***
##b pathway

##alcohol
model1.2 <- glm(alcohol ~ K6 + lca4_1, data = wave1lca, family = binomial(link =
"logit"))
summary(model1.2) ##b' pathway
exp(coef(model1.2))  ##for odds ratio
med1.2.out <- mediate(model1, model1.2, treat = "lca4_1", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med1.2.out)

##opioid
model1.3 <- glm(opioid ~ K6 + lca4_1, data = wave1lca, family = binomial(link =
"logit"))
summary(model1.3) ##b' pathway
exp(coef(model1.3))  ##for odds ratio
med1.3.out <- mediate(model1, model1.3, treat = "lca4_1", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med1.3.out)

##nicotine
model1.4 <- glm(nicotine ~ K6 + lca4_1, data = wave1lca, family = binomial(link =
"logit"))
summary(model1.4) ##b' pathway
exp(coef(model1.4))  ##for odds ratio
```

```
med1.4.out <- mediate(model1, model1.4, treat = "lca4_1", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med1.4.out)

##THC
model1.5 <- glm(THC ~ K6 + lca4_1, data = wave1lca, family = binomial(link =
"logit"))
summary(model1.5) ##b' pathway
exp(coef(model1.5))  ##for odds ratio
med1.5.out <- mediate(model1, model1.5, treat = "lca4_1", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med1.5.out)

##cocaine
model1.6 <- glm(cocaine ~ K6 + lca4_1, data = wave1lca, family = binomial(link =
"logit"))
summary(model1.6) ##b' pathway
exp(coef(model1.6))  ##for odds ratio
med1.6.out <- mediate(model1, model1.6, treat = "lca4_1", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med1.6.out)

##stimulant
model1.7 <- glm(stimulant ~ K6 + lca4_1, data = wave1lca, family = binomial(link =
"logit"))
summary(model1.7) ##b' pathway
exp(coef(model1.7))  ##for odds ratio
med1.7.out <- mediate(model1, model1.7, treat = "lca4_1", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med1.7.out)

##meth
model1.8 <- glm(meth ~ K6 + lca4_1, data = wave1lca, family = binomial(link =
"logit"))
summary(model1.8) ##b' pathway
exp(coef(model1.8))  ##for odds ratio
med1.8.out <- mediate(model1, model1.8, treat = "lca4_1", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med1.8.out)

##inhale
model1.9 <- glm(inhale ~ K6 + lca4_1, data = wave1lca, family = binomial(link =
"logit"))
summary(model1.9) ##b' pathway
```

```
exp(coef(model1.9))  ##for odds ratio
med1.9.out <- mediate(model1, model1.9, treat = "lca4_1", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med1.9.out)

##sed
model1.10 <- glm(sed ~ K6 + lca4_1, data = wave1lca, family = binomial(link = "logit"))
summary(model1.10) ##b' pathway
exp(coef(model1.10))  ##for odds ratio
med1.10.out <- mediate(model1, model1.10, treat = "lca4_1", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med1.10.out)

##hall
model1.11 <- glm(hall ~ K6 + lca4_1, data = wave1lca, family = binomial(link =
"logit"))
summary(model1.11) ##b' pathway
exp(coef(model1.11))  ##for odds ratio
med1.11.out <- mediate(model1, model1.11, treat = "lca4_1", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med1.11.out)

##bingeplus
model1.12 <- glm(bingeplus ~ K6 + lca4_1, data = wave1lca, family = binomial(link =
"logit"))
summary(model1.12) ##b' pathway
exp(coef(model1.12))  ##for odds ratio
med1.12.out <- mediate(model1, model1.12, treat = "lca4_1", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med1.12.out)

##nobinge
model1.13 <- glm(nobinge ~ K6 + lca4_1, data = wave1lca, family = binomial(link =
"logit"))
summary(model1.13) ##b' pathway
exp(coef(model1.13))  ##for odds ratio
med1.13.out <- mediate(model1, model1.13, treat = "lca4_1", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med1.13.out)

########################### class two a' pathway ###########################

model2 <- lm(K6 ~ lca4_2, data = wave1lca)
summary(model2)  ##a' pathway
```

```
########################### class two b' pathway ###########################

##binge
model2.1 <- glm(binge ~ K6 + lca4_2, data = wave1lca, family = binomial(link =
"logit"))
summary(model2.1) ##b' pathway
exp(coef(model2.1))  ##for odds ratio
med2.1.out <- mediate(model2, model2.1, treat = "lca4_2", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med2.1.out)

##alcohol
model2.2 <- glm(alcohol ~ K6 + lca4_2, data = wave1lca, family = binomial(link =
"logit"))
summary(model2.2) ##b' pathway
exp(coef(model2.2))  ##for odds ratio
med2.2.out <- mediate(model2, model2.2, treat = "lca4_2", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med2.2.out)

##opioid
model2.3 <- glm(opioid ~ K6 + lca4_2, data = wave1lca, family = binomial(link =
"logit"))
summary(model2.3) ##b' pathway
exp(coef(model2.3))  ##for odds ratio
med2.3.out <- mediate(model2, model2.3, treat = "lca4_2", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med2.3.out)

##nicotine
model2.4 <- glm(nicotine ~ K6 + lca4_2, data = wave1lca, family = binomial(link =
"logit"))
summary(model2.4) ##b' pathway
exp(coef(model2.4))  ##for odds ratio
med2.4.out <- mediate(model2, model2.4, treat = "lca4_2", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med2.4.out)

##THC
model2.5 <- glm(THC ~ K6 + lca4_2, data = wave1lca, family = binomial(link =
"logit"))
summary(model2.5) ##b' pathway
exp(coef(model2.5))  ##for odds ratio
```

```
med2.5.out <- mediate(model2, model2.5, treat = "lca4_2", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med2.5.out)

##cocaine
model2.6 <- glm(cocaine ~ K6 + lca4_2, data = wave1lca, family = binomial(link =
"logit"))
summary(model2.6) ##b' pathway
exp(coef(model2.6))  ##for odds ratio
med2.6.out <- mediate(model2, model2.6, treat = "lca4_2", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med2.6.out)

##stimulant
model2.7 <- glm(stimulant ~ K6 + lca4_2, data = wave1lca, family = binomial(link =
"logit"))
summary(model2.7) ##b' pathway
exp(coef(model2.7))  ##for odds ratio
med2.7.out <- mediate(model2, model2.7, treat = "lca4_2", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med2.7.out)

##meth
model2.8 <- glm(meth ~ K6 + lca4_2, data = wave1lca, family = binomial(link =
"logit"))
summary(model2.8) ##b' pathway
exp(coef(model2.8))  ##for odds ratio
med2.8.out <- mediate(model2, model2.8, treat = "lca4_2", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med2.8.out)

##inhale
model2.9 <- glm(inhale ~ K6 + lca4_2, data = wave1lca, family = binomial(link =
"logit"))
summary(model2.9) ##b' pathway
exp(coef(model2.9))  ##for odds ratio
med2.9.out <- mediate(model2, model2.9, treat = "lca4_2", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med2.9.out)

##sed
model2.10 <- glm(sed ~ K6 + lca4_2, data = wave1lca, family = binomial(link = "logit"))
summary(model2.10) ##b' pathway
exp(coef(model2.10))  ##for odds ratio
```

```
med2.10.out <- mediate(model2, model2.10, treat = "lca4_2", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med2.10.out)

##hall
model2.11 <- glm(hall ~ K6 + lca4_2, data = wave1lca, family = binomial(link =
"logit"))
summary(model2.11) ##b' pathway
exp(coef(model2.11))  ##for odds ratio
med2.11.out <- mediate(model2, model2.11, treat = "lca4_2", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med2.11.out)

##bingeplus
model2.12 <- glm(bingeplus ~ K6 + lca4_2, data = wave1lca, family = binomial(link =
"logit"))
summary(model2.12) ##b' pathway
exp(coef(model2.12))  ##for odds ratio
med2.12.out <- mediate(model2, model2.12, treat = "lca4_2", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med2.12.out)

##nobinge
model2.13 <- glm(nobinge ~ K6 + lca4_2, data = wave1lca, family = binomial(link =
"logit"))
summary(model2.13) ##b' pathway
exp(coef(model2.13))  ##for odds ratio
med2.13.out <- mediate(model2, model2.13, treat = "lca4_2", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med2.13.out)

########################### class three a' pathway ###########################

model3 <- lm(K6 ~ lca4_3, data = wave1lca)
summary(model3)  ##a' pathway

########################### class three b' pathway ###########################

##binge
model3.1 <- glm(binge ~ K6 + lca4_3, data = wave1lca, family = binomial(link =
"logit"))
summary(model3.1) ##b' pathway
exp(coef(model3.1))  ##for odds ratio
```

```
med3.1.out <- mediate(model3, model3.1, treat = "lca4_3", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med3.1.out)

##alcohol
model3.2 <- glm(alcohol ~ K6 + lca4_3, data = wave1lca, family = binomial(link =
"logit"))
summary(model3.2) ##b' pathway
exp(coef(model3.2))  ##for odds ratio
med3.2.out <- mediate(model3, model3.2, treat = "lca4_3", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med3.2.out)

##opioid
model3.3 <- glm(opioid ~ K6 + lca4_3, data = wave1lca, family = binomial(link =
"logit"))
summary(model3.3) ##b' pathway
exp(coef(model3.3))  ##for odds ratio
med3.3.out <- mediate(model3, model3.3, treat = "lca4_3", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med3.3.out)

##nicotine
model3.4 <- glm(nicotine ~ K6 + lca4_3, data = wave1lca, family = binomial(link =
"logit"))
summary(model3.4) ##b' pathway
exp(coef(model3.4))  ##for odds ratio
med3.4.out <- mediate(model3, model3.4, treat = "lca4_3", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med3.4.out)

##THC
model3.5 <- glm(THC ~ K6 + lca4_3, data = wave1lca, family = binomial(link =
"logit"))
summary(model3.5) ##b' pathway
exp(coef(model3.5))  ##for odds ratio
med3.5.out <- mediate(model3, model3.5, treat = "lca4_3", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med3.5.out)

##cocaine
model3.6 <- glm(cocaine ~ K6 + lca4_3, data = wave1lca, family = binomial(link =
"logit"))
summary(model3.6) ##b' pathway
```

```
exp(coef(model3.6))  ##for odds ratio
med3.6.out <- mediate(model3, model3.6, treat = "lca4_3", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med3.6.out)

##stimulant
model3.7 <- glm(stimulant ~ K6 + lca4_3, data = wave1lca, family = binomial(link =
"logit"))
summary(model3.7) ##b' pathway
exp(coef(model3.7))  ##for odds ratio
med3.7.out <- mediate(model3, model3.7, treat = "lca4_3", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med3.7.out)

##meth
model3.8 <- glm(meth ~ K6 + lca4_3, data = wave1lca, family = binomial(link =
"logit"))
summary(model3.8) ##b' pathway
exp(coef(model3.8))  ##for odds ratio
med3.8.out <- mediate(model3, model3.8, treat = "lca4_3", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med3.8.out)

##inhale
model3.9 <- glm(inhale ~ K6 + lca4_3, data = wave1lca, family = binomial(link =
"logit"))
summary(model3.9) ##b' pathway
exp(coef(model3.9))  ##for odds ratio
med3.9.out <- mediate(model3, model3.9, treat = "lca4_3", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med3.9.out)

##sed
model3.10 <- glm(sed ~ K6 + lca4_3, data = wave1lca, family = binomial(link = "logit"))
summary(model3.10) ##b' pathway
exp(coef(model3.10))  ##for odds ratio
med3.10.out <- mediate(model3, model3.10, treat = "lca4_3", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med3.10.out)

##hall
model3.11 <- glm(hall ~ K6 + lca4_3, data = wave1lca, family = binomial(link =
"logit"))
summary(model3.11) ##b' pathway
```

```
exp(coef(model3.11))  ##for odds ratio
med3.11.out <- mediate(model3, model3.11, treat = "lca4_3", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med3.11.out)

##bingeplus
model3.12 <- glm(bingeplus ~ K6 + lca4_3, data = wave1lca, family = binomial(link =
"logit"))
summary(model3.12) ##b' pathway
exp(coef(model3.12))  ##for odds ratio
med3.12.out <- mediate(model3, model3.12, treat = "lca4_3", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med3.12.out)

##nobinge
model3.13 <- glm(nobinge ~ K6 + lca4_3, data = wave1lca, family = binomial(link =
"logit"))
summary(model3.13) ##b' pathway
exp(coef(model3.13))  ##for odds ratio
med3.13.out <- mediate(model3, model3.13, treat = "lca4_3", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med3.13.out)

############################ class four a' pathway ############################

model4 <- lm(K6 ~ lca4_4, data = wave1lca)
summary(model4)  ##a' pathway

############################ class four b' pathway ############################

##binge
model4.1 <- glm(binge ~ K6 + lca4_4, data = wave1lca, family = binomial(link =
"logit"))
summary(model4.1) ##b' pathway
exp(coef(model4.1))  ##for odds ratio
med4.1.out <- mediate(model4, model4.1, treat = "lca4_4", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med4.1.out)

##alcohol
model4.2 <- glm(alcohol ~ K6 + lca4_4, data = wave1lca, family = binomial(link =
"logit"))
summary(model4.2) ##b' pathway
exp(coef(model4.2))  ##for odds ratio
```

```
med4.2.out <- mediate(model4, model4.2, treat = "lca4_4", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med4.2.out)

##opioid
model4.3 <- glm(opioid ~ K6 + lca4_4, data = wave1lca, family = binomial(link =
"logit"))
summary(model4.3) ##b' pathway
exp(coef(model4.3))  ##for odds ratio
med4.3.out <- mediate(model4, model4.3, treat = "lca4_4", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med4.3.out)

##nicotine
model4.4 <- glm(nicotine ~ K6 + lca4_4, data = wave1lca, family = binomial(link =
"logit"))
summary(model4.4) ##b' pathway
exp(coef(model4.4))  ##for odds ratio
med4.4.out <- mediate(model4, model4.4, treat = "lca4_4", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med4.4.out)

##THC
model4.5 <- glm(THC ~ K6 + lca4_4, data = wave1lca, family = binomial(link =
"logit"))
summary(model4.5) ##b' pathway
exp(coef(model4.5))  ##for odds ratio
med4.5.out <- mediate(model4, model4.5, treat = "lca4_4", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med4.5.out)

##cocaine
model4.6 <- glm(cocaine ~ K6 + lca4_4, data = wave1lca, family = binomial(link =
"logit"))
summary(model4.6) ##b' pathway
exp(coef(model4.6))  ##for odds ratio
med4.6.out <- mediate(model4, model4.6, treat = "lca4_4", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med4.6.out)

##stimulant
model4.7 <- glm(stimulant ~ K6 + lca4_4, data = wave1lca, family = binomial(link =
"logit"))
summary(model4.7) ##b' pathway
```

```
exp(coef(model4.7))  ##for odds ratio
med4.7.out <- mediate(model4, model4.7, treat = "lca4_4", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med4.7.out)

##meth
model4.8 <- glm(meth ~ K6 + lca4_4, data = wave1lca, family = binomial(link =
"logit"))
summary(model4.8) ##b' pathway
exp(coef(model4.8))  ##for odds ratio
med4.8.out <- mediate(model4, model4.8, treat = "lca4_4", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med4.8.out)

##inhale
model4.9 <- glm(inhale ~ K6 + lca4_4, data = wave1lca, family = binomial(link =
"logit"))
summary(model4.9) ##b' pathway
exp(coef(model4.9))  ##for odds ratio
med4.9.out <- mediate(model4, model4.9, treat = "lca4_4", mediator = "K6", robustSE =
TRUE, sims = 100)
summary(med4.9.out)

##sed
model4.10 <- glm(sed ~ K6 + lca4_4, data = wave1lca, family = binomial(link = "logit"))
summary(model4.10) ##b' pathway
exp(coef(model4.10))  ##for odds ratio
med4.10.out <- mediate(model4, model4.10, treat = "lca4_4", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med4.10.out)

##hall
model4.11 <- glm(hall ~ K6 + lca4_4, data = wave1lca, family = binomial(link =
"logit"))
summary(model4.11) ##b' pathway
exp(coef(model4.11))  ##for odds ratio
med4.11.out <- mediate(model4, model4.11, treat = "lca4_4", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med4.11.out)

##bingeplus
model4.12 <- glm(bingeplus ~ K6 + lca4_4, data = wave1lca, family = binomial(link =
"logit"))
summary(model4.12) ##b' pathway
```

```
exp(coef(model4.12))  ##for odds ratio
med4.12.out <- mediate(model4, model4.12, treat = "lca4_4", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med4.12.out)

##nobinge
model4.13 <- glm(nobinge ~ K6 + lca4_4, data = wave1lca, family = binomial(link =
"logit"))
summary(model4.13) ##b' pathway
exp(coef(model4.13))  ##for odds ratio
med4.13.out <- mediate(model4, model4.13, treat = "lca4_4", mediator = "K6", robustSE
= TRUE, sims = 100)
summary(med4.13.out)

################################### end coding ##############################
```

Appendix B. Data Use Permission Letter

AMERICAN COLLEGE HEALTH ASSOCIATION

August 26, 2021

Alicia Holod, BSN, BA, RN
The Ohio State University
1585 Neil Ave.
Columbus, OH 43210

Dear Alicia,

Thank you for submitting a request to use ACHA-NCHA data in your project, "Polyvictimization and Associated Substance Use in College Students." Your request has been approved and enclosed you will find the ACHA-NCHA Reference Group Datasets you requested and the corresponding survey codebook. Both institutional and student identifiers have been removed from the files.

Please note that due to the COVID-19 pandemic, schools that began data collection after March 16, 2020 were not included in the Spring 2020 reference group. The Fall 2020 and Spring 2021 were collected during the COVID-19 pandemic.

I have enclosed a copy of our data use guidelines and agreement for your information. Your signed copy is on file in my office. Please note that additional studies using the ACHA-NCHA data acquired through this request require submission of a new data use request to the ACHA-NCHA Program Office.

As stated in the agreement, we would appreciate a copy of any final products that result from your research. We also ask that you add the following disclaimer to any article or presentation you make using the ACHA-NCHA data:

> *The opinions, findings, and conclusions presented/reported in this article/presentation are those of the author(s), and are in no way meant to represent the corporate opinions, views, or policies of the American College*

Health Association (ACHA). ACHA does not warrant nor assume any liability or responsibility for the accuracy, completeness, or usefulness of any information presented in this article/presentation.

Please don’t hesitate to contact me if you have any questions. Best of luck with your research,

Mary Hoban, PhD, MCHES
Director, ACHA-NCHA Program Office
Enclosure: ACHA-NCHA Data Use Guidelines and Agreement

Appendix C. Data Use Guidelines and Agreement

Data Use Guidelines

The ACHA-NCHA data contain information about high-risk behaviors, and all data are confidential. ACHA will not release data on any institution, nor will it release data sets where it is possible to identify any participating schools. Individuals who are granted access to any ACHA-NCHA data
must adhere to ACHA's data use guidelines, which follow. Failure to sign or to adhere to the attached agreement will result in immediate termination of data use privileges.

The accuracy of the users' statistical analyses and the findings they report are not the responsibility of the American College Health Association. ACHA shall not be held liable for improper or incorrect use of the data.

Data Use Agreement

By signing below, I agree to the following:

- I acknowledge that the ACHA-NCHA data is the exclusive property of ACHA. The data is confidential and proprietary, and I will take all reasonable precautions to prevent unauthorized disclosure or access, including through necessary communications with, and oversight of, the persons named herein. I will use the data solely for the purposes stated, and I shall not transfer the data to, or share the data with, any person not identified in this Request Form. Upon completion of my use of the data, or at any time if so directed by ACHA, I shall return the data to ACHA, without retaining a copy, and shall purge such data from any print or electronic records.
- I will reference the American College Health Association when reporting any data obtained from the ACHA-NCHA utilizing the following standard format (items in red font are specific to the data you receive and must be completed appropriately):

    American College Health Association. American College Health Association-National College Health Assessment, Survey Period(s) [data file]. Silver Spring, MD: American College Health Association [producer and distributor]; (YYYY-MM-DD of distribution).

- I will include the following disclaimer language in any published article or presentation:

  The opinions, findings, and conclusions presented/reported in this article/presentation are those of the author(s), and are in no way meant to represent the corporate opinions, views, or policies of the American College Health Association (ACHA). ACHA does not warrant nor assume any liability or responsibility for the accuracy, completeness, or usefulness of any information presented in this article/presentation.
- I will grant access to ACHA-NCHA data to only those individuals specified in this Data Use Request Form. Should the need to grant access to additional individuals arise, I will contact the ACHA Research Director immediately.
- my institution requires, I will obtain all necessary Institutional Review Board (IRB) approval for secondary data analysis prior to beginning my research, and I will provide ACHA with appropriate documentation of IRB approval.
- I will provide ACHA with any final products produced using ACHA-NCHA data, which include but are not limited to: professional journal manuscripts, professional conference presentations, student theses/dissertations, book chapters, policy documents, fact sheets, and brochures.

Signed copy on file at ACHA, 8-26-2021