The Ecology of Campus Sexual Assault: A Latent Class Analysis

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Dedication

This dissertation is dedicated to survivors of sexual violence everywhere. I see you. I hear you. I believe you.

Acknowledgments

This journey could not have been possible without the unrelenting support of many individuals personally, and professionally. Throughout the past 5 years, I have been incredibly grateful for the support, encouragement, and love I have received from so many important individuals. Thank you.

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Abstract

The Ecology of Campus Sexual Assault: A Latent Class Analysis

Campus sexual assault (CSA) is a pervasive problem among US college students. Large scale, methodologically similar studies frequently find that between 20-25% of women and 6-7% of men are sexually victimized during their time at 4-year colleges and universities in the US (Cantor et al., 2015, 2019; Fisher, Cullen, & Turner, 2000; Krebs et al., 2007; Krebs, Lindquist, & Barrick, 2011). CSA is frequently associated with mental and physical health problems including depression, anxiety, PTSD, suicidality, insomnia, chronic pain, and gastrointestinal problems, making it a significant public health concern for institutions of higher education (IHEs; Campbell, Dworkin, & Cabral, 2008; Carey et al., 2018; Golding, 1999; Leone & Carroll, 2016; McDougall et al., 2016; Potter et al., 2018). Despite the dearth of research literature on CSA, there are several significant problems that have plagued the field from painting an accurate picture of the scope and context of the problem, including methodological challenges to gathering accurate incidence and prevalence rates and inconsistent language across research studies. The present study serves to partially fill the research gap by taking a latent variable mixture modeling approach to campus climate survey data in order to uncover subgroups of students based on their responses to elements of campus climate and understand the predictive capabilities of both individual and environmental variables as they relate to those latent subgroups. The purpose of the present study is to utilize a process-person-context framework in order to examine individual factors within the larger campus environment and sociopolitical landscape. Results confirmed the existence of latent subgroups of students on elements of campus climate, and latent class membership could

be predicted by victimization status, and a number of individual, environmental, and institutional variables. Of note, results highlighted disenfranchisement and fearful-based responses in students with marginalized identities. Additionally, results linked membership with on-campus organizations with possessing more knowledge of on-campus resources available to students. Finally, results linked university size, region, and class (public vs. private) to latent class membership highlighting the impact of allocation of funds and resources on perceptions of campus climate. Implications of the present study may help IHEs identify students who would benefit from specialized outreach efforts to regain trust in their IHE and increase overall levels of students' knowledge of on-campus resources to increase safety of campus communities.

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Chapter One: Introduction

The following chapter provides an overview of the present study including a summary of the current research literature on Campus Sexual Assault (CSA), statement of the problem, purpose of the present study and research questions proposed. Additionally, the current chapter summarizes the theoretical foundation for the present study and presents the limitations and delimitations of the current study. Finally, the chapter includes definitions of key terms used throughout.

Overview

Campus sexual assault (CSA) is a pervasive problem among US college students. Large scale, methodologically similar studies frequently find that between 20-25% of women and 6-7% of men are sexually victimized during their time at 4-year colleges and universities in the US (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). In recent years, the media has highlighted several high-profile CSA cases, such as the case of Brock Turner, the Stanford student-athlete who assaulted an unconscious woman behind a dumpster in 2016 (Stack, 2016), or the Vanderbilt rape case, where a group of football players took turns raping a Vanderbilt university student in 2013 (Goldgier, 2017). Media attention and the current trend of digital activism (e.g., #MeToo movement) has further highlighted the devasting reality of many college students who have been sexually victimized during their time in college (Mendes et al., 2018). CSA is frequently associated with mental and physical health problems including depression, anxiety, PTSD, suicidality, insomnia, chronic pain, and gastrointestinal problems, making it a significant public health concern for institutions of higher

education (IHEs; Campbell et al., 2008; Carey et al., 2018; Golding, 1999; Leone & Carroll, 2016; McDougall et al., 2016; Potter et al., 2018).

While CSA has been a pervasive problem on college and university campuses since the integration of men and women at American IHEs, it was not until the passage of Title IX in 1972 that gender discrimination in schools was prohibited under federal law (Kirkpatrick & Kanin, 1957; Title IX of the Education Amendments of 1972). Title IX has been a key piece of legislation dictating the ways in which IHEs are required by law to respond to allegations of gender discrimination, sexual misconduct, and harassment on college campuses and has been amended as recently as August 2020 under the Trump administration. Since the passage of Title IX, there have been several other keys pieces of legislation including the Clery Act, and the Campus Sexual Violence Elimination Act that were drafted to combat the problem of CSA (McCallion, 2014). Additionally, interpretation of Title IX guidelines depends on the current presidential administration's Secretary of Education, and has historically been interpreted using a Dear Colleague Letter (DCL), a formal letter stating guidance on the ways in which Title IX should be implemented. Of note, the 2011 DCL introduced sweeping changes in the way that Title IX cases were adjudged on college campuses. In 2014, the Obama administration formed a task force partially in response to the many stories highlighted by the media and student activists, which was designed to strengthen and address Title IX compliance issues as well as provide IHEs additional tools to respond to and address CSA (Obama, 2014). Since the creation of this task force, there has been a sharp increase in research on CSA, especially sexual assault and misconduct campus climate surveys, inclusive of the large-scale sexual assault and misconduct campus climate survey utilized in the present study,

which surveyed students from 27 IHEs (Cantor et al., 2015; Krause et al., 2019). Additionally, colleges and universities have also attempted to improve their campus-specific policies and strengthen Title IX offices in response to CSA incidences (DeLong et al, 2018).

Despite intervention at the federal and institutional levels, CSA continues to occur at a similar rate, and it is still unclear what specific elements contribute to a college campus climate that perpetuates CSA incidents (Cantor et al., 2019). Previous research has identified several individual characteristics and behaviors associated with victimization including LGBTQ+ identity, disability status, binge drinking behaviors, and previous victimization experience (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). However, these individual predictors do little to describe what elements of campus climate make a safe or unsafe environment. The literature frequently notes that students living on-campus are more at risk than those living off-campus or with family of origin (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). Additionally, research has found support for peer group influence on attitudes about sexual victimization and likelihood of sexual assault perpetration (DeKeseredy et al., 2018; Gwartney-Gibbs & Stockard, 1989; Kaczkowski, et al., 2016). Specifically, students who are connected to peers with cavalier attitudes towards sexual assault are more likely to be victimized than those who are surrounded by peers who are concerned about CSA on campus (DeKeseredy et al., 2018).

In addition to peer group influence of a survivor's immediate social circle, there are several elements about socialization processes of college students that are related to perpetration of CSA. Firstly, many scholars have studied how elements of college parties

including casual sexual encounters (i.e., “hook-ups”), binge drinking, and Greek organization affiliation are related to sexual assault perpetration (Adam-Curtis & Forbes, 2004; DeKeseredy et al., 2018; Flack et al., 2007; Martin, 2016; Sutton & Simons, 2015). Greek organizations host parties that include alcohol and promote binge drinking in combination with misunderstood sexual expectancies during student “hook-ups” (Adam-Curtis & Forbes, 2004; Barriger & Velez-Basini, 2013; Flack et al., 2007; Sutton & Simons, 2015). This environment promotes risky sexual encounters while intoxicated, which can blur lines of consent and perpetuate CSA. Additionally, group masculinity dynamics of men’s organizations like fraternities and sports teams promote cultures of toxic masculinity, competition, and peer acceptance of assaultive behaviors, which prevent members from holding each other accountable for sexual misconduct (McCray, 2015).

The research literature also describes the sociopolitical landscape of US colleges and universities in the adjudication of CSA cases, which often includes the interests of opposing stakeholders. At the institutional level, colleges and universities are incentivized to handle reported cases of CSA internally to protect their “brand” (Dick, 2015). If adjudicated cases fail to find enough evidence to support CSA allegations, the university is not required to make a report to the Department of Education, further incentivizing them to silence victims (Dick, 2015; Martin, 2016; McCallion, 2014; US Department of Education, 2020). These conflicts of interest at the institutional level can doubly harm survivors of CSA by creating an unsafe, hostile environment for students who have been victimized (Smith & Freyd, 2013; Stader & Williams-Cunningham, 2017).

While the research literature has captured a few elements of campus environment that seem to foster CSA perpetration, other researchers look to the greater cultural fabric that blindly perpetuates sexual victimization of college students. Feminist scholars have approached the problem of CSA from the lens of the greater patriarchal society which places women inferior to men and promotes the idea of "rape culture" (Burt, 1980; O'Connor et al., 2018). Specifically, they argue that college students, and society as a whole, adhere to rape-prone beliefs such as victim blaming/shaming, objectification of women's bodies, and glamorization of sexual violence (Burt, 1980). The acceptance of these "rape myths" contributes to unsafe environments for women on college campuses and further exacerbates the other environmental predictors of CSA (O'Connor et al., 2018).

Despite the dearth of research literature on CSA, there are several significant problems that have plagued the field from painting an accurate picture of the scope and context of the problem. First, many CSA studies and campus climate surveys have yielded varied results in terms of incidence and prevalence (Fedina et al., 2018). Researchers cite methodological challenges in the measurement of sexual assault and potentially biased response rates (Muehlenhard et al., 2018; Krause et al., 2019). Specifically, the language used to describe nonconsensual sexual contact can vary between campus climate surveys, making measurement of the same type of victimization inconsistent (Krause et al., 2019). Additionally, most campus climate surveys utilize a census approach to gathering CSA data, which can lead to low response rates and students self-selecting into these surveys, which may produce biased sexual assault

estimates (Krause et al., 2019). These methodological problems have led to inconclusive results regarding who is victimized on college campuses, and under what conditions.

Above and beyond methodological challenges to studying the incidence and prevalence of CSA, are the critical needs of college students who continue to be victimized and IHEs who seek to prevent such events from happening on their campuses. The present study serves to partially fill the research gap by taking a latent variable mixture modeling approach to campus climate survey data in order to uncover subgroups of students based on their responses to elements of campus climate and understand the predictive capabilities of both individual and environmental variables as they relate to those latent subgroups. The purpose of the present methodology is to utilize a process-person-context framework in order to examine individual factors within the larger campus environment and sociopolitical landscape.

Statement of the Problem

Numerous high-profile cases of sexual assault and misconduct on college campuses in addition to the tireless efforts made by student activists have prompted national attention to the problem of CSA. Following the creation of the White House Task Force to encourage IHEs to rectify Title IX noncompliance issues in 2014, IHEs employed many sexual assault and misconduct campus climate surveys to clarify and define the issue. While the effort was not unsuccessful in its attempt to determine the scope of the problem in terms of incidence and prevalence, it did little to provide IHEs with practical intervention and prevention strategies. Additionally, inconsistent methodology across IHEs has made it difficult for sexual victimization researchers to

make conclusive remarks about CSA as a public health crisis affecting IHEs across the United States.

Despite continued attempts to intervene at the institutional and federal level, CSA continues to be a significant public health issue plaguing college campuses and endangering the lives and well-being of millions of college students during their time on campus (Campbell et al., 2008; Carey et al., 2018; Golding, 1999; Leone & Carroll, 2016; McDougall et al., 2016; Potter et al., 2018). Large methodologically similarly campus climate and sexual assault studies have identified some individual characteristics of survivors, which help to identify who might be most at risk, but there is a lack of research on environmental and context specific factors that contribute to perpetuation of sexual violence on campus (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). Similarly, some research has been devoted to understanding the effects of interpersonal processes, institutional policies and procedures, and the effect of the larger cultural zeitgeist on incidence and prevalence of CSA, but there is limited research using a process-person-context approach to bring these elements together. In May 2020, President Trump's Secretary of Education, Betsey DeVos delivered sweeping changes to Title IX, garnering concerns from sexual assault advocates (Department of Education, 2020). Specifically, the 2020 Title IX changes place greater protections for students being accused of sexual violence and shy away from the intervention and prevention efforts put forth by the Obama administration. These changes defy evidence-based practices and procedures set forth by the previous administration and sexual victimization scholars and advocates, potentially endangering students to even greater risk of CSA and perpetuating the problem of sexual assault on college campuses. In order

to understand the nuances and complexity of sexual assault on college campuses, an ecological, multi-level research approach is required. There are several gaps in the literature related to CSA. In a special issue of *Sexual Abuse,* Harris and colleagues (2019) call for action-oriented research initiatives that shed even greater light on the problem of CSA, its dynamics on campus and a critical examination of the impact of existing institutional initiatives put in place to prevent CSA. Additionally, CSA research largely focuses on the "typical" victim, and overlooks marginalized populations who are victimized. For example, most CSA research excludes men and downplays the potential impact CSA has on the experiences of LGBTQ+ and BIPOC survivors (Harris, Terry, & Ackerman, 2019). Thus, it is critical that CSA research works to capture the voices of all survivors and other stakeholders who have been indirectly affected by CSA who might hold the key to the solution.

To this end, the present study serves to partially achieve this goal by taking on a latent variable mixture modeling approach to examining a large campus climate and CSA dataset. Taking on this type of methodological approach takes the perceptions of campus climate among victims and non-victims and classifies them based on response patterns. Additionally, ecological variables at the individual, micro-, meso-, exo-, and macro-levels will be used to predict latent subgroups.

Purpose and Research Questions

The purpose of the present study is to identify hidden subgroups based on patterns of responses from students about their perceptions of campus climate and CSA. Specifically, the present study uses latent class analysis (LCA) to identify homogenous subtypes of students. Additionally, the present study identifies variables that are

embedded in the ecology of the campus at multiple levels of the ecological system and seeks to understand their predictive capabilities on latent subgroups. To this end, the following research questions were generated:

RQ1: Among a sample of college students are there distinct latent subgroups of students based on measures of campus climate?

RQ1.a: Can latent class membership be predicted by victimization status (i.e., having a victimization experience, or never having a victimization experience)?

RQ2: Can latent class membership be predicted by individual-level characteristics such as, gender identity, age, sexual orientation, race/ethnicity, and disability status?

RQ3: Can latent class membership be predicted by micro- and mesosystem measures such as group/club membership, partnered relationship status, and living situation?

RQ4: Can latent class membership be predicted by exo- and macrosystem measures such as university affiliation (i.e., public or private), size of university, and location of university?

Statement of Potential Significance

The scope of CSA as a public health issue facing millions of college students annually is well documented (Campbell et al., 2008; Carey et al., 2018; Leone & Carroll, 2016; McDougall et al., 2016; Potter et al., 2018). However, there have been challenges in gathering and interpreting meaningful data to inform prevention and intervention efforts (Fedina et al., 2018; Krause et al., 2019; Muehlenhard et al., 2017). The present study seeks to take on a latent variable mixture modeling approach to existing CSA data with the intention of uncovering hidden subgroups and hopefully revealing meaningful overlap between victims and non-victims of CSA. Results of the present study could

potentially inform university policies tailored to their culture-specific problems related to sexual misconduct. By utilizing measures of campus climate to track patterns of responses of students who have and have not been victimized, the present study hopes to identify ways in which campus climate contributes to CSA. Ultimately, results of the present study could help to inform prevention and intervention strategies to avoid further victimization and support students who have been victimized.

Armed with knowledge of latent subgroups, the present study will also assess the predictive power of variables at the individual, micro-, meso-, exo-, and macro- system levels on group membership. Taking on an ecological approach to understanding CSA victimization in conjunction with latent variable mixture modeling has not, to my knowledge, been done before. This novel approach to interpreting the data can contribute to understanding ecological level data for institutions and policymakers to use to complement individual level data.

Theoretical Framework

The present study utilizes Ecological Systems Theory (EST) as the theoretical framework for the proposed research questions. Urie Bronfenbrenner's (1979) EST examined the evolving interaction between the developing person and their environment. Bronfenbrenner (1979) theorized that human development is defined by lasting change in the way in which a person perceives and deals with their environment. Like a set of nested Russian dolls, the ecological systems model contains concentric structures starting with the innermost structure of the individual, surrounded by their immediate environment, followed by the systems in which the person participates, the environment in which the person may not participate in, but that affects their world, and finally, the

outermost layer of the overarching pattern of ideology and organization of the social institutions common to a particular culture or subculture (Bronfenbrenner, 1979). These structures are known as the micro-, meso-, exo-, and macro- systems, with each outer structure enveloping the inner ones, and affecting each other simultaneously.

Bronfenbrenner's (1979) EST model of human development has since been applied in a number of contexts, including child abuse and violence against women (Belsky, 1980; Heise, 1999). Using Bronfenbrenner's (1979) model, Belsky (1980) applied the division of ecological space (micro-, meso-, exo-, and macro-) to consider what takes place in the context of the household of abused children, any forces at work in the larger social system in which the family exists, and cultural beliefs and values that influence the macrosystem of abused children and their families. Heise (1998) similarly applied EST to that of violence against women. According to Heise (1998), survivors of gender-based violence have individual characteristics such as witnessing marital violence in childhood or having a child abuse history that informs the way in which they respond to their micro-, meso-, exo- and macro- systems. Heise (1998) posited that microsystem components like male dominance in the family, exosystem components like low SES and unemployment, and macrosystem factors like rigid gender roles in the greater community or subculture all contribute to higher levels of violence against women.

Previous research has shown that taking an ecological approach to CSA research is an effective way to conceptualize the problem from a more holistic stance. Specifically, interactions among variables at the individual, micro-, meso-, exo-, and macrosystem levels have been identified as significant predictors of CSA and PTSD following victimization (Herres et al., 2018). Specifically, Herres et al., (2018) found a

significant interaction between minority status and CSA, such that racial/ethnic minorities who have experienced CSA reported higher levels of PTSD symptoms than nonminority participants. Additionally, there is evidence for taking an ecological approach to the response and prevention of CSA by framing risk and protective factors within the context of interpersonal processes, institutional and community factors, and public policy (ACHA, 2016).

The present study serves to examine CSA through an ecological lens by identifying individual, micro-, meso-, exo-, and macrosystem variables and understanding their predictive capabilities in identifying class membership of victims and non-victims of CSA. EST takes on a process-person-context framework to understand the complexity associated with CSA. Coupled with the goal of uncovering subgroups within a large sample of college students on measures of campus climate, the present study serves to identify specific variables at each level of ecology related to victimization.

Summary of the Methodology

The present study uses existing data which was collected for the Association of American Universities (AAU) by a third-party company, Westat in 2015 (Cantor et al., 2015). In total, 27 IHEs were sampled. The total sample size of invited participants was 779,170 undergraduate, graduate, and professional students. The final response rate of the sample was 19.3%, with a total of 150,072 students participating. The Campus Climate Survey on Sexual Assault and Sexual Misconduct was designed to collect a significant amount of detail on a wide range of victimizations, including harassment, stalking, intimate partner violence (IPV), and various forms of nonconsensual sexual contact (NSC). The survey instrument was developed for the White House Task Force to Protect

Students from Sexual Assault, and then was adapted around the informational needs of the IHEs. In total, the survey contained 10 subsections with a total of 63 items shown to each participant. The survey included items about several different types of nonconsensual sexual contact including rape and sexual battery by physical force, by threat of physical force, or by incapacitation.

The present study uses all non-missing data from the AAU Campus Climate Survey on Sexual Assault and Sexual Misconduct. In order to address the research questions posed in the present study, three analyses are conducted. First, a confirmatory factor analysis (CFA) is conducted to confirm the factor structure of three measures of campus climate and provide additional evidence for construct validity. The CFA includes 14 items from the measures of campus climate: perceptions of sexual assault risk, knowledge of campus resources and policies, and perceptions of responses to reporting. After confirmation of the factor structure, these items are used to conduct a latent class analysis (LCA). LCA is used to classify cases into groups with similar response patterns on a series of observed variables. In LCA, one or more latent, categorical variables are assumed to be responsible for observed response patterns (Samuelson & Dayton, 2019). The present study uses LCA to make hypotheses about qualitative differences among respondents in the AAU survey. The purpose of utilizing LCA in the present study is to identify items that indicate classes of victims and non-victims, estimate class probabilities, and classify individuals into those classes (Muthen, 2009). Following LCA, a series of latent class regression (LCR) analyses are conducted. LCR can use covariates to predict individual class membership (Linzer & Lewis, 2011). In the present study, a series of LCR models are analyzed to include variables at the individual, micro-

/mesosystem, and exo-/macrosystem levels to determine their predictive capabilities relative to the identified latent classes.

Limitations and Delimitations

At the outset, there are a few limitations that should be noted, specifically with the methodology of the dataset being used. First, data collection utilized a census approach with participants self-selecting into the survey. This type of sampling approach may have led to a biased sample. Cantor et al. (2015) did note that there were some statistically significant differences in response rates among the sample. Specifically, Cantor et al. (2015) noted that graduate students were much more likely to respond to the survey than undergraduate students, and women were much more likely to respond to the survey than men. Additionally, there was some evidence that survivors of CSA were more likely to respond to and complete the survey than those who had not been victimized, suggesting a slight bias in the prevalence rate obtained by Cantor et al. (2015). While the sample was large at over 150,000 participants, it was not representative in terms of race/ethnicity, sexual orientation, or gender identity.

The survey instrument utilized drew from several existing, reliable and valid scales, in addition to incorporating guidance from the White House Task Force with regards to campus climate surveys. However, in the original report, the authors failed to report measures of reliability and validity for their sample in addition to altering several items from the original scales cited. This oversight calls into question the reliability and validity of the specific measures used in the study.

To combat some of the challenges encountered with the existing data, there are several methodological decisions that can remedy those issues. First, because there is

some question as to the reliability and validity of some of the items in the original survey, a CFA is conducted to confirm the factor structure of the campus climate measures, and a reliability analysis is conducted to examine evidence for internal consistency.

The AAU survey asked several questions about specific victimization experiences of students in terms of type of victimization and tactic under which the victimization occurred. In the present study, sexual harassment, stalking, and intimate partner violence are not included as sexual assault victimization experiences. While these types of victimization may overlap with CSA, they are considered distinct victimization experiences and therefore were not included in the scope of this study. Additionally, despite the plethora of data collected on the type of sexual victimization (i.e., sexual penetration or sexual touching) and the tactics by which these victimization experiences occurred (i.e., physical force or threat of physical force, being incapacitated due to drugs alcohol, or being unconscious, coercive threats, and failure to obtain affirmative consent), the present study will collapse these victimization experiences into a dichotomous variable designating participants as victims or non-victims. This methodological decision may alter the nuanced experiences of survivors, however, the present study serves to understand the ecological, contextual processes of hostile campus climates that promote and perpetrate CSA. Therefore, the type of victimization matters less than the ecological variables in which CSA occurs.

The purpose of the present study is to take on an ecological approach to understanding CSA. The present study conducts secondary analyses to this end by utilizing variables at the individual, micro-, meso-, exo-, and macro- systems to understand their predictive abilities related to latent class membership. Because the

present study is a secondary analysis of existing data, some ecological levels needed to be collapsed to accommodate the variables available. Specifically, the micro- and mesosystem levels have been combined to reflect one analysis and research question, and the exo- and macrosystem levels have been combined to reflect another analysis and research question. The chronosystem level was not assessed in the present study because there was not a measure that could have been associated with it. The combination of adjacent levels in EST reflects the dynamic relationship that each of the levels have among one another. For instance, the mesosystem can be thought of as the system of microsystems affecting the individual, therefore, combining variables representing the micro- and mesosystems is intuitive and does not affect our ability to take on an ecological perspective in the interpretation of the results.

Definitions of Key Terms

Annual Security Report (ASR): A federal requirement set forth by the Clery Act for colleges and universities to publish a report containing detailed and publicly accessible crime logs which also protect victim confidentiality.

Campus Climate: In the present study, campus climate is defined as self-reported perceptions of risk of being sexually victimized, perceptions of response to reporting a sexual victimization experience, and knowledge of campus policies and resources regarding sexual victimization.

Campus Sexual Assault (CSA): Sexual victimization occurring on college and university campuses. In the present study, CSA is defined as (1) sexual penetration, OR (2) sexual touching; by (1) physical force or threat of physical force, (2) being incapacitated due to drugs, alcohol or being unconscious, asleep, or passed out, (3)

coercive threatens of non-physical harm or promised rewards, or (4) failure to obtain affirmative consent.

The Campus Sexual Violence Elimination Act (Campus SaVE): The most recent amendment to the Clery Act, which requires IHEs to track forcible and non-forcible sexual offenses, stalking, and intimate partner violence.

Clery Act: Also known as the Student Right to Know and Campus Security Act of 1990 and the Jeanne Clery Disclosure of Campus Security Policy and Campus Crime Statistics Act. Federal law requiring colleges and universities receiving federal funding to disclose information about criminal activity on or near campus.

Dear Colleague Letter (DCL): Formal letter from the OCR which gives guidance on how Title IX should be interpreted and abided by. Two DCLs are of note in the context of the present study, the 2011 DCL and 2017 DCL were particularly impactful in terms of Title IX guidance as it relates to sexual assault and misconduct.

Ecological Systems Theory (EST): A multilevel model consisting of five concentric structures stemming from the individual known as the microsystem, mesosystem, exosystem, macrosystem and chronosystem. The theory helps to explain the complex interaction between a developing person and their environment which in the context of the larger community, culture, and society.

Exo-/Macrosystem level factors: The exosystem includes all indirect environmental influences in an individual's life. The macrosystem contains the underlying philosophy or cultural orientation within which the individual lives. In the present study, university affiliation (i.e., public or private), size of the university by enrollment numbers, and location of university.

Exploratory Factor Analysis (EFA): Factor analysis is a method of modeling the covariance among a set of observed variables as a function of its latent constructs (Bandalos & Finney, 2019).

Confirmatory Factor Analysis (CFA): CFA is a specific form of structural equation modeling in which the purpose is to evaluate hypothesized structures of the latent constructs (Bandalos & Finney, 2019).

Individual-level factors: In the present study, individual-level factors are defined as self-reported personal characteristics of the participants. In the present study, age, gender identity, sexual orientation, racial/ethnic background, and disability status are included as individual-level factors.

Institutions of Higher Education (IHEs): 2- or 4- year colleges or universities in the United States.

Latent Class Analysis (LCA): LCA is used to classify cases into groups that are not specified a priori; specifically, cases with similar response patterns on a series of manifest variables are classified into the same latent class (Samuelson & Dayton, 2019).

Micro-/Mesosystem level factors: The microsystem is the immediate environment surrounding the individual. The mesosystem is the system of microsystems, or connections that surround the individual. In the present study, membership of a group of club (e.g., Greek life, athletic team, school-sponsored club or organization), partnered relationship status, and living situation (i.e., online student or on-campus student).

Office of Civil Rights (OCR): Refers to the Office of Civil Rights which is housed within the US Department of Education and oversees compliance of Title IX.

Sexual Victimization: In the present study, sexual victimization is defined as nonconsensual, unwanted sexual penetration (when one person puts a penis, fingers, or object inside someone else's vagina or anus), oral sex (when someone's mouth or tongue makes contact with some else's genitals), and/or sexual touching (kissing, touching someone's breast, chest, crotch, groin, or buttocks, grabbing, groping or rubbing against the other in a sexual way, even if the touching is over the other's clothes) by any of the following tactics: (1) physical force or threat of physical force, (2) being incapacitated due to drugs, alcohol, or being unconscious, asleep, or passed out (3) coercive threats of non-physical harm or promised rewards, and (4) failure to obtain affirmative consent (Cantor et al., 2015).

Title IX: Refers to the Title IX of the Education Amendments of 1972, which prohibits discrimination based on sex in education programs and activities receiving federal funding.

Chapter Two: Review of the Literature

This chapter gives pertinent information about the scope of the problem of campus sexual assault (CSA) in addition to the context under which CSA is occurring at institutions of higher education (IHEs) across the United States. Additionally, an overview of Ecological Systems Theory (EST) as the theoretical framework from which CSA is being conceptualized is also explained in detail. Finally, the ecology of CSA is explored with a review of previous research to understand the individual, microsystem, mesosystem, exosystem, macrosystem, and chronosystem factors involved in the perpetration of CSA.

Campus Sexual Assault

Campus Sexual Assault (CSA) involves a complex web of social, legal, and institutional systems that all exist within the ecology of survivor's experiences and victimhood. In the 1990s, implementation of the Clery Act helped to shed light on CSA as a national issue (McCallion, 2014). While CSA has been a continued problem since the integration of men and women at most US colleges and universities (Kirkpatrick & Kanin, 1957), it wasn't until the Clery Act that college campuses began to make concerted efforts to prevent such events and conduct research on the prevalence of CSA (McCallion, 2014). The Clery Act, in addition to Title IX, which withholds federal funding from institutions which are noncompliant, have encouraged institutions to not only protect students from being sexually assaulted, but also to understand the greater scope of cultural and institutional factors involved in perpetuating unsafe college environments (McCallion, 2014; Obama, 2014; US Department of Education, 2011; US Department of Education, 2020). Research on CSA has steadily continued since the

1990s which help to frame the scope of the problem, however, inconsistencies in language and the definitions used to describe sexual victimization has proved problematic in understanding the full picture of CSA as a nationwide concern. Since the implementation of the Clery Act and subsequent amendments to Title IX, the sociopolitical impact of these laws and regulatory measures has affected the experiences of survivors and institutional responses to the problem. Together, understanding the scope of CSA as a public health issue, the challenges researchers face in understanding CSA, and the impact of sociopolitical regulations all help to contextualize the problem of CSA.

CSA as a Public Health Issue

Following the first amendment to the Clery Act, the National Institute of Justice and the Bureau of Justice Statistics launched a national study on the sexual victimization of college women (NCWSV; Fisher et al., 2000). This was one of the first studies of its kind to employ a nationally representative sample of college women, assess a range of sexual victimization by using behaviorally specific screening questions, and examining risk factors of victimization (Fisher et al., 2000). Results of the NCWSV study are based upon a telephone survey of randomly selected, national sample of 4,446 women attending 2- or 4- year colleges or universities. According to the NCWSV study, 2.8% of the sample had experienced a completed or attempted rape incident, or 27.7 rapes per 1,000 female students, over the 7-month reference period (Fisher et al., 2000). Extrapolating the results out for a 1-year period, Fisher et al. (2000) estimated that nearly 5% of college women are victimized in any given calendar year, and over the course of their college career, the percentage of completed or attempted rape among women in IHEs is between

20-25%. The NCWSV survey also collected information about the circumstances under which students were victimized. Of the participants who experienced completed and attempted rape, 9 in 10 offenders were known to the victims and were most often a boyfriend, ex-boyfriend, classmate, friend, acquaintance, or coworker. Additionally, the survey found that about 60% of rapes occurred in the victim's residence on campus, 30% occurred in other living quarters on campus, and 10% took place in a fraternity. The results revealed that fewer than 5% of completed and attempted rapes were reported to law enforcement or college officials. The NCWSV study also found four factors consistently increased the risk of sexual victimization including (1) frequently drinking enough to get drunk, (2) being unmarried, (3) having a previous victimization, and (4) living on campus (Fisher et al., 2000).

Seven years later, another National Institute of Justice funded study (hereafter known as the CSA Study) was undertaken by Krebs and colleagues (2007) to further document the prevalence of sexual victimization and the prevalence of CSA achieved by physical force or incapacitation. The CSA study conducted a web-based survey of a random sample of 5,446 undergraduate women and 1,375 undergraduate men (however, the men were surveyed as an exploratory measure and were not a primary focus of the main report). Of the 5,446 women who participated in the study, 28.5% reported having experienced an attempted or completed sexual assault either before or since entering college, and since entering college, 19% of the women reported experiencing completed or attempted sexual assault (Krebs et al., 2007). Nearly 5% of the sample was forcibly sexually assaulted since entering college, and about 11% of the sample experienced sexual assault while incapacitated since entering college. Additionally, the CSA study

found that about 6.1% of men had experienced completed or attempted sexual assault since entering college. Like the NCWSV study, the CSA study also identified several risk factors including previous experience of sexual assault, years in college, frequency with which women reported getting drunk, frequency with which women attended parties, and number of sexual partners (Krebs et al., 2007). Also similar to the NCWSV study, the CSA study found that most of the survivors knew their assailant and a small percentage of survivors reported the sexual assault either to police or a university official.

In an effort to fill in some of the research gaps regarding CSA of women of color, Krebs et al. (2011) conducted a large study of CSA experiences of women at Historically Black Colleges and Universities (HBCUs). The study consisted of 3,951 undergraduate women from four HBCUs and found that 14.2% of women had experienced completed or attempted sexual assault since entering college (Krebs et al., 2011). Similar to the NCWSV and CSA studies, the HBCU-CSA study identified a number of different risk factors in experiencing sexual assault including previous victimization, Hispanic ethnicity, fraternity party attendance, getting drunk, and accepting a drink from a stranger. Krebs et al. (2011) also found significant differences in the context by which sexual assaults were happening: physically forced sexual assault was more likely to be perpetrated by a dating partner, while incapacitated sexual assaults were more likely to be perpetrated by a member of a fraternity. Like the conclusions made in both the NCWSV and CSA studies, survivors at HBCUs also had very low reporting rates to police and university officials.

Prompted by the 2014 White House Task Force on CSA, the American Association of Universities (AAU) launched the AAU Campus Climate Survey on Sexual

Assault and Sexual Misconduct (Cantor et al., 2015). The AAU survey included 27 IHEs and garnered a response rate of 19.3% for a total sample size of 150,072 participants. The survey utilized behavioral language to identify distinct types of sexual victimization and method by which sexual victimization was occurring (by physical force, threat of physical force, incapacitation, or absence of affirmative consent; Cantor et al., 2015). According to the AAU survey, 16.5% of college seniors experienced completed nonconsensual sexual contact as a result of physical force or incapacitation. Senior women (26.1%) and transgender, genderqueer, and gender nonconforming students (29.5%) are much more likely to experience this type of victimization than senior men (6.3%). If attempted nonconsensual sexual contact is included, 27.2% of college women report attempted or completed forcible penetration, and 30.8% of transgender, genderqueer and gender nonconforming students experience attempted or completed forcible penetration. If all four tactics are included in an overall prevalence measure, the AAU survey estimates that 21.2% of college seniors have been victimized since entering college; one-third of senior women (33.1%) and 39.1% of transgender, genderqueer, and gender nonconforming seniors report being a victim of nonconsensual sexual contact at least once during college by physical force, threat of physical force, incapacitation, or absence of affirmative consent (Cantor et al., 2015). The AAU study found varying rates at which students reported sexual victimization. For students who experienced forcible penetration, about 25% of victims reported the incident to police or university officials, while those who experienced sexual touching either by force or incapacitation only reported these victimizations between 5-7% of the time (Cantor et al., 2015).

As a follow-up from the 2015 study, the AAU conducted a second iteration of the AAU survey in 2019 assembling 33 IHEs for a total of 181,752 student participants (Cantor et al., 2019). The overall rate of nonconsensual sexual contact by physical force or inability to consent since entering college was 13%, with the rates for undergraduate women (25.9%), undergraduate transgender, genderqueer, and gender nonconforming students (22.8%) being significantly higher than rates for undergraduate men (7%) and graduate students (2%-15% depending on gender identity; Cantor et al., 2019).

Results of large scale, methodologically similar studies over the past 20 years have consistently found prevalence rates of CSA hovering around 20-25% of women and 6-7% of men having experienced some form of attempted or completed nonconsensual sexual contact during their time at American colleges and universities (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). Previous research has shown that white women and women of color experience about the same risk of sexual assault, but, women of color who attend HBCUs are at a slightly lower risk than women of color at other universities (Cantor et al., 2015, 2019; Krebs et al., 2011). Additionally, LGBTQ+ women and women with disabilities are at a significantly higher risk than heterosexual women, cisgender women, and women without disabilities (Cantor et al., 2015, 2019. CSA is associated with poorer mental health outcomes including post-traumatic stress, anxiety, depression, and suicidality (Campbell et al., 2008; Carey et al., 2018; Leone & Carroll, 2016; McDougall et al., 2016; Potter et al., 2018). Additionally, CSA is associated with physical health problems including insomnia, migraines, broken bones, gastrointestinal problems, chronic pain, and reproductive health problems including sexually transmitted infection and unwanted pregnancy (Golding, 1999; Potter

et al., 2018; World Health Organization, 2013). Mental and physical health problems following CSA are also associated with academic challenges, perceived underachievement, and poorer work performance (Potter et al., 2018). With over 11 million women enrolled in college in Fall of 2019 (NCES, 2019), the scope of the problem paints itself: CSA is a problem that affects millions of college students every year and contributes to a variety of mental and physical health problems, making it a significant public health issue for college students.

Challenges to Understanding CSA

While CSA is acknowledged to be a pervasive problem on university and college campuses in the United States, there have been challenges to fully understanding the scope and context of the problem. During his announcement of the 2014 White House Task Force to Protect Students from Sexual Assault, President Obama estimated "1 in 5 women on college campuses has been sexually assaulted during their time there" (Obama, 2014). While this figure has been quoted widely across both academic and nonacademic platforms, critics have questioned its validity (Muehlenhard et al., 2017). Since 2000, at least 34 unique, independent prevalence studies have been conducted to determine the overall prevalence of sexual assault on college campuses (Fedina et al., 2018). However, the results of these studies can vary widely in terms of prevalence rates gathered from the data, methodology and data collection strategies, and their definitions of sexual assault. As a result, it has been difficult to identify consistent prevalence rates of sexual assault occurring on university and college campuses.

An example of inconsistent prevalence rates is highlighted in a review done by Fedina et al. (2018), who examined the results of 34 unique studies and found that

prevalence rates ranged drastically. The study found that prevalence rates of completed rape ranged from 0.5% to 8.4%, prevalence rates for attempted rape ranged from 1.1% to 3.8%, prevalence of incapacitated rape ranged from 1.8% to 14.2%, and unwanted sexual contact rated from 1.8% to 34%. Fedina et al. (2018) cited a number of different reasons for the drastic variability in prevalence estimates noting that research design differences, methodological and sampling strategy differences, and inconsistent operational definitions used to define and measure sexual victimization help to explain the inconsistent results among studies on CSA.

Conversely, in a stringent review conducted by Muehlenhard and colleagues (2018) results of four large and methodologically consistent CSA prevalence studies supported the one-in-five statistic cited by President Obama as an accurate estimate of women's risk of sexual assault during college. Within their review, Muehlenhard et al. (2018) noted that college seniors reported greater prevalence rates closer to one-in-four, and LGBTQ+ women were at a slightly higher risk than heterosexual women. Additionally, the authors noted that women who attended Historically Black Colleges and Universities (HBCUs) were at a slightly lower risk of sexual assault during college at about one-in-seven (Muehlenhard et al., 2018).

Krause et al. (2019) conducted a systematic review of the gray literature including technical and annual reports, conference abstracts and other documents that are not published through peer-reviewed journals or books, to identify methodological and measurement differences in sexual assault and misconduct campus climate surveys. In total, Krause and colleagues (2019) identified 107 reports from 101 schools that were included in the systematic review. Results of the systematic review revealed several

themes of methodological challenges associated with campus climate surveys. First, most colleges and universities utilized a census approach to implement the survey which led to low response rates and students self-selecting into the survey, which may have produced biased sexual assault estimates (Krause et al., 2019). Additionally, this type of sampling may have systematically excluded underrepresented student populations including LGBTQ+ students, students of color, and students with disabilities. Krause et al. (2019) also noted inconsistencies in the ways in which schools developed their instruments, offered incentives, and named the survey, which could have also affected participation levels.

Krause et al. (2019) weren't the only researchers interested in low response rates of campus climate surveys. In a systematic review by Rosenberg and colleagues (2019), the overall response rate of campus climate and sexual assault surveys was found to be 24.6%. Rosenberg et al. (2019) conducted a simulation study of pseudo-populations to determine what potential effects low response rates and missing data have on reported CSA prevalence rates. In a series of nine simulations, the authors predicted that prevalence could have theoretically ranged from 1 to 84%. The authors' findings contribute to the context of unpredictability in prevalence rates in that it highlights challenges to interpreting results of CSA surveys.

Like other researchers on CSA, Krause et al. (2019) found that colleges and universities used varying definitions of sexual assault that often did not match the definition used by the White House Task Force, or the Centers for Disease Control (CDC). Muehlenhard and her colleagues (2017) noted that the definitions of terminology such as rape, sexual assault, and sexual battery vary across research studies and

legislative statutes, making it difficult for researchers to consistently measure the same experiences of victimization. Because of the inconsistencies in the operational definition of sexual assault, rape, and sexual battery, Muehlenhard et al. (2017) noted that some researchers use a definition that is much too broad, overestimating prevalence, while others use a definition that is too narrow, only capturing the most egregious cases. Muehlenhard et al. (2017) reported that researchers are able to avoid the pitfalls of language, confusion, and potential for bias by using behavioral definitions of specific nonconsensual sex acts. Krause et al. (2019) noted that this problem is not unique to campus climate surveys, but is a problem that plagues peer-reviewed literature regarding sexual assault. Like Muehlenhard et al. (2017), Krause et al., (2019) similarly advocated for behaviorally specific language that asks participants about unwanted sexual experiences rather than referring to them as "rape" or "sexual assault." Krause et al. (2019) takes these ideas a step further by also advocating for measuring victimization while also considering a trauma-informed care approach.

Despite variance found in prevalence rates and methodological challenges experienced by sexual assault scholars, researchers agree that sexual victimization of college students continues to be an area of great concern. Above and beyond incidence and prevalence rates of CSA, there is a need for action-oriented research pertaining to "hidden populations" of survivors, that is, understanding the multifaceted victimization experiences of college students (Harris et al., 2019, p. 267). Additionally, Harris and colleagues (2019) advocate for sexual victimization research that captures the experiences of both victims and nonvictims, as nonvictims might hold the key to a critical part of the solution. The present study seeks to partially achieve this goal by taking a

latent variable modeling approach to understanding the context and ecology of CSA above and beyond prevalence. This type of methodological approach can help to identify hidden subgroups within a population, and as such, can help to identify latent variables related to CSA victimization. Outside of the research realm, outcry from survivors, student activists, and sexual assault advocates coupled with the mass of research on incidence and prevalence of CSA has prompted a series of responses to the problem at the federal and institutional level.

Sociopolitical Regulations Related to CSA

Intervention at the federal and institutional levels have attempted to prevent CSA from occurring and support survivors when it does occur. Research has demonstrated that a comprehensive response at the institutional level can lead to fewer CSA cases (DeLong et al., 2018), but critics argue that heavy-handed federal policies restrict universities from handling cases fairly (Harper et al., 2017). Since the introduction of Title IX in 1972, the ways in which IHEs respond to gender-based discrimination and violence have changed tremendously, and as of this writing, continue to change as recently as August 14, 2020 (US Department of Education, 2020). The tangled web of federal laws and guidelines including Title IX and subsequent interpretations via Dear Colleague Letters, the Clery Act, the Campus SaVE Act, and the White House Task Force have dictated the ways in which CSA should and should not be handled at the institutional level.

Title IX

Title IX of the Education Amendments of 1972 (hereafter known as Title IX), prohibits discrimination based on sex in education programs and activities in federally

funded schools at all levels (primary, secondary, and post-secondary). Title IX is meant to protect students, employees, applicants for admission and employment, and other persons from all forms of sex discrimination, including discrimination based on gender identity. Title IX states, "No person in the United States shall, on the basis of sex, be excluded from participation in, be denied the benefits of, or be subjected to discrimination under any education program or activity receiving Federal financial assistance" (Title IX of the Education Amendments of 1972). This statement has had several implications for increasing gender equality in primary, secondary, and post-secondary schools, and especially for student-athletes.

Over time, the interpretation of Title IX was expanded to include protection against sexual harassment, sexual assault, and gender-based violence (Sharp et al., 2017). In 2001, the Office of Civil Rights (OCR) in the US Department of Education issued revised Title IX guidance on sexual harassment (U.S. Department of Education, 2001). This revision stated that schools have a responsibility to recognize and respond to sexual harassment to end the harassment and prevent it from recurring, but allowed schools discretion on how they respond to reports of harassment. The revision only included reference to sexual harassment, defined as "unwelcome conduct of a sexual nature" which many universities did not take to include peer-on-peer sexual violence (U.S. Department of Education, 2001, p. 14; Sharp et al., 2017). Since 2001, each Presidential administration has utilized their own Secretary of Education to interpret and enforce Title IX. Most recently, the Trump administration and Secretary of Education Betsy DeVos amended Title IX as it relates to sexual harassment and sexual violence in May 2020, which is explored in greater detail later on in this section.

Clery Act

In an effort to make college campuses safer for all students, the U.S. Congress passed the Student Right to Know and Campus Security act of 1990 (also known as the Jeanne Clery Disclosure of Campus Security Policy and Campus Crime Statistics Act, or Clery Act for short). The Clery Act requires colleges and universities that receive federal funding to disclose information about criminal activity on or near campus by publishing an annual security report (ASR) and maintaining a detailed and publicly accessible crime log while also maintaining victim confidentiality (McCallion, 2014). Additionally, the Clery Act requires IHEs to have an emergency response system in place as well as the means to issue "timely warnings" for serious or ongoing threats to student safety (Violence Against Women Reauthorization Act, 2013). The Clery Act was amended in 1992 to include the Campus Sexual Assault Victims' Bill of Rights, which requires universities to report and investigate incidences of sexual assault on campus (McCallion, 2014). The Clery Act has since been amended in total five times (1992, 1998, 2000, 2008, and 2013), and has been a key piece of legislation in the protection of students against violent crime on colleges campuses (McCallion, 2014).

2011 Dear Colleague Letter

In 2011, the Office of Civil Rights (OCR) issued a Dear Colleague Letter (DCL), that formally included sexual violence, including sexual assault, sexual battery, and rape as classified forms of sexual harassment, and therefore, would be violations of the 2001 amended Title IX guidelines. This letter became an important shift in the way IHEs were required to handle sexual assault cases on campus. The 2011 DCL reiterated Title IX guidelines mandating IHEs have policies in place with regard to CSA allegations and

investigations, must have a designated Title IX coordinator, and timely investigation, grievance, and remedy procedures in place (U.S. Department of Education, 2011). Additionally, the 2011 DCL required a preponderance of evidence standard in the investigation of CSA cases, encouraged the allowance of accusers to appeal not-guilty findings, and discouraged cross-examination of accusers (Sharp et al., 2017; U.S. Department of Education, 2011).

While the 2011 DCL introduced sweeping reform into the way IHEs handle CSA cases, it drew criticism from a number of sources (Caldwell, 2017). Firstly, because the issuance of a DCL is considered a significant guidance document of the existing law rather than the more formal process of notice-and-comment rule-making, the 2011 DCL drew criticism from the legal community who felt as though the DCL was an improper use of the OCR's power, and not a legitimate legislative document (Caldwell, 2017). Specifically, legal scholars note that guidelines set forth in the 2011 DCL went above and beyond significant guidance and required additional legal requirements under Title IX, making it invalid and unenforceable because it did not go through notice-and-comment procedures (Caldwell, 2017).

One of the biggest criticisms of the 2011 DCL was its guidelines on the mandatory preponderance of evidence standard, which critics noted unfairly treated the accused without due process (Caldwell, 2017; Harper, Maskaly, Kirkner, & Lorenz, 2017). While prior to the 2011 DCL, many schools already utilized a preponderance of evidence standard (as it is the most common standard of evidence in civil litigation); some schools had no evidence standard in place (Caldwell, 2017; Harper et al., 2017). Critics of the preponderance of evidence standard in CSA cases argue that it unfairly biases the case in

favor of the victim, and does not allow the accused their right to due process (Harper et al., 2017). These criticisms largely came from the legal and criminal justice communities who noted that the enforcement of the 2011 DCL infringed on students' constitutional rights. Additionally, critics note that the inability for the accused to cross-examine their accuser face-to-face, is a direct violation of due process (Harper et al., 2017). Supporters of the 2011 DCL argue that IHEs are not judicial systems and are not equipped to conduct full-scale investigations to adhere to a higher evidence standard nor do they need to grant students the right to due process when implementing disciplinary procedures (Butler et al., 2019; Caldwell, 2017). When one student launches a complaint of misconduct against another student, the most drastic outcome would be that the student adjudged to have participated in sexual misconduct would be expelled from the institution. This result does not resemble that of the consequences of criminal legal proceedings (even if the accused behavior may rise to the criminal level); and as such, the evidentiary standard does not need to match that of criminal litigation (Caldwell, 2017). Additionally, Caldwell (2017) argues against the clear and convincing proof standard, as a false middle ground between the preponderance of evidence standard and the beyond a reasonable doubt standard. Supporters of the utilization of the preponderance of evidence standard in CSA cases while questioning the legality of the 2011 DCL note that in order for the ruling to be legitimate, they need to go through the proper channel of notice-and-comment rule-making (Caldwell, 2017). Other criminology and legal scholars argue for a complete overhaul of the way in which OCR dictates Title IX by instead advocating for a restorative justice approach in CSA cases, making the process a more fair one for both the accused and accusers, while also supporting survivors (Harper et al., 2017).

The Campus Sexual Violence Elimination Act

The Campus Sexual Violence Elimination Act (Campus SaVE) was passed into law by Congress in 2013 and is the most recent amendment to the Clery Act. Campus SaVE was put in place to increase transparency on gender-based violence on campus and required IHEs to keep track of forcible and nonforcible sexual offenses, stalking, and intimate partner violence (McCallion, 2014). Additionally, IHEs must include a description of their policies and procedures addressing sexual violence on their ASRs. The Campus SaVE Act also introduced new accommodations for survivors of CSA including academic, housing, transportation, and employment assistance as needed in addition to requiring IHEs provide resources that are accessible to survivors both on and off campus. Additionally, the Campus SaVE Act required IHEs to provide CSA education and prevention efforts to students to combat sexual violence and have established disciplinary procedures for students accused of sexual violence (McCallion, 2014).

2014 White House Task Force

In 2014, President Obama directed the Office of the Vice President and the White House Council on Women and Girls to lead an interagency effort to address CSA by coordinating Federal enforcement efforts by executive departments and agencies in helping IHEs meet their obligations under Federal Law (Obama, 2014). The task force included the Vice President, the Attorney General, the Secretary of the Interior, the Secretary of Health and Human Services, the Secretary of Education, and the Director of the Office of Science and Technology Policy, the Director of the Domestic Policy Council, the Cabinet Secretary, and others (Obama, 2014). The members of the task force

were tasked with developing a coordinated Federal response to CSA including creating detailed action plans which would provide schools with evidence-based information and practices for intervention and prevention of CSA, promote increased transparency of reports and foster improvements to the coordination of agencies, organizations, and institutions (Butler et al., 2019).

The 2014 White House Task Force produced incredible momentum for IHEs and student activists to create change in the ways in which CSA is handled. Many institutions were encouraged to collect data with Campus Climate surveys to understand the rate at which CSA is happening and to whom (Butler et al., 2019). The 2014 White House Task Force also prompted a wave of student activism initially led by two University of North Carolina, Chapel Hill students, Annie Clark and Andrea Pino, which prompted the Office of Civil Rights to conduct nearly 200 investigations of universities for Title IX violations (Sharp et al., 2017). While the Obama administration's response to CSA garnered national attention on the problem, the Trump administration's disdain for the previous administration marked rollbacks in the progress that had been made.

2017 Dear Colleague Letter and 2020 Title IX Changes

In 2017, the Trump administration submitted a Dear Colleague Letter retracting the previous DCL guidelines set forth in 2011. Specifically, President Trump's Secretary of Education, Betsy DeVos, rescinded the 2011 DCL on Sexual Violence in a 2017 DCL and later, proposed a notice-and-comment change to the application of Title IX to CSA in 2018. Under the pretense of allowing universities more freedom to handle CSA cases, the 2017 DCL dropped the mandatory preponderance of evidence standard in CSA investigation and instead noted that schools should use "either the preponderance of the

evidence standard, or the clear and convincing evidence standard" (OCR, 2017; p. 5) with the caveat that using a lower standard of proof for sexual misconduct cases versus other disciplinary proceedings "suggests a discriminatory purpose and should be avoided" (p. 5). Additionally, the 2017 DCL also reversed guidelines on appeals processes, noting that only the accused party has the ability to request an appeal to a sexual misconduct decision (OCR, 2017). The changes set forth by the Trump administration shifts the attention from survivors, prevention and protection efforts, and focuses on due process rights for students who have been accused of committing an act of sexual misconduct (Butler et al., 2019). Not only was this a significant departure from the previous administration's approach to the issue of CSA, but was condemned by sexual assault advocates nation-wide (Meckler, 2020).

In 2018, Secretary DeVos submitted to the Federal Register a proposal to amend Title IX with the intention of making modifications in the ways in which Title IX is applied to CSA cases (Butler et al., 2019). The most notable departure from the previous administration's interpretation of and guidelines on Title IX are the statutes requiring due process protections for the accused (U.S. Department of Education, 2020). In the 60-day period during which the Title IX proposal would be open for public comments, over 120,000 comments were submitted to the Federal Register (Butler et al. , 2019). While there is no formal summary of all of the public comments made, the Division of Women and Crime (DWC) of the American Criminological Society and the Campus Advocacy and Prevention Professionals Association (CAPPA) were two prominent voices who raised concerns over the changes stating that the proposed changes would be a significant departure from data-driven policies and practices surrounding

CSA, the proposed changes would severely limit a school's responsibility to respond to CSA, and the changes would harm survivors (Butler et al., 2019).

On May 6, 2020, the US Department of Education sent out a press release stating that Secretary DeVos' new Title IX regulations will take effect August 14, 2020 (US Department of Education, 2020). The final regulations set forth by DeVos were largely unchanged from her 2018 proposal, narrowly defining sexual harassment to only include the most egregious offenses, reducing university responsibility in their responses to CSA and giving more rights to the accused (Meckler, 2020). Since those Title IX changes went into effect, the historic 2020 US Presidential election championed Joe Biden, former Vice President and leader of the 2014 White House Task force against sexual violence, to become the 46th president of the United States. While his entry into the presidency is plagued by the lingering impact of the COVID-19 pandemic, sexual assault advocates and educators hope to see tangible change to Title IX yet again that is in support of survivors.

Campus Policies

Since 1972, the sociopolitical landscape has largely shaped the ways in which IHEs respond to issues of CSA and gender-based discrimination on campus. Additionally, laws, guidelines, and regulations at the federal level dictate the ways in which IHEs implement policies surrounding these issues. Given that the most recent changes to Title IX allow universities more flexibility and leniency in their CSA policies, it's important to understand the ways in which enforced CSA policy affects the prevalence of CSA.

A content analysis of a stratified random sample of 995 IHEs revealed that while most 4-year-degree schools have CSA policies and definitions of sexual assault and consent widely available, there are significant differences in the language used between schools (Graham et al., 2017). Specifically, Graham and colleagues (2017) found that larger, public schools tended to have more comprehensive CSA policies compared to smaller, private institutions. This difference found between large and small institutions is likely due to the differences in resources available with larger institutions having access to more resources than smaller institutions (Graham et al., 2017). Results of the study by Graham and colleagues (2017) are important because more comprehensive CSA policies and consent definitions are linked to lower CSA prevalence. A study by DeLong and colleagues (2018) found evidence linking greater comprehensiveness of CSA policies with lower CSA prevalence. Specifically, they found that greater comprehensiveness among CSA policy elements was linked to lower CSA prevalence among women (DeLong et al., 2018). DeLong et al. (2018) also explored the relation between particular CSA policy topics and CSA prevalence. Schools that described having a sexual assault response team, deemed mediation between the accused and accusers as inappropriate, and having a set appeals process were all linked to lower CSA prevalence among men and women. Additionally, schools that prohibited the use of prior sexual conduct as evidence were also linked to lower CSA prevalence, which prevents the use of both the survivors' and the accused's previous sexual history from being discussed during the adjudication process (DeLong et al., 2018).

The existence of comprehensive CSA policies alone is insufficient to ensure students understand them and know where to turn for help for themselves or a peer. An

extensive research study of seven IHEs examined the efficacy of delivery methods of sexual misconduct policies on first-year students. Potter and colleagues (2016) found that students who read and discussed the policies with a group of peers led by one of the researchers retained and understood the policies better than students who only read the policies without discussion and the control group. The study by Potter et al. (2016) also revealed that delivering the sexual misconduct policies via video resulted in very little engagement from students. The results of the study highlight the importance of engaging students in open dialogue about sexual assault and consent as a first-line prevention effort of CSA.

As previously mentioned, the existence of CSA policies is not sufficient to prevent sexual assault from happening on campus. The implementation of written policy into practice by faculty and staff is also an important process in the prevention of CSA as well as their performing appropriate and adequate response when it does occur. A study of 190 higher education personnel examined perceptions of the implementation and execution of CSA policies at IHEs (Moylan et al., 2020). Results of the study revealed most higher education personnel believe that the implementation of CSA policies led to much more improvement of the problem of CSA rather than frustration, or belief that the problem of CSA is being exaggerated by the federal government (Moylan et al., 2020). Respondents were more likely to name due process as a priority over victim-centered responses; however, they did not believe that focusing on due process or a victim-centered approach were mutually exclusive from one another. In fact, most higher education personnel noted that implementing a fair process for the accused in addition to

supporting survivors were both top priorities in implementing CSA policy (Moylan et al., 2020).

Research Gap

Despite the dearth of literature highlighting the scope of CSA as a public health crisis with 20-25% of college women and 6-7% of college men having been sexually assaulted during their time at 4-year colleges and universities, the problem continues to persist at a similar rate (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). Additionally, researchers and higher education administrators continue to experience several problems in the use of consistent operational definitions of violent sexual acts in relevant laws, policies, and research (Krause et al., 2019; Muehlenhard et al., 2017). IHEs also continue to be challenged by low reporting rates among survivors (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011), and low response rates in campus climate surveys (Krause et al., 2019; Rosenberg et al., 2019). While the federal government has attempted to intervene by amending Title IX guidance and regulations (U.S. Department of Education, 2001; U.S. Department of Education, 2020), introducing new laws regarding campus reporting processes of CSA (Violence Against Women Reauthorization Act, 2014), and task forces to help IHEs combat the problem utilizing evidence-based practices (Obama, 2014), CSA is still affecting millions of college students annually. The present study serves to fill this knowledge gap by contributing to the research literature regarding precipitating individual, environmental, and sociopolitical factors involved in the victimization of college students. The purpose of this kind of research methodology is to identify possible subgroups in the larger population. Specifically, the goal of the present study is to

identify subgroups of victims and nonvictims of CSA to understand patterns of responses on measures of campus climate including perceptions of personal risk of CSA, perceived response to reporting, and knowledge of campus policies and resources. These latent subgroups are used to determine the predictive capabilities of ecological factors on latent subgroups of college students. Sexual assault on college and university campuses is a complex sociocultural problem with implications for understanding the problem ecologically, at the individual, institutional, and cultural level.

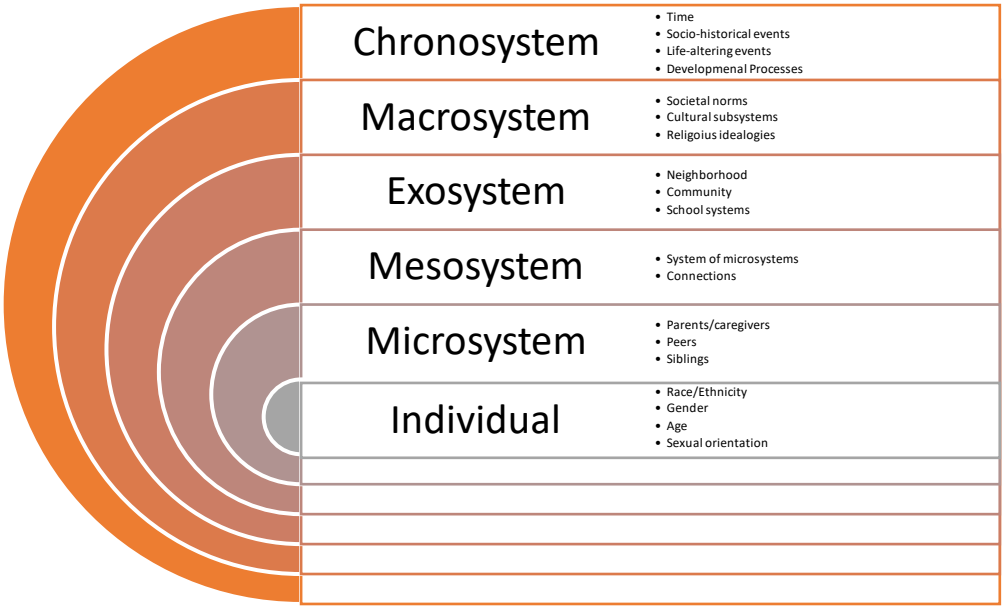
Ecological Systems Theory

One way in which to conceptualize CSA and other victimization experiences is through the theoretical lens of Ecological Systems Theory, which is a cultural level of analysis. In his seminal text, "The Ecology of Human Development," Urie Bronfenbrenner details his Ecological Systems Theory (EST), which helps to explain the complex interaction between a developing person and their environment within the context of the larger community, culture, and society they are in (1979). Inspired by Kurt Lewin's ideas regarding person and environment interaction and Jean Piaget's ideas regarding the evolution of child perceptions of nature and reality, Bronfenbrenner believed that human development involves the mutual accommodation between the growing human being and the changing properties of their immediate surroundings in the context of the greater ecological environment (Bronfenbrenner, 1979). Bronfenbrenner asserts that the ecological environment is akin to "a set of nested structures, each inside the next, like a set of Russian dolls" (1979, p. 3). This nested arrangement of concentric structures are referred to as the micro-, meso-, exo-, and macrosystems (Figure 1). Since its conception, ecological systems theory has been applied in a number of different

contexts and has been expanded upon by Bronfenbrenner to include the influences of biological systems and the greater socio-historical circumstances, which he later named the chronosystem (Bronfenbrenner, 1986; Bronfenbrenner & Ceci, 1994). At its core, EST proposes a way in which to conduct and understand research from an ecological stance; taking the properties of within and between the person, process, and environment and viewing each as interdependent of the others within the larger system (Bronfenbrenner, 1979).

Figure 1

Bronfenbrenner's Ecological Systems Theory



Basic Concepts of EST

The purpose of EST is to summarize and explain the reciprocal relationship between a developing person and their complex environment (Bronfenbrenner, 1979). EST posits that the enduring interaction between a person and their environment are known as *proximal processes*, and are the primary component in effective and healthy

human development in addition to serving as the mechanism by which genetic potential is actualized (Bronfenbrenner & Ceci, 1994). EST notes that not all genotypic possibilities will be actualized unless the necessary opportunity structures exist, or are provided in the levels of a developing person's ecosystem (Bronfenbrenner & Ceci, 1994).

EST has been applied in a number of different research studies since its inception (Belsky, 1980; Campbell et al., 2009; Casey & Lindhorst, 2009; Kubiak, 2018; Heise; 1998; Pittenger et al., 2016; Zhu et al., 2020). Belsky (1980) was one of the first researchers to use Bronfenbrenner's young theory and apply it to understand the maltreatment of children. Since Belsky's application of EST to understand the process-person-context framework of child abuse, EST has been used successfully to understand a number of different circumstances of victimization of children, adolescents, and adults (Belsky, 1980; Cambell et al., 2009; Casey & Lindhorst, 2009; Kubiak, 2018; Heise; 1998; Pittenger et al., 2016; Zhu et al., 2020). The flexibility of EST recognizes that humans develop within a broader culture, with multiple, interactive variables, which in turn allows researchers to take on a creative, multi-level problem solving approach to individual victimization (Belsky, 1980; Cambell et al., 2009; Casey & Lindhorst, 2009; Kubiak, 2018; Heise; 1998; Pittenger et al., 2016; Zhu et al., 2020).

In the present context, an illustrative example of how EST might be used would be to consider an incoming college freshman who has a lot of immediate and extended family support (microsystem), has had experience with part-time jobs after school, and participated in extra-curricular activities such as sports or clubs (mesosystem). Bronfenbrenner (1979) wrote that a student such as the one described above will come

into college with greater developmental potential than a freshman student whose mesosystem is not as enriched, even when you hold age and socioeconomic status constant. The college student is also affected by university faculty and staff and the ways in which university administration implement campus policies and procedures (exosystem) as well as the overarching campus culture that envelopes beliefs, attitudes and behaviors for the university community (macrosystem). Finally, there is a generational component that encompasses the time during which the college student is enrolled in college. For example, much of the incoming freshman class of Fall 2020 will have the chronosystem impact of attending their first semester of college online due to the COVID-19 pandemic. The way in which the settings an individual participates in interact with one another have many implications for human development in addition to how those settings are impacted by socio-political, generational, cultural, and institutional factors. Because EST takes on a multi-level approach to understanding human development, it's important to understand each of the concentric structures in the model, starting with the developing individual and moving out to the chronosystem.

The Developing Individual

Starting from the innermost layer of EST's theoretical model begins with examination of the individual characteristics of the developing person. In his seminal text, Bronfenbrenner (1979) didn't focus much of his writing on individual characteristics of developing persons, namely because (1) there was already a plethora of research available about individual characteristics, and (2) because his model differentiates itself by the interrelationships between environments surrounding the individual. That being said, Bronfenbrenner did not discount the importance of individual characteristics in his

model. Bronfenbrenner (1979) cites the work of Kurt Lewin as a major influence in the development of EST. Specifically, Lewin's famous equation B = *f* (PE), which states that an individual's behavior is a function of both their personal characteristics and their environment, is the basic framework from which Bronfenbrenner created EST (Bronfenbrenner, 1979; Lewin, 1935). There are many individual characteristics that may affect one's behavior in any given ecology. For example, temperament, personality characteristics, affective characteristics, race/ethnicity, sexual orientation, gender identity, ability, developmental level, and age are all important individual characteristics which may affect how one moves about their environment (Bronfenbrenner, 1979; Martinello, 2020). While it is critical to examine the individual when understanding the ecology of victimization, utilizing individual characteristics as the lens through which victimization is understood is common among research. What makes EST unique is that it seeks to understand individual characteristics in the greater context of the individual's ecology, so that those characteristics do not exist in a vacuum.

Microsystem

The microsystem can be defined as the immediate environment surrounding the individual. Examples of microsystem influences are parents, caregivers, siblings, teachers, peers/classmates, and friends. Additionally, Bronfenbrenner (1979) writes that the microsystem also includes the pattern of activities, roles, and interpersonal relationships experienced by the individual in any given setting. Important to the conceptualization of the microsystem is Bronfenbrenner's definition of relationships; he notes, "A relation obtains whenever one person in a setting pays attention to or participates in the activities of another" (1979; p. 56). Within the developing individual's

microsystem are several relationships that the individual engages in; interpersonal relationship structures become the context of the person's development (Bronfenbrenner, 1979). For example, the existence of reciprocity in a relationship, the balance of power in the relationship, or the mutuality of positive feelings in a relationship are all building blocks in the individual's microsystem (Bronfenbrenner, 1979). Bronfenbrenner (1979) notes that a rich, responsive microsystem that consists of both physical and social engagement encourage healthy development. College students are unique in that they start to develop multiple rich microsystem environments that affect their development, especially if their time at college is their first time living away from their family of origin. For college students, they are dually influenced by their family of origin microsystem and their on-campus microsystem including their roommate or housemates, others in their dormitory or living quarters, and peers in their classes.

Mesosystem

The mesosystem is comprised of the connections around the individual. This can include settings like school or places of worship, or environments in which the individual participates, for example, sports teams, clubs, or social groups. Bronfenbrenner (1979) notes that the mesosystem includes the "…interrelations among two or more settings in which the developing person actively participates" (p 25). The mesosystem can be thought of as a system of microsystems; it is formed or extended whenever the developing person moves into a new setting (Bronfenbrenner, 1979). When the developing individual enters a new setting, if a person from their microsystem accompanies them into that setting, the developmental potential of the mesosystem is enhanced (Bronfenbrenner, 1979). For example, if a caregiver accompanies a child to

school, the developmental potential for the interaction between the child's home microsystem and school microsystem are enhanced. Additionally, Bronfenbrenner (1979) notes that the greater number of settings a developing person participates in, and therefore, the larger mesosystem they have, the more developmental potential they will have, especially if they have an increased number of relationships with older, more mature individuals within each setting. Bronfenbrenner (1979) theorized that the increased number of positive, enriched settings an individual participates in, the greater their cognitive and emotional ability to adjust between environments, putting them at a greater advantage than those with limited mesosystems. Other mesosystem examples include the way in which the individual's family and friends interact, or, the way in which the individual's family is involved or uninvolved in the child's schooling (Bronfenbrenner, 1986).

Exosystem

The exosystem consists of all indirect environmental influences included in the individual's life. In his original writing, Bronfenbrenner defined the exosystem as "…one or more settings that do not involve the developing person as an active participant, but in which events occur that affect, or are affected by what happens in the setting containing the developing person" (p. 25). Bronfenbrenner (1986) often cited parental work environments, or the social group of parents, as exosystem influences, but it could also include policies of one's workplace or school, administrators or leaders in one's company or university system. The ways in which the settings that do not include the developing individual, but which nonetheless impact the individual's microsystems, has implications for understanding how IHEs can doubly harm survivors of CSA. Bronfenbrenner (1979)

indicated that there are two necessary conditions to establish a causal sequence from the exosystem to the developing person: (1) there must first be connecting events from the external setting to processes occurring in the developing person's microsystem, and (2) microsystem processes to developmental changes in the person within that setting.

Macrosystem

The macrosystem contains the underlying philosophy or cultural orientation within which the individual lives (Salkind, 2005). Bronfenbrenner (1979) wrote that the macrosystem included lower-order systems that exist at the level of subculture or culture, along with any belief systems or ideologies. The macrosystem is inclusive of institutional patterns of culture, and economic, social, legal, and political systems of which the exo-, meso-, and micro- systems are affected. The macrosystem can also include religious or spiritual ideologies that may encompass the individual's cultural beliefs (Salkind, 2005). Bronfenbrenner also discussed what he called, "ecological transitions" or shifts in role or setting that occur throughout the lifespan (1979; p. 6). Ecological transitions occur in the macrosystem when the individual moves from one setting into another. These transitions are important because they are implicated in the change of an individual's roles, expectations for their behavior, and position in society (Bronfenbrenner, 1979). In his original writing, Bronfenbrenner's theory stopped at the level of the macrosystem. In 1986, Bronfenbrenner revised his theory to include the influence of the passage of time and the life course on human development.

Chronosystem

Similar to Elder's (1974) work in what he referred to as the "life course" the chronosystem can be thought of as the effect of changes over time. Bronfenbrenner

(1986) describes the chronosystem as "the influence on the person's development of changes (and continuities) over time in the environments in which the person is living" (p. 724). The power of the chronosystem is in the interaction between changes within the person over time, but also changes in their sociocultural environment over time, and the "dynamic relation" between those two processes (Bronfenbrenner, 1986, p. 724). Chronosystem effects focus around major life transitions that serve as the agent of developmental change (Bronfenbrenner, 1986). Examples of chronosystem influences may be the long-lasting effect on the individual child after parental separation, or, the generational effects of historical events such as The Great Depression (Bronfenbrenner, 1986). To support his ideas on the chronosystem in the EST, Bronfenbrenner utilized Elder's famous study on children of the Great Depression to highlight the effects of generational hardship on human development (Bronfenbrenner, 1986; Elder, 1974). As another example of chronosystem influence, Martinello (2020) writes that each experience of sexual abuse changes the child's interactions within and between their ecosystem, making each abuse experience a chronosystem factor. Similarly, multiple sexual trauma victimization of college students also serves to be a chronosystem factor, as each assaultive experience changes the survivor's interactions within and between their greater ecosystem.

Upon its conception, EST furthers the ideas behind Lewin's person by environment interaction by looking at human development through a process-person-context-time lens. The basic concepts of EST take on a multi-level view of human development, which is crucial in understanding the experiences of survivors of

victimization. Bronfenbrenner's EST provides a holistic, context-specific, multi-level view of victimization. Taking on a multi-level, ecological lens when examining CSA can help uncover institutional and cultural risk factors on college campuses.

The Ecology of Campus Sexual Assault

While understanding the prevalence and scope of CSA gives an idea of the rate at which college students are being sexually victimized, it fails to give the entire picture of the context of who is being victimized and under what conditions. Multivariate analyses in large-scale CSA and Campus Climate surveys have identified several individual characteristics and behaviors of survivors associated with greater risk of sexual victimization such as minority sexual orientation and gender identity, disability status, alcohol use, and previous sexual victimization (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). Examining the literature regarding risk of CSA, the two most frequently cited risk factors are: (1) alcohol use of both victims and perpetrators, and (2) previous victimization experiences (Abbey, 1991, 2002, 2011; Cantor et al., 2015, 2019, Dir et al., 2018; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011).

Understanding the individual characteristics and behaviors of survivors highlight who is most vulnerable to victimization, however, these do not fully explain what risk factors contribute to a campus environment that is safe or unsafe for college students. Moving beyond the individual factors associated with CSA, there are several factors related to the survivor's interpersonal relationships, peer groups, the campus environment, and the greater cultural fabric that are related to CSA experiences and outcomes. The research literature has identified a few environmental characteristics

associated with CSA, including the existence of Greek life on campus (DeKeseredy et al., 2018; Lasky et al., 2017; Martin, 2016), having Division I sports teams (Stozer & MacCartney, 2015), and punitive institutional policies that prevent reporting and doubly harm survivors (Smith & Freyd, 2013; Stader & Williams-Cunningham, 2017). Additionally, feminist scholars often cite the existence of a patriarchal society as a major cultural influence that perpetuates sexual assault victimization (Martin, 2016; O'Connor et al., 2018)

One of the challenges to understanding the relationship between individual characteristics and behaviors in sexual victimization, is that if not understood within the nuanced context of heteronormative relationships, traditional ideals of masculinity and femininity, cultural sexual expectancies, and the impact drugs and alcohol can have on survivors and perpetrators, it might be easy to misunderstand risk and protective factors as victim blaming/shaming or the reduction of personal responsibility for perpetrators. For example, alcohol use in both survivors and perpetrators is linked to environmental characteristics, especially Greek life and Division I sports, as these organizations are associated with on- and off-campus parties that usually involve the consumption of alcohol (Lasky et al., 2017; Martin, 2016; Radina, 2017). Additionally, group masculinity dynamics in traditionally all-male groups such as men's fraternities and sports teams, is related to perpetuation of toxic masculinity as a function of a patriarchal society (McCray, 2015).

It is important to understand the impact these individual and environmental risk factors have on the probability of sexual victimization occurring and these risk factors should not be oversimplified. Victims are never at fault for being victimized, and

perpetrators are always responsible for their actions. Considering the flexibility of EST and its demonstration of applicability to other victimization experiences, it is a natural extension to understand CSA through the lens of EST. The following sections will explore the ecology of CSA in the style of Bronfenbrenner's Ecological Systems Theory.

Individual Factors

In the innermost circle of EST lies the developing individual. Previous research has identified several individual factors and characteristics associated with increased risk of CSA. These individual factors can be traits and identities held by the individual, or predilections for certain behaviors that the individual participates in that increases their risk of being assaulted. While individual characteristics are not the focus of Bronfenbrenner's EST, they are important to understand as they do give us an idea of who is most often victimized on college campuses. Additionally, understanding the individual factors related to CSA gives us a starting point in which to understand the greater ecology of victimization.

Results of large-scale, methodologically similar studies seeking to understand the prevalence of CSA have found a few individual characteristics related to increased risk of CSA. Survivors of CSA are most often women aged 18-22, and several studies have shown that first-year college women are at highest risk (Fedina et al., 2018). In terms of race and ethnicity, results of several large-scale CSA prevalence studies have found inconclusive evidence regarding differences in victimization of women of various racial and ethnic backgrounds (Fisher et al., 2000; Krebs et al., 2007). Cantor et al. (2015) found that Asian women were the least likely to be assaulted compared to women of other races, while Krebs et al. (2011) found that Black women attending HBCUs had

an overall lower prevalence rate of CSA than women at non HBCUs. Minority sexual orientation and gender identity have consistently been found to be related to higher rates of CSA. Women who identify as LGBTQ+ experience sexual assault at a significant higher rate than heterosexual women, and transgender, genderqueer and gender nonconforming folks are also significantly more likely to experience sexual assault compared to their cisgender counterparts (Cantor et al., 2015). Finally, women with disabilities also experience sexual assault at a higher rate than women without disabilities (Cantor et al., 2015; Campe, 2019). There is also some evidence linking individual personality characteristics to increased risk of CSA. Specifically, women who experience social interaction anxiety may be less sexually assertive, putting them at risk to be victimized (Schry & White, 2013).

One of the most frequently cited sources of sexual assault risk on college campuses is use and consumption of alcohol (Abbey, 1991, 2002, 2011; Dir et al., 2018; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). In fact, many studies have shown that alcohol use is one of the strongest predictors of CSA (Abbey, 1991, 2002; Dir et al., 2018). College students' use of alcohol is thought to both increase women's chance of victimization and increase men's likelihood of perpetration (Abbey, 1991, 2002). A study by Abbey and colleagues (1998) found that in 81% of alcohol-related sexual assaults, both the victim and perpetrator had consumed alcohol.

It is important to note that despite the close relationship between alcohol consumption and sexual assault, it does not demonstrate a causal relationship between the two, as the process by which alcohol impacts sexual assault risk is complex (Abbey, 2002). Alcohol is thought to be associated with increased occurrence of CSA by several

mechanisms of action including (1) lowering perpetrators inhibitions; (2) perpetrators misperceptions of women who drink as being more willing to engage in sexual activity; (3) perpetrators belief that it is okay to force sex with someone who is intoxicated and; (4) reducing women's ability to recognize risk and evade sexual assault by decreasing cognitive abilities (Dir et al., 2018).

Similarly, other researchers have posited several ways in which alcohol affects pre-existing beliefs on sexual behavior and aggression, heterosocial interactions, and the way in which alcohol impairs cognitive and perceptual abilities (Abbey, 2002; Abbey et al., 1998). Specifically, perpetrators of sexual assault may have pre-existing beliefs about alcohol's effects on sexual behavior and aggression, that is, perpetrators may believe that alcohol naturally increases sexual appetite and increases proclivity for aggressive behaviors (Abbey, 2002). Once alcohol is consumed, alcohol has detrimental effects on perception, appraisal, and communication during heterosocial interactions. Specifically, the effects of alcohol can encourage a biased appraisal of a partner's sexual motives. Abbey et al. (1998) noted that men often misjudge women's friendliness as sexual invitation or flirtation while under the influence of alcohol. The combination of the pre-existing beliefs about alcohol's effect with the actual effect alcohol has on communication and perception impairs perpetrator's ability to rectify misperceptions, justifies their aggressive or coercive behavior, and diminishes the victim's ability to resist (Abbey, 2002; Abbey et al., 1998)

The frequency and amount in which college students are drinking alcohol has also been shown to be related to sexual victimization. A study by Mellins et al. (2007) found that for both men and women, individuals who endorsed risky or hazardous

drinking were more likely to have experienced sexual assault than those who did not. Specifically, Mellins et al. (2007) found that those who engaged in binge drinking (having 6 or more drinks on a single occasion) at least monthly were more likely to experience sexual assault than those who did not. Steele and Josephs (1990) noted a dosage effect in the perceptual and cognitive impairment caused by alcohol. The more someone drinks, the more thoroughly peripheral cues and embedded meanings will be excluded from the drinker's perceptual awareness, which ultimately increases alcohol's disinhibiting effect (Steele & Josephs, 1990).

To add to the complexity of the relationship alcohol has with CSA, it has been found that women with sexual assault histories will often drink alcohol as a way to cope (Gidycz et al, 2007; Neilson et al., 2018). Gidycz et al. (2007) identified a significant interaction effect between women's drinking behavior and past history of victimization on their experiences of CSA. Similarly, results of a study by Neilson et al. (2018) revealed that sexual assault severity was positively associated with drinking to cope with anxiety, weekly drinking behavior, perception of revictimization, and latency of response time in hypothetical sexual assault vignettes. Results of these studies demonstrate a circuitous problem: alcohol use puts women at risk to be victimized, after being victimized, women turn to alcohol to cope with anxiety, which in turn further increases their risk of being revictimized as drinking behavior increases and risk perception is impaired from both alcohol use and previous traumatic victimization.

Alcohol use, and especially risky, episodic, binge drinking increases the risk of victimization and likelihood of perpetration. Alcohol myopia distorts impelling and inhibitory cues in perpetrators, which decreases the perpetrator's ability to pick up on

resistance cues from a victim, while also narrowing their perceptual field, only allowing them to perceive cues that encourage them to pursue sexual activity (Abbey, 1991, 2002; Mellins et al., 2007; Steele & Josephs, 1990; Zawacki et al., 2005). Additionally, women who have been previously victimized may have increased alcohol use to help them cope, which puts them at further risk for revictimization, creating a circular problem (Gidycz et al., 2007; Neilson et al., 2018). Taken together, the relationship between alcohol use and CSA is complex, and while not causal, individual alcohol use serves as an agent that promotes risky circumstances for victims and ripe circumstances for perpetrators.

Alongside alcohol use, previous victimization experiences stand to be one of the strongest individual predictors of CSA (Cantor et al., 2015, 2019; Krebs et al., 2007; Krebs et al., 2011). Risk identification research frequently uses vignette methodology to understand identification and interpretation of sexual assault risk. Specifically, it has been posited that women who have had a previous sexual victimization experience may have challenges identifying risky situations and emotion identification in others (Melkonian et al., 2017; Walsh et al., 2012).

Individual-level factors related to experiences of CSA help to start the conversation around who is victimized, but their importance should be considered in the greater context of the individual's ecology. Individual risk factors such as sexual and gender identity, sexual assertiveness behaviors, alcohol use, and previous victimization experiences only give a partial picture of sexual victimization of college students. These individual risk factors exist within the greater ecology of the survivor's life and the interpersonal connections around the survivor can inform the ways in which individual factors are displayed and understood.

Microsystem Factors

The microsystem of the CSA survivor consists of both family of origin people/places, and the peers surrounding the individual's living circumstances (e.g., roommates or housemates) as well as those in their classes and greater social circle. A college student living on campus might have several microsystems they operate within in addition to their family of origin microsystem.

Even though college students living on campus are separated from the microsystem of their family of origin, there is evidence linking family of origin influences to victimization experience. The theory of intergenerational transmission of violence suggests that hostile and physically harsh parenting and/or aggression teaches developing children that coercive and aggressive behaviors are normative in the context of an intimate relationship (Simons et al., 2013). In a study of 711 undergraduate students, it was found that inter-parental hostility and harsh parenting was significantly related to sexual assault victimization (Sutton & Simons, 2015). Other family of origin influences related to CSA victimization may be attachment style. Attachment organization to caregivers is the blueprint in which interpersonal relationships are felt and experienced (Bowlby, 1973). When parents are hostile and aggressive towards their children, this can lead to the development of anxious or avoidant attachment behaviors in interpersonal and romantic relationships (Hazan & Shaver, 1987). Sutton and Simons (2015) found that both anxious and avoidant attachment styles are related to sexual assault victimization.

While the developing child or adolescent may be more influenced by the microsystem influences of the members in the household, namely, caregivers and

siblings, the college student's microsystem expands to include roommates, close-knit peer groups, and friends in their greater social circle. Previous research has demonstrated that students who live on campus are at greater risk of being victimized (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). For many CSA survivors, their perpetrator may be within their microsystem as a current dating partner or a friend. Research has shown some evidence linking social group influence and CSA. A study by DeKeseredy and colleagues (2018) sought to find empirical support for Gwartney-Gibbs and Stockard's (1989) paper asserting that sexual victimization of college students may be engrained into the social fabric of peer groups. Specifically, DeKeseredy et al. (2018) looked at the effect of pro-abuse informational support, or the guidance and advice that encourages and accepts men to sexually, physically, and/or psychologically abuse their dating partners on college peer relationships and sexual assault experiences. The authors found that women who had received pro-abuse informational support from their peers were three times more likely to have been sexually assaulted; additionally, women with attachments to peers who they know have committed assaultive acts against others were 3.2 times more likely to have been sexually assaulted (DeKeseredy et al., 2018). Results of the DeKeseredy et al. (2018) study highlight the impact of an individual's microsystem and their risk of CSA beyond one's family of origin.

Kaczkowski and colleagues (2016) also supported this idea in finding that for men, perceived peer rape justification was significantly related to their sense of hostility toward women and the odds of them committing sexual violence. Conversely, the authors found that men who have greater social network diversity had less hostility towards

women and were less likely to commit sexual violence (Kaczkowski et al., 2016). Specifically, rates of sexual violence perpetration were found to decrease by 19% for every 1 SD increase in men's social network diversity, meaning that men who have larger and more diverse microsystems tend to have less hostility and aggression towards women (Kaczkowski et al., 2016).

Students who come from families of origin that exhibit hostile and coercive behavior and have insecure attachment styles are at risk of CSA (Sutton & Simons, 2015). Extending beyond their family of origin, college students' microsystem also includes friends and peers that live with them and are in their classes. For students that live on campus with other students, the collective effect of their peers' understanding and acceptance of assaultive behaviors can put them at risk (DeKeseredy et al., 2018). For men, the diversity of their friend group is related to CSA perpetration (Kaczkowski et al., 2016). Taking the reviewed literature together, microsystem risk factors of CSA are coercive and hostile parenting in the family of origin, insecure attachment to caregivers, connection to peers who provide pro-abuse informational support, and connection to male peers whose friend group lacks diversity are related to increased risk of CSA.

Mesosystem Factors

The mesosystem of a CSA survivor involves the interconnections surrounding an individual. The individual's mesosystem can be thought of as the system of the individual's microsystems, and is extended whenever the individual moves from one microsystem to another. Some examples of a college student's mesosystem might be extended social circles, Greek life, their cohort of peers, and college parties. A sorority member attending a fraternity party might be an example of the sorority member

extending her mesosystem. Bronfenbrenner (1979) also noted that when a member of one's microsystem accompanies the individual into a new setting, the developmental potential of the new setting is enhanced. An example of this in the present context might be an individual and her roommate attending a party together, which extends the party into her mesosystem, and allows her to feel as though the new setting is an extension of the safety of her microsystem.

College parties can be thought of as mesosystem environments because they extend an individual's microsystem to include an environment and others who are not in their immediate surroundings. Excessive alcohol use and binge drinking at college parties contribute to what many students describe as "hook-up culture," or casual sexual encounters without the expectation of future commitment or interaction with the person they are "hooking up" with (Sutton & Simons, 2015). High levels of alcohol use are a well-known aspect of college "hook-up culture," as alcohol serves as a social lubricant which lowers inhibitions and allows students to approach potential hook-up partners more freely (Sutton & Simons, 2015). This combination of binge drinking and a culture of "hooking up" leads to a minefield of misunderstood intentions, blurred lines of consent, sexual expectations and pressures and impaired judgment that ultimately lead to sexual assault (Sutton & Simons, 2015). A study by Flack et al. (2007) highlighted the complexities of hook-ups, alcohol use, and risk of sexual assault. The study found that hooking up is a risk factor for CSA, and that 78% of unwanted sexual intercourse experiences occurred during a hook-up (Flack et al., 2007). Results from the study highlight the blurred lines of consent during college student hook-up encounters, possibly due to sexual expectancies and misunderstood perceptions and intentions while

intoxicated. A review conducted by Adam-Curtis and Forbes (2004) noted that the impersonal nature of hook-ups and their association with alcohol use strongly parallels aspects of CSA. Research has found that social norms surrounding college hook-ups are often misperceived by college students. A study by Barriger and Velez-Basini (2013) identified important gender differences in men's and women's perceptions of peers' comfort level during hook-ups. Consistently, men perceive their level of comfort with sexual encounters as being largely the same as their peers, while women perceive peers' comfort levels during hook ups to be greater than their own (Barriger & Velez-Basini, 2013). This pattern of men's underestimation of peer's comfort level during hookups, and women's overestimation of peer's comfort during hookups may partially explain the relationship between "hookup culture," drinking, and CSA.

Another extension to the survivor's mesosystem related to college "hook-up" culture are parties hosted by men's Greek organizations. Greek organizations, and men's fraternities in particular, have been identified as a significant predictor of the perpetration of CSA (DeKeseredy et al., 2018; Lasky et al., 2017; Martin, 2016). There are multiple features of men's fraternities that contribute to a rape prone culture including homogeneity of members, a culture of secrecy and penchant for loyalty to the group, and the abundance of alcohol at social gatherings (Martin, 2016). Similarly, men's college athletic teams have also been a focus of CSA literature, with some research asserting that male college athletes are disproportionately accused of sexual assault compared to non-athletes (McCray, 2015). Male college athletes who are accused of perpetrating sexual violence have been a focus of media attention over the past 15 years, the high-profile case of a University of Notre Dame football player accused of sexually assaulting a freshman

woman, Lizzy Seeberg, at nearby St. Mary's College is one such example. The case of Lizzy Seeberg ends in tragedy after failure on the university's behalf to take appropriate adjudication actions against the accused and her devastating suicide (Henneberger, 2012). A study by Stozer and MacCartney (2015) found that schools classified as NCAA Division I were more likely to have reported cases of sexual assault that schools without NCAA athletics or only intercollegiate sports.

Feminist scholars attribute the increase in sexual assault perpetration in groups like men's fraternities and athletic teams is partially explained by group masculinity dynamics, competition, and more peer acceptance of assaultive behavior (McCray, 2015). Several studies note that sorority women are at higher risk of being sexually assaulted due to a number of factors including, (1) greater exposure to fraternity men, (2) greater attendance of on-campus parties, (3) more likely to endorse traditional gender roles, and (4) greater likelihood of binge drinking behavior (Lasky et al., 2017; Martin, 2016; Radina, 2017). Results of these studies highlight how the extension of a sorority member's ecosystem to include traditionally all-male groups like men's fraternities and sports teams are significant mesosystem factors in the perpetration of CSA.

The mesosystem of a CSA survivor includes the connections among her various microsystems which can include her greater social circle of peers including members of Greek organizations and athletic teams on campus, but that she is not a member of. The mesosystem stands to be one of the most important interpersonal factors in understanding CSA perpetration because literature has shown that CSA is often committed by an acquaintance. These perpetrators may not be in the survivor's microsystem, but just outside of it, providing a false sense of trust and safety.

Exosystem Factors

The exosystem is an environment that does not include the survivor of CSA directly, but in which encompasses the individual's meso- and microsystems, operating in such a way that trickles down to affect the individual's development. On college campuses, this includes the larger campus population including faculty, staff, and administrators that make decisions and policies about the ways in which CSA is handled on campus.

IHEs are political economies that must answer to several aims in their operation that often seem in direct contradiction to one another. In her 2016 essay, Martin points out that university officials and administrators are often beholden to stakeholders that protect perpetrators from being prosecuted, and alienate victims. An illustrative example of this kind of macrosystem factor that goes into the perpetuation of CSA is the way in which sexual assault allegations are typically handled on college campuses. As is highlighted in Martin's (2016) essay, and in the documentary film, *The Hunting Ground* (Dick, 2015), colleges are motivated by a number of factors to handle sexual assault allegations internally. Colleges and universities are reticent to invite outside law enforcement to handle sexual assault allegations, as these can harm their "brand" and discourage students from wanting to attend the university (Dick, 2015). Additionally, as was explored earlier, Title IX and the Clery Act require colleges and universities to report all adjudicated cases of sexual assault to the Department of Education (McCallion, 2014; US Department of Education, 2011, 2017; Violence Against Women Reauthorization Act, 2014). If universities can document that an internal investigation found no such acts of sexual violence, they are not required to report it. This loophole in the way in which

CSA cases are handled in combination with university presidents' desire to increase university donations and enrollment by curating the university's image is in direct opposition with prosecuting perpetrators of sexual violence to the highest level.

There is evidence to support the implementation of hardline institutional policies regarding sexual misconduct thwart CSA prevalence rates. DeLong et al. (2018) found that institutions with more comprehensive sexual assault policies in place had fewer reported instances of CSA. However, institutions should consider the ways in which the culture of their institution is impacted by campus policy. Fedina and colleagues (2018) highlight the need for changes in campus response and prevention efforts, policy efforts by universities, and more concerted research efforts to understand the prevalence at which CSA is occurring. Specifically, the authors suggest that prevalence rates vary from campus to campus; therefore, prevention and intervention strategies should start with a detailed understanding of the specific campus culture and student needs for their campus population (Fedina et al., 2018).

Campus policy and the ways in which those policies are implemented have been shown to have a significant impact on survivors of CSA. Smith and Freyd (2013) introduced the idea of "institutional betrayal" by examining the relationship between institutions and their responses to victimization. Smith and Freyd (2013) took the ideas behind betrayal trauma theory and applied it to a more indirect source of betrayal: institutional betrayal, or betrayal at the exosystem level. Examples of institutional betrayal are when the criminal justice systems fails to protect intimate partner violence survivors, when social services fails to protect children from abusive situations, or when religious organizations silence survivors of abuse while protecting abusing religious

leaders. Survivors of CSA feel doubly traumatized by institutional betrayal, when the college or university has failed to keep them safe or made matters worse by deliberately or unknowingly causing harm. Examples of institutional betrayal on college campuses can include unclear reporting methods, punitive policies upon reporting, victim blaming, silencing survivors, creating danger by not removing the perpetrator, failure to respond to allegations, and failing to adjudicate accusations (Stader & Williams-Cunningham, 2017). Survivors of CSA who also experience institutional betrayal experience more severe posttraumatic stress symptoms including depression, anxiety, and dissociation (Smith & Freyd, 2013). A study by Smidt et al. (2019) found that LGBTQ+ survivors of CSA experience higher rates of institutional betrayal, putting them at even higher risk for negative psychological outcomes. While survivors of CSA interact mostly with their IHE in the adjudication process of their case, they can feel similar levels of institutional betrayal by legal and medical institutions. An ecological review of sexual assault survivors found consistent evidence linking increased PTSD and depressive symptomatology in survivors who had received non-trauma informed care from legal and medical helpers (Campbell et al., 2008).

While exosystem factors do not directly involve the survivor of CSA, institutional actions and policies that suppress CSA reports and favor respondents accused of sexual assault are harmful to the mental health of survivors (Smidt et al., 2019; Smith & Freyd, 2013; Campbell et al., 2008). Institutional policies should not only be written to protect survivors of sexual assault, but also should be a reflection of the greater needs of students, faculty, and staff on campus.

Macrosystem Factors

The macrosystem consists of the underlying cultural or philosophical orientation in which the individual lives (Bronfenbrenner, 1979; Salkind, 2005) Thinking about survivor's experiences of CSA in the US from a macrosystem lens, the existence of a patriarchal society which places women as inferior to men is crucial to understanding the lived experiences of survivors of CSA. Feminist scholars and sociologists often cite reasons for continued prevalence of CSA as the existence of "rape culture." Rape culture is an environment in which rape is prevalent and in which sexual violence against women is normalized and excused in the media and popular culture (Burt, 1980). Rape culture is perpetuated through the use of misogynistic language, the objectification of women's bodies, and the glamorization of sexual violence, thereby creating a society that disregards women's rights and safety (Burt, 1980). Burt (1980) was one of the first to embark upon an empirical inquiry of rape culture, and in the process coined the term *rape myth acceptance*. Rape myths are myths that we, as a collective rape culture, accept as truth. Examples of rape myths are victim blaming and shaming, citing false rape accusations as occurring more often than they do, and dissolving perpetrators' responsibility from their actions. Rape myths serve to excuse sexual aggression, create hostility towards victims, and bias criminal prosecution (Burt, 1980).

Several studies have linked greater rape myth acceptance with prevalence of CSA. O'Connor et al. (2018) conducted a series of six focus groups of college students and found that when asked about sexual assault, students often produced responses consistent with rape myths. The study highlights the existence of rape culture on college campuses and serves to inform prevention efforts by IHEs to target nuanced rape-prone beliefs.

Rape myths extend far beyond individual beliefs and spill over into media portrayal of survivors. A study of the effects of daily television viewing of crime dramas and daytime soap operas revealed that those who watched television daily were more likely to endorse rape myths and more likely to perceive rape accusations as false (Kahlor & Eastin, 2011). Additionally, Kahlor and Eastin (2011) found that those who watched daytime soap operas were also more likely to endorse rape myths than those who do not. The study by Kahlor and Eastin (2011) took an ecological approach to their research by utilizing television as a purveyor for cultural norms in the macrosystem. An analysis examining headlines about Kobe Bryant's sexual assault allegations found that 10% of newspaper headlines contained rape myths (Frank et al., 2008). The authors also demonstrated the effects of media headlines containing rape myths on attitudes towards sexual assault victims, such that male participants who had been exposed to rape myth endorsing headlines were more likely to think the accused was innocent and the accuser was lying. O'Boyle and Li (2019) conducted a content analysis of 500 newspaper articles from 10 liberal and conservative newspapers that covered both regional/local and national coverage of CSA spanning 23 years of news coverage. Overwhelmingly, both liberal and conservative media framed individual behavior as the greatest cause of sexual assault, with 34.6% of all news stories analyzed accused the perpetrator for the incident, while 37.4% of stories considered the victim for being responsible for the incident. The study reflects the news media's contribution to continuation of stereotypes about rape victims and

rape myths as well as a cultural measure of society's ideas about campus sexual assault generally.

While feminist scholars have been writing about the concept of rape culture as a part of the second-wave feminist movement for some time, quantitative researchers and latent variable theorists have done little research on understanding the components of rape culture from a quantitative standpoint (Johnson & Johnson, 2017). Quantitative researchers have attempted to measure aspects of rape culture with varied success. Burt (1980) identified a number of attitudinal variables that were strong predictors of rape myth acceptance in the creation of her 19-item Rape Myth Acceptance Scale. As an expansion of Burt's original (1980) scale, Lonsway and Fitzgerald (1995) developed a new Rape Myth Scale seeking to measure acceptance of commonly held rape myths, and by proxy, understand the pervasive ideas that promote rape culture. While prior research has contributed to the greater empirical understanding of rape culture, these scales measure attitudes of individuals rather than the components of a culture that contribute to increased incidences of rape and sexual assault. In attempt to take on a more all-encompassing view of rape culture, a study by Johnson and Johnson (2017) attempted to model rape culture based upon a theoretical definition. The proposed model of rape culture encompassed traditional masculine and feminine gender roles, sexism, hostility towards women, adversarial sexual beliefs, and acceptance of violence (Johnson & Johnson, 2017). While the study by Johnson and Johnson (2017) proposed an initial model of rape culture, the model that was developed did not include any contextual variables related to survivors' environment. Additionally, the model only focused on

individual characteristics that contribute to the perpetration of rape and sexual assault, not larger systemic or cultural components that contribute to a rape culture.

The macrosystem consists of commonly held beliefs and philosophies of a culture that affect individual behavior from the outside in. In the present context, the United States as a patriarchal society that implicitly and explicitly endorses rape culture is the overarching cultural phenomenon that perpetuates sexual violence on and off college campuses.

Chronosystem Factors

The chronosystem includes the influence of passage of time on human development and can include the ways in which big events shape one's development over time, or sociohistorical events that shape the development of generations. For individual survivors, each instance of sexual victimization becomes a chronosystem factor, as the trauma experienced following the event sets into motion life-altering changes throughout the life span. In a review by Zhu and colleagues (2020), the authors discuss the chronosystem effects of revictimization and poly-victimization on long-term mental health outcomes including symptoms consistent with complex trauma reactions and an increase in feelings of shame. As was explored earlier, previous victimization is an individual risk factor for CSA, but it also stands to be a chronosystem factor in the way in which each victimization experience creates an indelible mark on one's life.

One sociohistorical event relevant to survivor's experience of sexual assault is the #MeToo movement. Started by Tarana Burke in 2006, and revitalized in 2017 following sexual assault allegations put forth against media mogul Harvey Weinstein, a

digital activism movement was started (Mendes et al., 2018). The viral #MeToo movement not only dominated social media feeds but also news cycles as new allegations of sexual misconduct by high-profile men came out. Now, over three years after the beginning of the Twitter trend, journalists and scholars refer to the movement as a new era of feminism, where digital platforms become a public forum for women to share their stories worldwide (Goldberg, 2020; Mendes et al., 2018; Pellegrini, 2018). In a qualitative study analyzing the effects of digital activism movements such as #MeToo, Mendes and colleagues (2018) found that participants often found solidarity in the discovery that sexual violence is a structural problem rather than only a personal problem. In 2016, the world watched in awe as Donald J. Trump, a man who has at least 25 outspoken accusers of sexual misconduct against him and who infamously boasted on tape about grabbing women by their genitalia, won the presidential election (Relman, 2020). This event is also paramount to understanding the potential chronosystem effect of survivors of sexual assault in the Trump era. In fact, some feminist scholars believe that following the defeat of Hilary Clinton's presidential campaign and the election of Donald Trump facilitated a generational movement. Pellegrini (2018) coined the term, "facilitative displacement," to describe the uprising of the #MeToo movement as an effort to displace collective hurt following the 2016 presidential election. Other scholars have called Trump's presidency coinciding with the #MeToo movement an "unprecedented public reckoning" with the patriarchy (Gentile, 2018; p. 701). Waves of digital activism, a so-called fourth wave of feminism, combined with a collective feeling of exasperation at the Trump administration's willingness to diminish survivor of CSA's

rights puts us in the middle of an era that will alter generations' development from the outside in.

Use of EST in CSA Research

Previous research has shown effectiveness in approaching CSA research from an ecological stance. A study by Herres and colleagues (2018) sought to study factors associated with CSA and PTSD across multiple ecological systems. In order to do this, the researchers examined variables at the individual, micro-, and macro- levels to understand their relatedness to one another. While the study did take an ecological approach to understanding CSA, a limitation of the study was the lack of understanding of the interrelations of the levels in the college ecosystem. One of Bronfenbrenner's main tenets of his original theory was the importance of the reciprocity amongst the nested ecological structures. Unfortunately, Herres et al. (2018) was limited in their ability to understand these interrelations by their methodological approach. In terms of prevention efforts, The American College Health Association (ACHA) released guidelines on addressing sexual and relationship violence on college and university campuses by taking an ecological approach to response and prevention (ACHA, 2016). Specifically, the ecological approach for prevention of CSA frames risk and protective factors within the context of interpersonal processes and primary groups, institutional factors, community factors, and public policy (ACHA, 2016). In order to provide an adequate response to CSA, the ACHA encourages colleges and universities to respond at every level of campus ecology.

Taken together, no one particular risk factor has shown to cause CSA completely, instead, like other social issues, a cocktail of individual, interpersonal, environmental,

and cultural factors come together to form a dangerous and harmful phenomenon that affects millions of women and men annually. Examining CSA from an ecological standpoint gives researchers a sophisticated, multilevel approach to understand the problem and provide solutions that are context specific, as CSA is the result of the complex weave of the individual, micro-, meso-, exo-, macro-, and chronosystem factors on a college campus.

Conclusion

Approximately 20-25% of college women and 6-7% of college men experience sexual violence during their time at American colleges and universities (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). CSA is considered a significant public health concern as it is associated with poorer mental and physical health outcomes (Campbell et al., 2008; Carey et al., 2018; Golding, 1999; Leone & Carroll, 2016; McDougall et al., 2016; Potter et al., 2018). While existing research on CSA has given some context regarding who is most affected by CSA and under what conditions, the literature fails to give explanations for the heterogeneity of experiences of victims and nonvictims, even when conditions are similar (Fedina et al., 2018; Krause et al., 2019; Muehlenhard et al., 2017).

Given the scope and some context to the problem of CSA, utilizing an ecological stance in research and prevention efforts is an appropriate and effective way to conceptualize the problem. Existing literature has identified key individual, microsystem, mesosystem, exosystem, macrosystem and chronosystem influences related to the prevalence of CSA. For example, LGBTQ+ women and women with disabilities are at greater risk to be sexually assaulted, in addition to women who frequently engage in

binge-drinking or have a sexual assault history (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). Microsystem influences on sexual assault risk include family of origin parenting style and attachment organization as well as peer group influences (DeKeseredy et al., 2018; Kaczkowski et al., 2016; Sutton & Simons, 2015). Mesosystem influences include groups such as Greek life and university athletic teams, as well as student socialization patterns including on- and off-campus parties and casual "hook-ups" (Adam-Curtis & Forbes, 2004; DeKeseredy et al., 2018; Flack et al., 2007; Lasky et al., 2017; Martin, 2016; McCray, 2015; Sutton & Simons, 2015). The political economy of IHEs create exosystem environments with opposing stakeholders which often leaves students with a sense of institutional betrayal, worsening student outcomes following CSA (Dick, 2015; Smith & Freyd, 2013). Finally, cultural factors operating at the macro- and chronosystem levels including a patriarchal society, rape myth acceptance, and the aftershock of the 2016 US Presidential election envelop the individual's ecosystem and exacerbate and perpetuate CSA (Burt, 1980; Gentile, 2018; O'Connor et al., 2018). Despite the dearth of literature linking individual and environmental factors to CSA prevalence, there are few quantitative research studies that take on a holistic, multi-level approach to understanding risk factors related to CSA with consideration to factors operating at the individual, micro-, meso-, exo-, macro, and chronosystem levels.

The future of sexual victimization research is in need of a novel approach to understanding the complexity associated with CSA. In a special issue of *Sexual Abuse*, Harris et al. (2019) advocate for action-oriented research that can shed light on the nature and dynamics of CSA including its scope and impact, and promote the development of

novel initiatives that respond to the needs to victims and IHEs. The present study serves to understand existing data on CSA through an ecological lens, and will help to fill gaps in the research literature by shedding light on individual, process, and context variables related to CSA. Specifically, the present study takes on a latent variable mixture modeling approach to uncover subgroups within the population, which identifies unobserved variables related to CSA victimization. Taking on this type of methodological approach is novel in its attempt to identify unrecovered variables operating beneath the surface of sexual assault and misconduct campus climate surveys.

Chapter Three: Methods

This chapter describes the methodological framework from which the present study's research questions will be examined. As was explored in Chapter Two, taking on an ecological stance in understanding the problem and context of CSA is a needed approach in the current literature. The present study utilizes latent variable mixture modeling to achieve this goal. Specifically, data collected from the Association of American Universities (AAU) Campus Climate Survey on Sexual Assault and Sexual Misconduct (Cantor et al., 2015) is used to understand latent subgroups of students, based on measures of campus climate, by performing a latent class analysis. Additionally, variables representing individual, microsystem, mesosystem, exosystem, and macrosystem factors are used to predict latent class membership by conducting a series of latent class regression models. The present study plans uses three levels of analyses to answer the proposed research questions.

Research Questions

RQ1: Among a sample of college students are there distinct latent subgroups of students based on measures of campus climate?

RQ1.a: Can latent class membership be predicted by victimization status (i.e., having a victimization experience, or never having a victimization experience)?

RQ2: Can latent class membership be predicted by individual-level measures such as, gender identity, age, sexual orientation, race/ethnicity, and disability status?

RQ3: Can latent class membership be predicted by micro- and mesosystem measures such as group/club membership, partnered relationship status, and living situation?

RQ4: Can latent class membership be predicted by exo- and macrosystem measures such as university affiliation (i.e., public or private), size of university, and location of university?

Data Source

The present study is a secondary analysis of data from the AAU Campus Climate Survey on Sexual Assault and Sexual Misconduct (hereafter known as the AAU survey; Cantor et al., 2015). The study was a product of collaboration between 27 AAU members and a private research company, Westat. Prompted by the 2014 White House Task Force on CSA, the AAU decided to develop and implement a scientific survey to better understand the attitudes and experiences of students with respect to sexual assault and sexual misconduct (Cantor et al., 2015). Data collection occurred in April 2015, and data were initially analyzed and reported on later in 2015.

Participants

Participants were undergraduate, graduate, and professional students enrolled at 27 IHEs across the United States. The total sample size was 779,170 with a response rate of 19.3% and 150,072 students participating in total. Participants ranged from 18 to 25+ (the oldest age categories were collapsed in the survey instrument), and were mostly undergraduate students (61.5%). Participants were mostly likely to identify as white (71.9%), non-Hispanic or Latino (92.1%), female (58.5%), and heterosexual (88.1%). Demographic information on the complete sample can be found in Table 1.

Table 1

Characteristics of the Sample

Characteristic Category	n	%
Age		
18	8,683	6.5
19	18,967	14.3
20	18,299	13.8
21	18,206	13.7
22	13,568	10.2
23	7,942	6.0
24	6,980	5.3
25+	39,863	30.0
Missing	270	0.2
Student Affiliation		
Undergraduate	81,782	61.6
Graduate or Professional	50,947	38.4
Missing	49	<0.01
Hispanic or Latino		
Yes	10,405	7.8
No	122,130	92.0
Missing	243	0.2
Race		
White only	93,688	70.6
Black only	5,352	4.0
Asian only	24,058	18.1
Other or multi-racial	9,680	7.3
Gender Identity		
Woman	76,963	58.0
Man	53,795	40.5
Transgender, genderqueer, non-conforming Questioning or not listed	1,218	0.9
Missing	802	0.6
Sexual Orientation		
Heterosexual	116,825	88.0
LGBTQ+	13,969	10.5
Missing	1,984	1.5
Disability Status		
Yes	4,412	3.3
No	128,265	96.6
Missing	101	0.1
Partnered Relationship Status		
Yes	101,735	76.7
No	30,934	23.3
Missing	109	0.1
Victimization Status		

Yes	20,712	15.6
No	112,066	84.4
University Enrollment Size		
< 21,000	35,922	27.1
21,000 – 40,000	40,018	30.1
> 40,000	56,838	42.8
University Region		
Northeast	56,001	42.2
Midwest	42,024	31.6
South	21,922	16.5
West	12,831	9.7
University Affiliation		
Public	88,791	66.9
Private	43,987	33.1

Note. N = 132778.

Survey Instrument

The AAU Campus Climate Survey on Sexual Assault and Misconduct was produced by a group of researchers, program administrators, and methodologists from the participating IHEs and a third-party research company, Westat. The survey development process was a collaboration between the Westat and AAU Survey Design Teams. These teams were comprised of methodologists and multidisciplinary university professors and administrators with expertise in survey design, methodology, and campus sexual assault and misconduct (Cantor et al., 2015). Survey development was based on the survey initially developed for the White House Task Force to Protect Students from Sexual Assault and the "informational needs" of the participating IHEs (Cantor et al., 2015; p. vi). The survey design process took into consideration the suggestions put forth by the first report of the White House Task Force to Protect Students from Sexual Assault and following the systematic review of decades of research literature on the measurement of sexual misconduct and sexual victimization of college students (Cantor et al., 2015). The

survey development team drew inspiration from the procedures and surveys developed by other IHEs and other victimization surveys such as the National Intimate Partner and Sexual Violence Survey and the National Crime Victimization Survey (Cantor et al., 2015). The survey development team sought to measure incidence and prevalence of a variety of victimization experiences on campus including sexual violence, sexual harassment, stalking, and intimate partner violence, in addition to a number of campus climate measures, all while condensing the survey length to about 15 minutes per participant (Cantor et al., 2015). The survey structure is made up of 10 sections (A-J) and concludes with a final debriefing question about the survey experience. A core set of 63 items were presented to each participant. Details about the survey instrument inclusive of all sections of the survey can be found in Table 2. The sections of the survey that will be used in the present study are examined hereafter.

Table 2

AAU Campus Climate Survey on Sexual Assault and Misconduct Survey Instrument

Section	Section Title	Number of Items	Scaling	Adapted From	Used in Present Study?
A	Background	17	Various	–	Yes
B	Perceptions of Risk	3	5 point Likert-style Scale (Not at all to Extremely)	Fisher & Sloan (2003)	Yes
›C	Resources	5	Drop-down list of IHE specific resources & 5 point Likert-style scale (Not at all to Extremely)	McMahon, Stepleton, & Cusano (2014) Rankin & Associates Consulting, 2008	Yes
D	Harassment	14	Various (Dichotomous with Skip Logic)	Leskinen & Cortina (2014) Freyd, Rosenthal & Smith (2014	No
E	Stalking	12	Various (Dichotomous with Skip Logic)	Black et al. (2011), Catalano (2012), and Tjaden and Thoennes (1998)	No
F	IPV/DV	12	Various (Dichotomous with Skip Logic)	Black et al. (2011)	No
G	Sexual Violence Screener	9	Dichotomous	Koss et al. (2007) Krebs et al. (2007)	Yes
G1-G9	Immediate follow-ups and detailed incident forms	40	Various	Koss et al. (2007) Black et al. (2011) NCVS (2013)	No
H	Sexual Misconduct Prevention Training	2	Various (Dichotomous with Skip Logic)	–	No
I	Perceptions of Responses to Reporting	7	5 point Likert-stye Scale (Not at all to Extremely)	McMahon et al. (2014)	Yes
J	Bystander Behavior	3	Various (Dichotomous with Skip Logic)	Banyard et al. (2014) McMahon et al. (2014)	No
K	Debriefing	1	5 point Likert-style Scale (Not at all to Extremely)	–	No

Note. Adapted from "Report on the AAU Campus Climate Survey on Sexual Assault and Sexual Misconduct" by D. Cantor et al., 2015, Westat, Copyright 2015 by Westat.

Background/Demographic Information

The background section of the survey consisted of 17 demographic information items. The section collected the following information: participant age, student affiliation (i.e., undergraduate, graduate, or professional), year in school, race/ethnicity, citizenship, gender identity, sexual orientation, partnered relationship status, marital status, and disability status. This section also gathered information about the student's interaction with the IHE by asking students to report on their school/program affiliation (e.g., college of arts and sciences, school of education, school of engineering, etc.), the first year of student enrollment, group/club membership (e.g., Greek life, athletic team, student-run club, etc.), living situation (i.e., on-campus or off-campus), and online student status.

Perceptions of Risk

This section was adapted from Fisher and Sloan (2003) and contained three items related to perception of sexual assault risk on campus. Each item utilized a 5 point Likert-style response scale, ranging from "Not at all" to "Extremely." An example of an item in this section is, "How likely do you think it is that you will experience sexual assault or sexual misconduct on campus?" (Cantor et al., 2015; p. A5-6). The three items in this section were altered from Fisher and Sloan (2003) to capture participants' fear of sexual misconduct on campus without capturing perception of other victimization risk, such as fear of theft or fear of nonsexual violence as was examined in the original scale. Additionally, the item response scaling was altered from the original 10 point scale to a 5 point scale.

Campus Resources

This section asked questions related to the available resources on campus. The first item in this section included a university specific list of resources where students could mark each of the services they were aware were available to them, producing a frequency count of the total number of resources participants were knowledgeable of. In the present study, this item will not be analyzed. Additionally, this section included four 5-point Likert-style items asking participants to rate how knowledgeable students were about university policies regarding CSA from "Not at all" to "Extremely." The items in this section were adapted from McMahon and colleagues' Awareness of Campus Services Scale (2014) and The Carleton College Climate Assessment (Rankin & Associates Consulting, 2008). The original scale from McMahon et al. (2014) included 8 items asking students to rate their knowledge of eight unique on-campus resources on a Likert-type scale. Only one item in this scale was adapted from Rankin & Associates Consulting (2008), as the original scale was a campus climate survey for Carleton College. An example item from this section is, "How knowledgeable are you about where to get help at [University] if you or a friend experienced sexual assault or sexual misconduct?" (Cantor et al., 2015; p. A5-7).

Sexual Victimization

Items in this section were modified from the Sexual Experiences Survey (Koss et al., 2007) and the CSA Study (Krebs et al., 2007). The language used in the survey in this section mirrored the recommendations set forth by the White House Task Force Report (Cantor et al., 2015). The sexual violence screener contained nine dichotomous items which defined sexual assault and misconduct with two types of victimization (1) sexual

penetration, and (2) sexual touching; these victimization experiences were specified by four tactics: (1) physical force or threat of physical force, (2) being incapacitated due to drugs, alcohol or being unconscious, asleep, or passed out, (3) coercive threatens of non-physical harm or promised rewards, and (4) failure to obtain affirmative consent. The above victimization experiences measured were defined using behaviorally specific language, and each sexual victimization experience question provided both a definition and examples of the behavior and use of the tactics to provide clarity for each distinct victimization experience (Cantor et al., 2015). The survey design team sought to estimate the incidence and prevalence of nonconsensual sexual contact by each combination of behavior and tactic, and therefore, it was it was necessary to ask about each combination of behavior and tactics (Cantor et al., 2015). An example question from this section is, "Since you have been attending [University], has someone used physical force or threats of physical force to do the following with you: (1) Sexual penetration. When one person puts a penis, fingers, or object inside someone else's vagina or anus, or (2) Oral sex. When someone's mouth or tongue makes contact with someone else's genitals." (Cantor et al., 2015; p. A5-23).

If a participant endorsed any of the victimization experiences, skip logic led the participant to a "detailed incident report," which asked participants to answer several questions about their victimization. The immediate follow up section asked students to report on the number of times they have been victimized in the way they endorsed and when the victimization occurred. The survey design team sought to estimate both incidence and prevalence of sexual victimization during the students' entire time at the

university, and the current academic year (Cantor et al., 2015). Next, the survey led participants who endorsed victimization through a number of items asking participants to report the number of perpetrators, gender of perpetrators, relationship to perpetrator, drug/alcohol use of perpetrator, drug/alcohol use of self during incident, suspicion of drugging during incident, location of the assault, mental health outcomes of participant, utility of campus programs/reporting procedures post-assault, and reason for not reporting incident. The present study will only use data from the sexual violence screener, and not any data from the detailed incident forms.

Perceptions of Responses to Reporting

This section was adapted from McMahon and colleagues (2014) work at Rutgers University and from the White House Task Force (2014) guidelines regarding campus climate surveys. The section contains seven Likert-style items which asked participants to measure their perceptions of the university's response to a report of sexual misconduct on a 5-point scale from "Not at all" to "Extremely." An example item from this section is, "If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that campus officials would protect the safety of the person making the report?" (Cantor et al., 2015; p. A5-29). These items were nearly identical to the original scale as reported by McMahon et al. (2014).

Procedures

After development of the survey, Westat submitted an Institutional Review Board (IRB) package to the Westat IRB and to the 27 participating IHEs who elected to either submit their own IRB package to their review boards, or, elected to rely on Westat's IRB as the IRB of record (Cantor et al., 2015). The survey and research protocols were

approved in February of 2015. The AAU survey is protected by a Federal Certificate of Confidentiality issued by the National Institute on Alcohol Abuse and Alcoholism, National Institutes of Health as an additional protection for participants (Cantor et al., 2015).

All but one of the 27 IHEs participating in the study launched the survey over a three-week period in the spring of 2015. Most schools participating observed a 3-week field period, with three email requests asking students to participate in the survey for a variety of incentives such as being entered into a drawing, or a $5 gift card. Each email included a unique link to the student's online survey and was signed by a university representative. Two additional reminder emails were sent by Westat to prompt completion of the survey.

Upon entering the survey, students were shown an informed consent document. The informed consent provided details about the survey, set expectations for the types of questions that were being asked, and allowed students to opt out of participation (Cantor et al., 2015). If the student agreed, the survey began. The average time it took each participant to complete the survey was 17.9 minutes. Students who had experienced CSA took longer to complete the survey, averaging 23-36 minutes depending on the number of victimization experiences endorsed by the participant.

Because the AAU survey covered distressing and traumatic topics, several safeguards were put in place in the event a participant became overwhelmed. First, participants were reminded they could skip any questions in the survey they did not want to answer, they were also reminded that they could end their

participation at any time (Cantor et al., 2015). Additionally, each IHE provided students with campus-specific resources lists with contact information on national, campus, and community resource providers that offer support to students. This resource list was shown to participants twice, once during the initial landing page, and at the conclusion of the survey (Cantor et al., 2015). Additionally, the researchers developed a protocol for Help Desk staff to use if they received distress calls or questions about sexual assault resources (Cantor et al., 2015).

Survey data was collected via a secure web site hosted by Westat. All identifying information connected to participants (e.g., email addresses) were encrypted and stored on a secure server database. Upon completion of the survey, the students email address was automatically deleted from the database, removing any linkage between the survey and response and the student (Cantor et al., 2015). Data was initially released only to the participating IHEs in the first three years after the survey was collected.

The Current Study

The present study uses data from the AAU Campus Climate Survey on Sexual Assault and Sexual Misconduct. The data is available through University of Michigan's Inter-university Consortium for Political and Social Research (ICPSR) following completed Restricted Data Use Agreement, valid reasons for request, and IRB approval or IRB exemption from the institution using the data.

Participants

As previously mentioned, 150,072 respondents completed the survey. Cantor et al. (2015) defined a "completed survey" as all respondents who took at least 5 minutes to complete the questionnaire, and answered at least one question in each of the following

sections: sexual harassment, stalking, sexual assault/other misconduct. For completed surveys, Cantor et al. (2015) reported very low levels of missing data with no more than 7% missingness in any of the survey sections. While the overall level of missing data is relatively low, the present study will still attempt to use a complete data set by conducting a missing data analysis to understand the extent and nature of missingness. Missing data causes two primary problems, (1) loss of statistical power, and (2) bias of parameter estimates (Roth, 1994). The present study will use SPSS 27 to analyze the extent and nature of missing data, and to ensure there are no demographic variables associated with missingness. Then, depending on the pattern of missingness (i.e., missing at random, missing completely at random, not missing at random), a missing data procedure will be used, such as deleting listwise, or multiple imputation using the EM algorithm. The EM algorithm iterates through a process of estimating missing data and then estimating parameters (Roth, 1994). However, because the sample size is so large, a simpler missing data procedure may be appropriate.

Measures

The measures utilized in the present study are from the AAU survey and have been organized to represent the theoretical framework of the present study and research questions.

Campus Climate Measures

The AAU survey utilized several scales to measure different facets of "campus climate" as it relates to sexual assault and misconduct. The present study uses perceptions of risk, knowledge of campus resources and policies, and perceptions of response to reporting as the manifest variables in the primary analysis.

Perceptions of risk. The AAU survey included three items in this section to measure participants' perception of sexual assault risk on campus. In the present study, a CFA is conducted to confirm the factor structure and provide evidence for construct validity. These items utilize a 5-point Likert-style scale ranging from "Not at all" to "Extremely."

Knowledge of campus resources and policies. Items in this measure included four 5-point Likert-style items asking participants to rate how knowledgeable students were about university policies regarding CSA from "Not at all" to "Extremely." In the present study, a CFA is conducted to confirm the factor structure of the items and provide evidence of construct validity.

Perceptions of responses to reporting. Items in this measure included seven Likert-style items which asked participants to measure their perceptions of the university's response to a report of sexual misconduct on a 5-point scale from "Not at all" to "Extremely." In the present study, a CFA is conducted to confirm the factor structure of the items and provide evidence of construct validity.

Sexual Victimization Measure

The AAU survey includes 9 dichotomous items measuring experience of different types of sexual assault and battery by various tactics. In the present study, endorsement of any of the 9 types of nonconsensual sexual victimization is combined into one variable designating participants as victims or non-victim, with "1" being coded for those who endorsed victimization, and "0" for those who did not endorse victimization.

Individual-level Measures

The AAU survey included several background/demographic items. In the present study, the following demographic variables of interest are included in the secondary analyses: gender identity, age, sexual orientation, race/ethnicity, and disability status.

Micro- and Mesosystem Level Measures

In the present study, several variables serve as examples of microsystem and mesosystem level factors. Specifically, group/club membership (e.g., Greek organization, athletic teams, student run clubs, etc.), partnered relationship status, and living situation serve as micro- and mesosystem level measures that are included in secondary analyses.

Exo- and Macrosystem Level Measures

The AAU survey did not include any measures that would be considered exosystem or macrosystem factors, however, the original data collection did include information about each IHE in the study. In the present study, university affiliation (i.e., public or private), size of university enrollment, and location of university in terms of census region (i.e., Northeast, Midwest, South, West) are considered exo- and macrosystem level measures included in secondary analyses.

Statistical Analyses

In order to address the research questions posed in the present study, the researcher conducted three separate sets of analyses. First, a confirmatory factor analysis (CFA) is conducted to confirm the factor structure of the items and examine evidence for construct validity. Additionally, appropriate descriptive statistics including, frequencies, means, and standard deviations are determined among all variables of interest. Next, a latent class analysis (LCA) is used to identify unobserved groups of students based on

patterns of responses on the AAU survey. Following LCA, secondary analyses are conducted to answer additional research questions about the prediction capability of latent classes using latent class regression (LCR).

Preliminary Analysis

In preparation for the primary analysis, a CFA is conducted to verify the factor structure of the items to be included in the LCA. Broadly, factor analysis is a method of modeling the covariation among a set of observed variables as a function of one or more latent constructs (Bandalos & Finney, 2019). The purpose of using CFA in the present study is to evaluate the hypothesized structures of latent constructs, specifically, perceptions of risk, knowledge of campus resources, and perceptions of response to reporting. The AAU survey utilized 14 items in three subsections to measure elements of campus climate (Table 3). In the present study, three competing models are hypothesized. It is expected that a three-factor obliquely rotated model will demonstrate best fit, as the hypothesized factors are expected to correlate slightly with one another (Field, 2013). The present study will use the following rules in examining the hypothesized model: eigenvalues greater than one indicate appropriate factor structure, additionally, factor loadings greater than .3-.4 will be considered for item importance to the hypothesized factor (Field, 2013).

Table 3

Items included in the Confirmatory Factor Analysis

Construct	Item
Perceptions of Risk	1. How problematic is sexual assault or sexual misconduct at [University?]
	2. How likely do you think it is that you will experience sexual assault or sexual misconduct on campus?
	3. How likely do you think it is that you will experience sexual assault or sexual misconduct during off-campus university sponsored events?
Knowledge of Campus Resources/ Policies	4. How knowledgeable are you about how sexual assault and sexual misconduct are defined at [University]?
	5. How knowledgeable are you about where you get help at [University] if you or a friend experienced sexual assault or sexual misconduct?
	6. How knowledgeable are you about where to make a report of sexual assault or sexual misconduct at [University]?
	7. How knowledgeable are you about what happens when a student reports an incident of sexual assault or sexual misconduct at [University]?
Perceptions of Responses to Reporting	8. If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that students would support the person making the report?
	9. If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that the alleged offender(s) or their associates would retaliate against the person making the report?
	10. If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that campus officials would take the report seriously?
	11. If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that campus officials would protect the safety of the person making the report?
	12. If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that campus officials would conduct a fair investigation?
	13. If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that campus officials would take action against the offender(s)?
	14. If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that campus officials would take action to address factors that may have led to the sexual assault or sexual misconduct?

Note. Adapted from "Report on the AAU Campus Climate Survey on Sexual Assault and Sexual Misconduct" by D. Cantor et al., 2015, Westat, Copyright 2015 by Westat.

In order to test the factor structure of the items, CFA will be performed using the latent variable analysis (Lavaan) package in the statistical computing environment, R (Rosseel, 2012). CFA assumes that observed variables are continuous in nature and normally distributed, which oftentimes can pose an issue for Likert-style data (Bandalos & Finney, 2019; Finney & DiStefano, 2013; Satorra & Bentler, 1994). To account for this, Maximum Likelihood (ML) Estimation with the Satorra-Bentler correction is utilized (Satorra & Bentler, 1994). The Satorra-Bentler correction rescales the values of the ML-based χ^2 test statistic by an amount that reflects the degree of kurtosis (Rosseel, 2012). Model fit will be examined by use of several global, relative, absolute, and incremental fit indices in addition to the inspection of the matrices of standardized covariance residuals to identify any local areas of misfit not identified by the global fit indices (Bandalos & Finney, 2019). First, the Satorra-Bentler scaled chi-square goodness of fit test is examined. While the chi-square goodness of fit test is sensitive to sample size, with large sample sizes often demonstrating statistical significance, it should still be examined in understanding the fit of the model (Kenny, 2020; Bandalos & Finney, 2019). Then, the Akaike Information Criterion (AIC; Akaike, 1974) is examined as a relative measure of model fit, the Root Mean Square Error of Approximation (RMSEA) and the Standardized Root Mean Square Residual (SRMR) are examined as absolute fit measures, and the Comparative Fit Index (CFI), as an incremental measure of fit is considered for adequate fit (Hooper et al., 2007).

Primary Analysis

In order to address RQ1, a LCA will be conducted. LCA is used to classify cases into groups that are not specified a priori; specifically, cases with similar response

patterns on a series of manifest variables are classified into the same latent class (Samuelson & Dayton, 2019). LCA has been applied in a number of fields and contexts, especially in the identification of risk factors of behavioral and health outcomes (Cavanaugh et al., 2012; Chan et al., 2015; French et al., 2014; & Nelon et al., 2019). In LCA, one or more latent, categorical variables are assumed to be responsible for observed, or manifest, response patterns (Samuelsen & Dayton, 2019). LCA is one approach of a larger group of latent variable modeling techniques that also includes factor analysis, item response theory (IRT), and latent profile analysis (LPA). LCA and LPA utilize manifest, or observed, variables to uncover latent variables that are discrete, or categorical, in nature (Oberski, 2016). Depending on whether the manifest variables are categorical or continuous determines whether or not LCA or LPA should be used, with LCA utilizing categorical manifest variables and LPA utilizing continuous manifest variables. These approaches are distinct from factor analysis and IRT in that those approaches assume the underlying latent variable is continuous in nature (Oberski, 2016).

The present study will utilize an exploratory LCA to make hypotheses about qualitative differences among respondents. LCA is typically used with cross-sectional data with multiple items measuring a construct represented as a latent class variable (Muthen, 2009). In the present study, the AAU survey data is cross-sectional measuring several elements of CSA and campus climate. The items used in the present study are measured on a Likert-type scale within categories, making the manifest variables discrete in nature, and therefore the use of LCA is most appropriate over LPA. The purpose of utilizing LCA in this setting is to identify items that indicate classes of victims and

nonvictims, estimate class probabilities, and classify individuals into those classes (Muthen, 2009).

LCA assumes the following: (1) the model correctly specifies the number of classes, (2) each respondent belongs to only one latent class, and (3) respondents within a class are homogeneous (Samuelson & Dayton, 2019). Conditional independence (also sometimes referred to as local independence) is an important concept of LCA, meaning that the observed manifest responses are independent given that latent class membership is known (Samuelson & Dayton, 2019). McCutcheon (1987) notes that the conditional independence criterion in LCA proves a method for determining whether relationships among a set of observed measures are due to some unobserved, latent, explanatory variable. If such a variable can be defined, then its classes are taken to represent latent types of the variable as they are defined by the measured variables in the sampled population (McCutcheon, 1987).

There are two types of parameters in LCA, the conditional item probabilities for each class and the class probabilities (Muthen, 2009). The conditional item probabilities for each class represent the probabilities of an individual in a class at a particular level of the observed variables (McCutcheon, 1987). Subsequently, LCA estimates class probabilities for each individual (Muthen, 2009). The number of distinct conditional probabilities for each of the observed variables is equal to the number of levels measured for that variable (McCutcheon, 1987). The conditional probabilities parameter allows us to determine the nature of the each of the latent classes as a function of the nature of the latent variable being measured (McCutcheon, 1987). Latent class probabilities describe the distribution of classes of the latent variable within which the observed measures are

conditionally independent of one another (McCutcheon, 1987). McCutcheon (1987) describes two aspects of latent class probabilities: (1) the number of classes, and (2) the relative sizes of these classes. The number of classes in the latent variable represent the number of latent types defined by the latent class model for the observed variables (McCutcheon, 1987). The relative sizes of the latent class probabilities indicate whether the population is relatively evenly distributed among the classes, or relatively unevenly distributed (McCutcheon, 1987). Typically, parameters are estimated by maximum-likelihood estimation, which is an iterative process that runs until the change in the log likelihood between successive iterations is less than the convergence criterion (Samuelson & Dayton, 2019).

In the present study, all 14 items examined in the CFA are included in the LCA. These items were chosen for the analysis because (1) they represent key components of campus climate as it relates to a feeling of safety on campus, and (2) all items are scaled the same way. Each item is polytomous in nature, with a 5-point Likert-style scale ranging from "Not at all" to "Extremely." When conducting LCA with polytomous variables, justification for the number of scale points is encouraged, and therefore in the present study are closely examined (Samuelson & Dayton, 2019). To this end, item analysis is conducted using the Latent Trait Models (LTM) package in the statistical computing environment, R to gather psychometric descriptives for the items included in the model. The LTM package fits hypothesized Item Response Theory models using marginal maximum likelihood estimation (MMLE; Rizopoulos, 2006). Item descriptive statistics include proportions for each level of response, frequency of missingness for each item, Cronbach's alpha for each factor, and pairwise associations. In the event that

respondents did not utilize each response option for the items in the analysis, it might be appropriate to reduce the number of scale points for some or all of the items in the analysis (Samuelson & Dayton, 2019). Additionally, reducing the number of scale points increases the interpretability of response patterns in the latent classes.

After the initial item analysis to ensure suitability for LCA, the polytomous variable Latent Class Analysis (poLCA) package in the R statistical computing environment will be used to conduct the analysis (RStudio Team, 2019; Linzer & Lewis, 2011). PoLCA is a software package for the estimation of latent class and latent class regression models for polytomous outcome variables (Linzer & Lewis, 2011). PoLCA estimates the latent class model by maximizing the log-likelihood function using the expectation-maximization (EM) algorithm (Linzer & Lewis, 2011). To address RQ1.a, sexual victimization status is utilized as a covariate in the analysis. In the present study, victimization status is dichotomized (i.e, victim or non-victim), and is used in a multinomial logistic regression to determine if victimization status predicts latent class membership.

Model section and goodness of fit criteria are assessed to determine the number of latent classes, *R*, for the data. Because the analysis is exploratory in nature and RQ1 seeks to locate the best fitting and parsimonious latent class model, the best practice in model selection is to start with an "independence" model with $R = 1$, and then iteratively increase the number of latent classes by one until suitable fit has been accomplished (Linzer & Lewis, 2011). In order to measure parsimony of latent class models, the G^2 statistic, Akaike information criterion (AIC; Akaike, 1974), Consistent Akaike Information Criterion (CAIC), Bayesian information criterion (BIC), and the Sample-size

adjusted Bayesian Information Criterion (SABIC) will be used. AIC and CAIC are comparative measures of fit which estimates a constant plus the relative distance between the unknown true likelihood function of the data and the fitted likelihood function of the model (Kenny, 2020; PSU, 2018). BIC and SABIC are also comparative fit indices, which is an estimate of a function of the posterior probability of a model being true under a certain Bayesian model and places a high value on parsimonious models (Kenny, 2020; PSU, 2018). Models with best fit minimize the values of BIC, AIC, and G^2 (Linzer & Lewis, 2011). Additionally, in LCA it is also useful to evaluate the measurement instrument in terms of how well it identifies the latent classes by computing entropy (Asparaouhov & Muthen, 2018). The larger entropy is, the more clear the latent class identification is; that is, entropy with values approaching 1 indicate clear separation of the classes (Asparaouhov & Muthen, 2018). Following model fit selection, item response probabilities for each level of the variables of interest are examined in order to create a description of the latent classes.

Secondary Analyses

In order to answer RQ2-RQ4, a series of latent class regression (LCR) analyses are conducted using the poLCA package in R. The latent class regression model generalizes the basic latent class model by permitting the inclusion of covariates to predict individual class membership (Linzer & Lewis, 2011). In poLCA in the statistical computing environment R, LCR models refer to latent class models in which the probability of latent class membership is predicted by one or more covariates: this is also sometimes referred to as “latent class models with covariates” or “concomitant-variable latent class analysis” (Linzer & Lewis, 2011, p. 3). To this end, poLCA utilizes a

generalized logit link function for the effects of the covariates on class membership (Linzer & Lewis, 2011). poLCA selects the first latent class as a "reference class" and assumes that the log-odds of latent class membership are linear functions of the covariates (Linzer & Lewis, 2011). In the present study, several separate LCR models are analyzed to include variables at the individual, micro-/mesosystem, and exo-/macrosystem levels and understand their predictive capabilities relative to latent classes.

Procedures

In order to access the AAU survey data, ICPSR users must complete a Restricted Data Use Agreement, specify the reasons for the request, and obtain IRB approval or notice of exemption for the present study. The present study is considered exempt by the Institutional Review Board, as it is a secondary analysis of pre-existing data. After approval, the Restricted Data Use Agreement form is submitted to ICPSR. A data management plan was created and adhered to through the duration of the study to ensure the security of the data after approval. The data is stored on a password protected and encrypted external hard drive. After completion of the research, the data will be destroyed using a secure seven-pass erasure process. Data management and cleaning of the dataset was done using SPSS 27 (IBM, 2020). Then, the variables of interest are coded in preparation for analyses. The preliminary analyses and primary and secondary analyses will be conducted using the R statistical computing environment (RStudio Team, 2019).

Chapter Four: Results

The following chapter presents the results of all analyses in the present study. First, results of the preliminary analyses are discussed, followed by results of the primary and secondary analyses.

Preliminary Analyses

Prior to conducting any analyses, a missing data analysis was conducted in SPSS 27 (IBM, 2020). First, missing values among the variables of interest were examined. Then, descriptive statistics were used to determine if there was any evidence for missing at random, or missing completely at random by examining the demographic characteristics of those for whom data were missing. Missingness was not found to be related to any demographic characteristic, and overall, was found to be low in the variables of interest at 10.8%. Because there was no evidence for data missing not at random, missing data were deleted listwise, and only participants who had responded to each of the variables of interest were included the preliminary and primary analyses for a final sample size of N = 132,778.

To gather evidence for reliability of the variables of interest, psychometric descriptives were estimated using the Latent Trait Models (ltm; Rizopolous, 2006) package in the R statistical computing environment (RStudio Team, 2019). Statistical code for the analysis can be found in Appendix A. Means and standard deviations of each item can be found in Table 4. Next, Cronbach's alpha was calculated for all items in each scale as well as estimated Cronbach's alpha if items were deleted. The Perceptions of Risk scale contained three items and demonstrated acceptable evidence for internal consistency (α = .77). Upon inspection of the items, item B1 may be impacting the

overall internal consistency of the scale, as excluding it from the scale would result in increasing alpha to .84. The Knowledge of Campus Resources/Policies scale contained four items and demonstrated good evidence for internal consistency (α = .85). Upon inspection of the items, all items seem to contribute to the overall level of internal consistency and there are no items that need further inspection. The Perceptions of Responses to Reporting scale contained seven items and demonstrated acceptable evidence for internal consistency (α = .80). Upon inspection of the items, item I2 may be impacting the overall internal consistency of the scale, as excluding it from the scale would result in increasing alpha to .89. Both items B1 and I2 will be examined further using CFA.

Table 4

Means and Standard Deviations of Items included in the CFA

Scale	Item	M	SD
Perceptions of Risk	B1. How problematic is sexual assault or sexual misconduct at [University?]	2.73	1.04
	B2. How likely do you think it is that you will experience sexual assault or sexual misconduct on campus?	1.79	.94
	B3. How likely do you think it is that you will experience sexual assault or sexual misconduct during off-campus university sponsored events?	1.85	.93
Knowledge of Campus Resources/Policies	C2A. How knowledgeable are you about how sexual assault and sexual misconduct are defined at [University]?	2.73	1.10
	C2B. How knowledgeable are you about where you get help at [University] if you or a friend experienced sexual assault or sexual misconduct?	2.95	1.09
	C2C. How knowledgeable are you about where to make a report of sexual assault or sexual misconduct at [University]?	2.72	1.16
	C2D. How knowledgeable are you about what happens when a student reports an incident of sexual assault or sexual misconduct at [University]?	2.15	1.10
Perceptions of Responses to Reporting	I1. If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that students would support the person making the report?	3.55	.88
	I2. If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that the alleged offender(s) or their associates would retaliate against the person making the report?	2.84	.96
	I3. If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that campus officials would take the report seriously?	3.69	1.02
	I4. If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that campus officials would protect the safety of the person making the report?	3.54	1.05
	I5. If someone were to report a sexual assault or sexual misconduct to an official at [University], how	3.36	1.02

	likely is it that campus officials would conduct a fair investigation?		
	I6. If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that campus officials would take action against the offender(s)?	3.23	1.06
	I7. If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that campus officials would take action to address factors that may have led to the sexual assault or sexual misconduct?	3.09	1.09

Note. N = 132778

Confirmatory Factor Analysis

In order to confirm the factor structure of the variables of interest, a CFA was conducted in the R statistical computing environment using the Latent Variable Analysis package (lavaan; Rosseel, 2012; RStudio Team, 2019). Statistical code for the analysis can be found in Appendix A. The present study contained Likert-style data, which is often non-normal and can lead to issues in interpretation of fit statistics in CFA. In order to account for this, Maximum Likelihood (ML) Estimation with the Satorra-Bentler correction was utilized (Satorra & Bentler, 1994). The Satorra-Bentler correction rescales the values of the ML-based χ^2 test statistic by an amount that reflects the degree of kurtosis (Rosseel, 2012). In order to identify the best fitting model, several fit indices were compared in addition to Satorra-Bentler Scaled χ^2, including Akaike Information Criterion (AIC; Akaike, 1974) as a relative measure of model fit, where smaller values indicate better fit, the Root Mean Square Error of Approximation (RMSEA) and the Standardized Root Mean Square Residual (SRMR) as absolute fit measures where values below 0.05 and 0.08 accordingly are considered good fit (Kenny, 2020), and the Comparative Fit Index (CFI), as an incremental measure of fit where values above .95 are

considered adequate fit (Hu & Bentler, 1999). Complete fit statistics for each model can be found in Table 5.

Table 5

Fit Statistics for Confirmatory Factor Analysis Models

Model	SB-Scaled χ^2	*df*	AIC	CFI	RMSEA	SRMR
Three-Factor Oblique	33892.076	74	4640703.047	0.956	0.062	0.047
Three-Factor Orthogonal (Nested)	56857.938	77	4666766.830	0.928	0.079	0.127
One-Factor (Non-Nested)	325697.459	77	4971921.883	0.582	0.188	0.151
Post-Hoc Three-Factor Oblique	27800.490	62	4276119.703	0.963	0.062	0.041
Post-Hoc Four-Factor Oblique (Non-Nested)	29603.819	72	4635847.173	0.962	0.059	0.040

Note. N = 132778

Three hypothesized models and two post-hoc models were estimated. The three hypothesized models were as follows: a three-factor oblique model, a three-factor orthogonal model, and a single factor model. To compare the nested oblique and orthogonal models, a chi-square difference test was conducted, and was found to be statistically significant ($\Delta\chi^2 = 24926$, $p < .001$), indicating the oblique model is a better fit than the orthogonal model. Because the single-factor model is considered a non-nested model, the AIC difference between the three-factor oblique model and the single factor model was calculated and found to be -331218.84, with the three-factor oblique model demonstrating better fit. In conclusion, of the three hypothesized models, the three-factor oblique model demonstrated the best fit (CFI = .96, RMSEA = 0.06), however, upon inspection of the model, one item had a negative factor loading, indicating a negative

relationship between the observed variable and the latent construct. Parameter estimates of the three-factor oblique model can be found in Table 6.

Table 6

Parameter Estimates of Three-Factor CFA Model

Latent Factor	Item	B	SE	Z	Beta
Perceptions of Risk	B1	1.00	-	-	0.562
	B2	1.511	0.008	190.965	0.892
	B3	1.301	0.007	192.699	0.731
Knowledge of Campus Resources/Policies	C2A	1.00	-	-	0.710
	C2B	1.280	0.005	249.600	0.909
	C2C	1.392	0.006	248.210	0.989
	C2D	1.093	0.005	231.699	0.777
Perceptions of Responses to Reporting	I1	1.00	-	-	0.420
	I2	-0.613	0.008	-74.076	-0.258
	I3	2.027	0.012	164.013	0.852
	I4	2.076	0.013	162.013	0.872
	I5	1.981	0.013	157.871	0.832
	I6	2.069	0.013	159.675	0.869
	I7	1.958	0.012	156.940	0.823
Covariances					
Perceptions of Risk	Knowledge of Campus Resources/Policies	0.037	0.001	27.946	0.094
	Perceptions of Responses to Reporting	-0.92	0.001	-84.328	-0.389
Knowledge of Campus Resources/Policies	Perceptions of Responses to Reporting	0.066	0.001	60.052	0.221

Note. N = 132778. All unstandardized path coefficients were significant at $p < .001$.

While all unstandardized path coefficients were found to be statistically significant, and the three-factor oblique model was found to have adequate fit, two post-hoc model modifications were made. First, a trimmed three-factor oblique model following the removal of item I2, then, an additional four-factor oblique model with item I2 creating a path to a distinct latent factor. Fit statistics for the two post-hoc models are presented in Table 5. The post-hoc model modifications were justified to gather additional information about item I2. Item I2 demonstrated a negative relationship to the Perceptions of Responses to Reporting factor, indicating that responses to this item were opposite of the other items in the factor. Additionally, item I2 was already found to have a negative impact on the Perceptions of Responses to Reporting internal consistency. Item I2 reads, "If someone were to report a sexual assault or sexual misconduct to an official at [University], how likely is it that the alleged offender(s) or their associates would retaliate against the person making the report?" Given the evidence that the item is not internally consistent with the other items in the scale, and has a negative factor loading, it is appropriate to remove the item from the factor and modify the model post-hoc. Because the two post-hoc models were non-nested, AIC difference was used to compare the models. AIC difference was found to be -359,727.47, meaning the three-factor oblique model excluding I2 is the best fitting model. While the data supports the removal of item I2, there is a risk of underrepresenting the fullness of the construct. Therefore, an additional comparison between the three-factor oblique model and the four-factor oblique model was made using a chi-square difference test. The chi-square difference test between the four-factor oblique model and the three-factor oblique model was statistically significant ($\Delta\chi^2 = 4366.7$, $p < .001$), meaning that the four-factor oblique

model demonstrated superior fit to the three-factor oblique model. In view of the a priori and post-hoc models, the four-factor oblique model is the best fitting model for the data inclusive of all observed variables of interest. Parameter estimates for the four-factor oblique model can be found in Table 7.

Table 7

Parameter Estimates of the Four-Factor CFA Model

Latent Factor	Item	B	SE	Z	Beta
Perceptions of Risk	B1	1.00	-	-	0.546
	B2	1.487	0.008	194.110	0.902
	B3	1.297	0.007	192.754	0.795
Knowledge of Campus Resources/Policies	C2A	1.00	-	-	0.648
	C2B	1.280	0.005	249.564	0.837
	C2C	1.392	0.006	248.043	0.854
	C2D	1.093	0.005	231.487	0.707
Perceptions of Responses to Reporting	I1	1.00	-	-	0.477
	I3	2.028	0.012	163.813	0.833
	I4	2.076	0.013	162.793	0.833
	I5	1.983	0.013	157.706	0.813
	I6	2.069	0.013	159.500	0.822
	I7	1.959	0.012	156.776	0.755
Perceptions of Perpetrator Retaliation	I2	1.00	-	-	1.00
Covariances					
Perceptions of Risk	Knowledge of Campus Resources/Policies	0.038	0.001	27.266	0.094
	Perceptions of Responses to Reporting	-0.92	0.001	-84.171	-0.386
	Perceptions of Perpetrator Retaliation	0.155	0.002	82.531	0.285
Knowledge of Campus Resources/Policies	Perceptions of Responses to Reporting	0.066	0.001	60.237	0.222
	Perceptions of Perpetrator Retaliation	-0.016	0.002	-7.838	-0.024
Perceptions of Responses to Reporting	Perceptions of Perpetrator Retaliation	-0.105	0.001	-75.603	-0.261

Note. All unstandardized path coefficients were significant at $p < .001$.

In view of the data, the results of the preliminary analyses provided sufficient evidence for internal consistency and construct validity. Results of the item analysis and CFA supported the removal of item I2 from the Perceptions of Responses to Reporting factor, and alternately, interpreting participant responses to the item distinct from the original factor. Additionally, the item analysis supported collapsing the Likert-style scale points from a five-point scale to a three-point scale prior to conducting the primary analysis. Upon inspection of proportion of responses to the scale points for each item, it was found that small proportions of participants utilized the full range of the Likert-style scale (Table 8). Samuelson and Dayton (2019) recommend reducing the number of scale points in circumstances like these prior to conducting a LCA. In order to reduce the number of scale points to increase the interpretability of LCA with polytomous items, scale points Strongly Disagree (1) and Disagree (2) were combined, Neither (3) was left alone, and Agree (4) and Strongly Agree (5) were combined, to make a more interpretable 3-point scale, which is adapted as follows, (1) Disagree, (2) Neutral, (3) Agree.

Table 8

Proportion of Responses across Items and Scale Points

Item	Strongly Disagree (1)	Disagree (2)	Neither (3)	Agree (4)	Strongly Agree (5)
B1	0.130	0.270	0.383	0.169	0.047
B2	0.481	0.319	0.145	0.041	0.014
B3	0.437	0.334	0.174	0.044	0.001
C2A	0.151	0.267	0.339	0.186	0.055
C2B	0.101	0.239	0.352	0.232	0.078
C2C	0.177	0.249	0.320	0.185	0.069
C2D	0.358	0.277	0.250	0.082	0.033
I1	0.018	0.092	0.336	0.436	0.118
I2	0.077	0.276	0.419	0.183	0.045
I3	0.030	0.096	0.261	0.385	0.229
I4	0.040	0.113	0.302	0.354	0.191
I5	0.052	0.125	0.359	0.337	0.128
I6	0.060	0.170	0.367	0.283	0.120
I7	0.089	0.189	0.362	0.262	0.097

Note. Proportions for each level of response. N = 132778

Primary Analyses

In order to answer research question one, a LCA was conducted followed by a LCR analysis to answer research question 1.a. All primary analyses were conducted using the poLCA (Linzer & Lewis, 2011) package in the R statistical computing environment (RStudio Team, 2019). Statistical code for the analysis can be found in Appendix B. Missing data were deleted listwise prior to analysis. The variables of interest were re-scaled from a 5-point Likert-style scale to a 3-point Likert-style scale. To reflect the victimization status variable, victimization experiences were collapsed and dichotomized so that (1) indicated a sexual victimization experience of any type, and (0) reflected not having a victimization experience.

Research Question 1

In order to answer research question one, a LCA in the R statistical computing environment was conducted using poLCA (Linzer & Lewis, 2011; RStudio Team, 2019). PoLCA uses the expectation-maximization (EM) algorithm to maximize the log-likelihood function (Linzer & Lewis, 2011). Research question one posited that there were distinct latent subgroups of college students based on 14 items measuring campus climate, and specifically, measures of perceived risk of sexual assault, knowledge of campus resources, and perceptions of responses to reporting a sexual misconduct incident. To answer research question one, a series of LCA models were tested, beginning with a 1-class or independence model, and proceeding through a nine-class model. Model fit is assessed by examining global fit, local fit and substantive criteria (Nagelkerke et al., 2016). Model fit was determined by first examining multiple comparative fit statistics (AIC, BIC, ABIC, and CAIC), as well as G^2, and entropy (Table 9). Then, a scree plot was constructed with the fit statistics to examine the point of inflection (Figure 2; Ohlson, 2015). Finally, the interpretability of each solution was considered in order to identify the best fitting model. According to the model fit statistics and the scree plot, the point of inflection approximates at the 5-class model. However, upon inspection of the latent classes, a 4-class model was determined to be more interpretable, and therefore was decided upon as the model of best fit.

Table 9

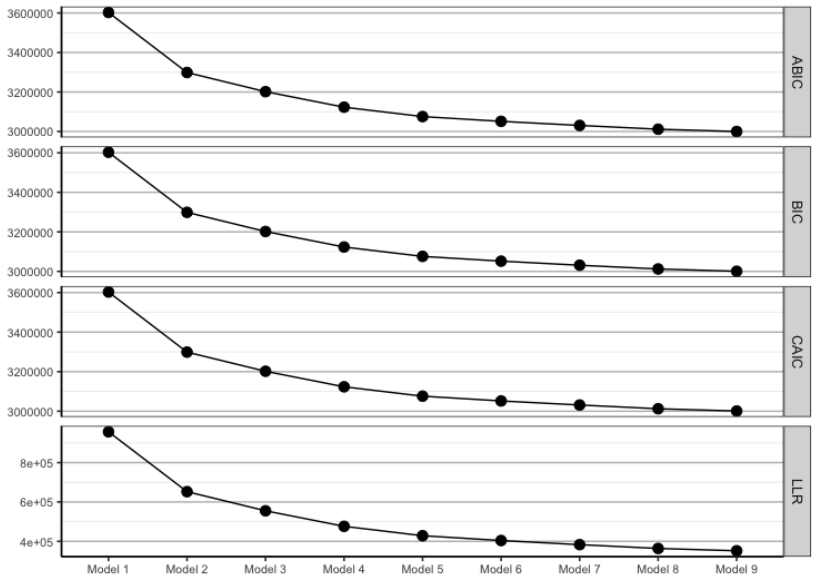
Model Fit Statistics of Latent Class Models

Number of Latent Classes	G^2	*df*	AIC	BIC	ABIC	CAIC	Entropy
1	956732.3	132750	3602582	3602856	3602767	3602884	-
2	652378.9	132721	3298286	3298845	3298664	3298902	0.871
3	555134.5	132692	3201100	3201943	3201669	3202029	0.848
4	**476285.5**	**132663**	**3122309**	**3123436**	**3123070**	**3123551**	**0.841**
5	428498.3	132634	3074580	3075990	3075533	3076134	0.835
6	404042.2	132605	3050182	3051877	3051327	3052050	0.829
7	383104.2	132576	3029302	3031281	3030639	3031483	0.820
8	363783.7	132547	3010039	3012302	3011568	3012533	0.828
9	351979	132518	2998292	3000840	3000013	3001100	0.822

Note. Model fit is assessed by examining fit statistics, parsimony, and interpretability. Fit statistics examined in the model are as follows: G^2 (likelihood-ratio chi-square statistic), Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), Sample-size Adjusted Bayesian Information Criteria (ABIC), Bozdogan's Consistent AIC, and entropy. N = 132778

Figure 2

Scree Plot of Competing Latent Class Models



Validation of the model

SPSS 27 was used to split the sample into two randomly selected halves in order to assess the validity of the four-class model. PoLCA (Linzer & Lewis, 2011) in the R statistical computing environment (RStudio Team, 2019) was used to test a series of models on each of the split data files, starting with an independence model and proceeding through a nine-class model. Tables 10 and 11 display the results of the cross-validation analysis. Results uncovered no evidence for measurement invariance among the two random halves of the data.

Table 10

Model Fit Statistics of Latent Class Models of Randomly Split Half of Data

Number of Latent Classes Split 1	G^2	*Df*	AIC	BIC	ABIC	CAIC	Entropy
1	518556.7	66449	1803471	1803726	1803637	1803754	-
2	366377.5	66420	1651350	1651869	1651688	1651926	0.871
3	317450.7	66391	1602481	1603264	1602991	1603350	0.849
4	**277933.2**	**66362**	**1563022**	**1564069**	**1563703**	**1564184**	**0.842**
5	254074.1	66333	1539221	1540532	1540074	1540676	0.836
6	241827.3	66304	1527032	1528607	1528057	1528780	0.830
7	231169.5	66275	1516432	1518271	1517629	1518473	0.822
8	221636.7	66246	1506957	1509060	1508326	1509291	0.829
9	215554.0	66217	1500933	1503300	1502474	1503560	0.837

Note. n = 66447

Table 11

Model Fit Statistics of Latent Class Models of Randomly Split Half of Data

Number of Latent Classes Split 2	G^2	*Df*	AIC	BIC	ABIC	CAIC	Entropy
1	517904.7	66273	1799146	1799401	1799312	1799429	-
2	365699.1	66244	1646999	1647517	1647336	1647574	0.872
3	317364.6	66215	1598722	1599505	1599232	1599591	0.848
4	**277944.8**	**66186**	**1559360**	**1560407**	**1560042**	**1560522**	**0.840**
5	254015.6	66157	1535489	1536800	1536342	1536944	0.835
6	241708.8	66128	1523240	1524815	1524265	1524988	0.829
7	231271.0	66099	1512861	1514699	1514057	1514901	0.836
8	221537.1	66070	1503185	1505287	1504553	1505518	0.827
9	215611.2	66041	1497317	1499683	1498857	1499943	0.835

Note. n = 66301

Description of the Four-Class Model

In order to label the latent classes, item response probabilities were examined and the response patterns of each class were considered. Latent class prevalences and item response probabilities are presented in tabular format in Table 12, and in graphical format in Figure 3. Class one was characterized by a general sense of neutrality towards the campus climate measures. Specifically, members of this class perceived only a moderate amount of risk of CSA, had moderate amount of knowledge of campus resources, and perceived the response to reporting an incident of CSA as being neutral. For these reasons, Class one was labeled, "Ambivalent." Members of this class had a .46 probability of responding neutrally to whether or not CSA is problematic on their campus. Members of class one also had a .81 probability of responding neutrally to whether or not campus officials would conduct a fair investigation. Overall, this class of students denied having strong feelings towards any of the measures of campus climate.

Class two was characterized by low to moderate agreement that CSA is a problem on their college campus. Members of class two had just short of a .5 probability of endorsing that they disagree that CSA is a problem on their campus. Members of class two endorsed strong agreement with knowledge of campus resources, with members having a .69 probability of endorsing that they agree that they know where to get help if they or a friend experienced sexual assault. Additionally, class two also endorsed strong agreement with the perceptions of responses to reporting items, indicating they felt that their university would support a survivor making a report of CSA. For these reasons, class two is labeled "Knowledge is power." Response patterns of this class suggest that members of this class might feel empowered by their knowledge of campus resources,

and feel as though their knowledge of campus resources may protect them against CSA. They also seem to think that their university would be supportive of someone making a CSA report, perhaps because of their knowledge of on-campus resources.

Class three was characterized by strong disagreement that CSA poses a risk on campus, very low levels of knowledge of campus resources, and strong agreement with perceptions of responses to reporting incidents of CSA. Members of class three had a greater than .6 probability of endorsing that they disagree that CSA is a problem on their college campus. Additionally, members in this class had a .95 probability of responding that they disagreed that they would be sexually assaulted on campus. Members of class three also had a nearly .95 probability of endorsing that they agree that the university would take a report of sexual assault seriously. For these reasons, Class three is labeled "Ignorance is bliss." Members of this class don't agree that CSA is a big problem, don't feel they themselves are at risk, and despite not knowing much about the on-campus resources, feel strongly that their University would be supportive of someone making a report of CSA.

Class four was characterized by strong agreement that CSA is problematic on their college campus, with members in this class having a .5 probability of agreeing that CSA was problematic. Class four also described a moderate amount of knowledge of campus resources. Class four was particularly distinguished by their strong disagreement with the perceptions of responses to reporting items, with members having a .9 probability of endorsing disagreement that their university would take action against a perpetrator of CSA. Of note, members in class four had a .45 probability of endorsing agreement that an accused perpetrator would retaliate against their accuser. For these

reasons, class four is labeled “Fearful and jaded,” Members of this class recognize that CSA is a big problem on campus, but while they possess some knowledge about campus resources, they have very little faith that the university would help. In fact, they might fear that reporting an incident might make things worse, because they are afraid that a perpetrator would retaliate.

Table 12

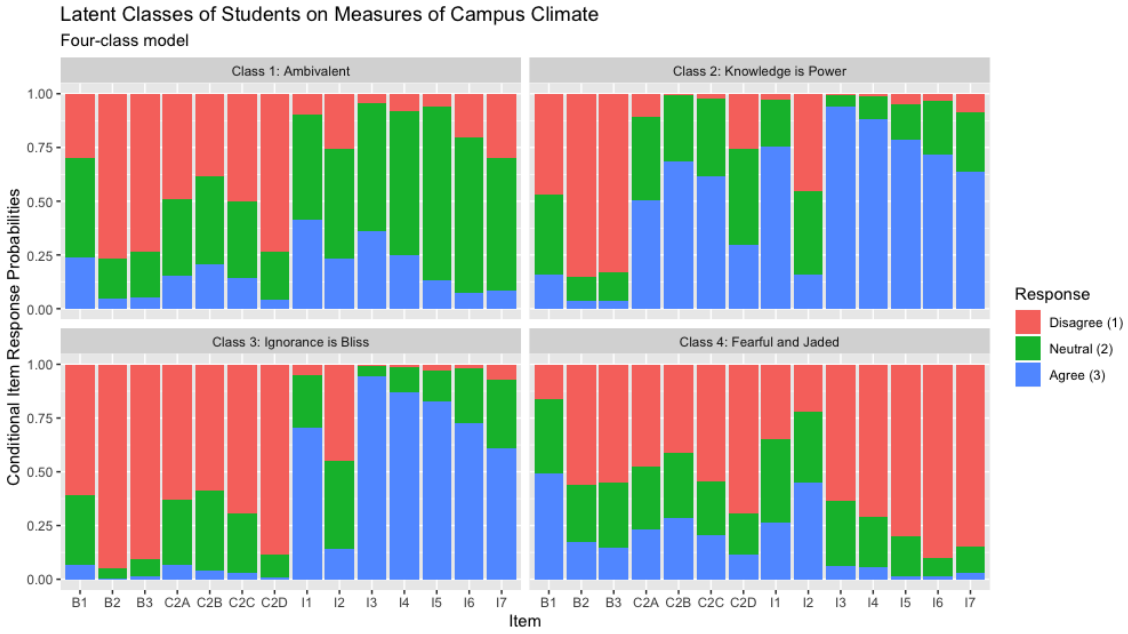
Latent Class Prevalences and Item Response Probabilities of the Four-Class Model

	Class 1: Ambivalent	Class 2: Knowledge is Power	Class 3: Ignorance is Bliss	Class 4: Fearful and Jaded
Latent Class Prevalences	0.305	0.273	0.251	0.172
Item Response Probabilities				
Perceptions of Risk				
B1				
Disagree	0.300	0.469	**0.608**	0.161
Neutral	**0.464**	0.373	0.327	0.344
Agree	0.237	0.158	0.066	**0.495**
B2				
Disagree	0.766	0.854	**0.947**	0.558
Neutral	**0.185**	0.111	0.048	0.036
Agree	0.049	0.036	0.006	**0.172**
B3				
Disagree	0.735	0.830	**0.904**	0.552
Neutral	0.212	0.134	0.085	**0.300**
Agree	0.052	0.036	0.011	**0.148**
Knowledge of Resources				
C2A				
Disagree	0.492	0.108	**0.629**	0.477
Neutral	0.355	**0.388**	0.303	0.291
Agree	0.153	**0.504**	0.068	0.232
C2B				
Disagree	0.385	0.008	**0.588**	0.414
Neutral	**0.406**	0.304	0.370	0.303
Agree	0.209	**0.687**	0.042	0.283
C2C				
Disagree	0.500	0.022	**0.695**	0.543
Neutral	0.358	**0.361**	0.276	0.251

Agree	0.143	**0.617**	0.030	0.205
C2D				
Disagree	0.733	0.257	**0.888**	0.696
Neutral	0.226	**0.448**	0.105	0.188
Agree	0.041	**0.295**	0.008	0.117
<u>Perceptions of Responses to Reporting</u>				
I1				
Disagree	0.096	0.029	0.048	**0.348**
Neutral	**0.491**	0.215	0.246	0.388
Agree	0.413	**0.756**	0.706	0.264
I3				
Disagree	0.043	0.007	0.009	**0.633**
Neutral	**0.599**	0.053	0.045	0.305
Agree	0.359	0.941	**0.946**	0.063
I4				
Disagree	0.079	0.012	0.014	**0.711**
Neutral	**0.670**	0.104	0.117	0.235
Agree	0.252	0.884	**0.869**	0.055
I5				
Disagree	0.061	0.051	0.028	**0.798**
Neutral	**0.809**	0.163	0.143	0.187
Agree	0.130	0.786	**0.829**	0.014
I6				
Disagree	0.201	0.035	0.019	**0.900**
Neutral	**0.726**	0.249	0.255	0.084
Agree	0.072	0.716	**0.726**	0.016
I7				
Disagree	0.301	0.088	0.071	**0.846**
Neutral	**0.614**	0.272	0.318	0.126
Agree	0.085	**0.639**	0.611	0.029
<u>Perceptions of Perpetrator Retaliation</u>				
I2				
Disagree	0.254	**0.455**	0.452	0.222
Neutral	**0.511**	0.387	0.404	0.326
Agree	0.235	0.158	0.144	**0.452**

Figure 3

Four Latent Class Model of Students on Measures of Campus Climate



Research Question 1.a

Research question 1.a sought to determine if latent class membership could be predicted by victimization status. To this end, victimization status was entered into the latent class model as a covariate. The Ambivalent class was specified as the reference group in the multinomial logistic regression. Results of the latent class regression model were found to be statistically significant, and are presented in Table 13. Specifically, when compared to non-victims, victims were 67.5% more likely to reside in the Fearful and Jaded class. Probability of latent class membership based on the levels of the covariate are displayed graphically in Figure 4.

When compared to the reference class, the Fearful and Jaded class (OR = 2.075), had over a 100% increase in the odds of having a victimization experience compared to the Ambivalent group. Additionally, the Knowledge is Power group (OR = 0.28), had a 72% decrease in the odds of having a victimization experience compared to the Ambivalent group. Finally, the Ignorance is Bliss group (OR = 0.68), had a 32% decrease in the odds of having a victimization experience compared to the Ambivalent group. Results of the latent class regression indicate that latent class can be predicted by victimization status, and, survivors of CSA are most likely to be members of the Fearful and Jaded class.

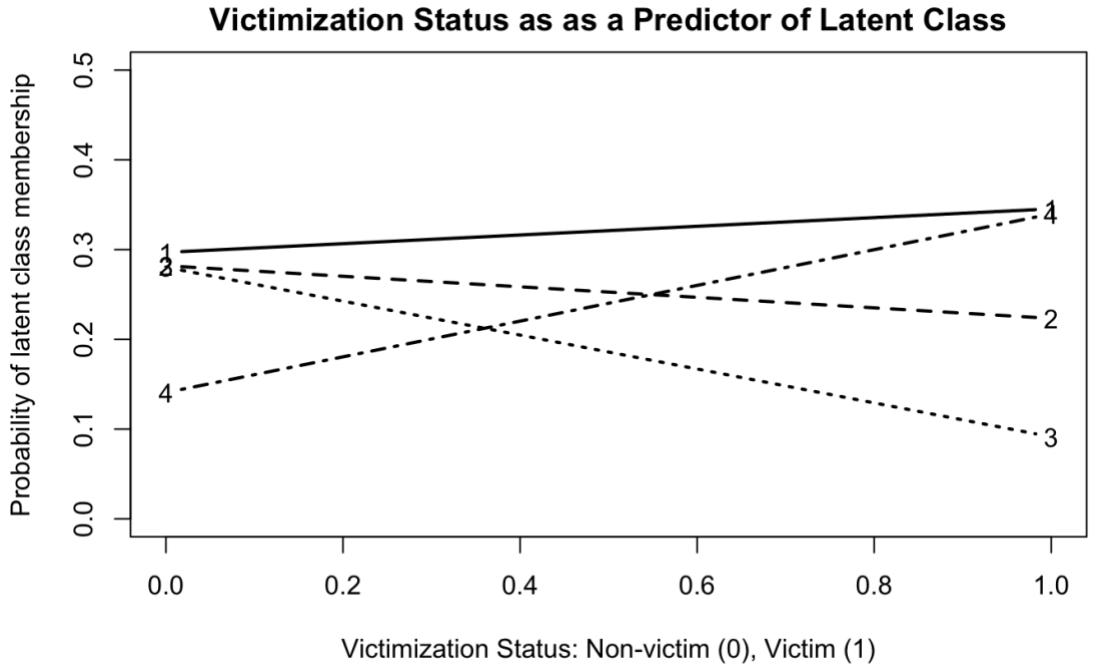
Table 13

Parameter Estimates and Odds Ratios for Effect of Victimization Status on Latent Class Membership

	Class 1: Ambivalent	Class 2: Knowledge is Power	Class 3: Ignorance is Bliss	Class 4: Fearful and Jaded
Beta	-	-0.385	-1.273	0.730
(SE)		0.010	0.033	0.024
OR	-	0.681	0.280	2.075
[95% CI]		[.667, .695]	[.262, .298]	[1.982, 2.175]

Figure 4

Victimization Status as a Predictor of Latent Class Membership



Secondary Analyses

Research questions two through four sought to understand the predictive power of variables at the individual, micro-/mesosystem level, and exo-/macrosystem levels. For all analyses were conducted in the R statistical computing environment using the PoLCA package (Linzer & Lewis, 2007; RStudio Team, 2019). Statistical code for the analysis can be found in Appendix C.

Research Question 2

Research question two sought to determine if latent class membership could be predicted by individual-level factors including age, gender identity, race/ethnicity, disability, and sexual orientation. To this end, each categorical individual level variable was transformed into a dummy variable in preparation for a series of latent class regression models. Each variable was tested individually for ease of interpretation.

Age

Age was entered into the latent class model as a covariate. The Ambivalent class was specified as the reference group in the multinomial logistic regression. Results of the latent class regression model found that age was a statistically significant predictor of the Knowledge is Power class and the Ignorance is Bliss class, and results are presented in Table 14. Probability of latent class membership based on the levels of the covariate are displayed graphically in Figure 5. For age, a continuous variable, odds ratios are interpreted as the increase in odds of membership in a particular latent class relative to the reference class corresponding to a one-unit increase in the covariate (Linzer, 2007). When odds ratios are less than one, the inverse often can be interpreted more easily (Linzer, 2007). For example, for each one-year increase in age, participants had an 8%

decrease in the odds of being in the Knowledge is Power class. Additionally, for each one-year increase in age, participants had about a 6% increase in the odds of being in the Ignorance is Bliss class.

Table 14

Parameter Estimates and Odds Ratios for Effect of Age on Latent Class Membership

	Class 1: Ambivalent	Class 2: Knowledge is Power	Class 3: Ignorance is Bliss	Class 4: Fearful and Jaded
Beta	-	-0.087	0.056	-0.002
(SE)		0.003	0.003	0.046
OR (inverse for values < 1)	-	0.917 (1.08)	1.058	1.00
[95% CI]		[0.91, 0.92]	[1.05, 1.06]	[0.91, 1.09]

Figure 5

Age as a Predictor of Latent Class Membership

Gender identity

Gender identity was entered into the latent class model as a covariate. The Ambivalent class was specified as the reference group in the multinomial logistic regression. Gender was categorized into three dummy variables to reflect the three levels of gender measured in the study (Man, Woman, or transgender, genderqueer, nonconforming, questioning [TGNQ]). Gender identity was found to be a significant predictor of latent class membership (Table 15). Specifically, when compared to men, women had a greater than 40% increase in the odds (OR = 1.42) of residing in the Fearful and Jaded class compared to the Ambivalent class. Women also had a 50% decrease in the odds of being in either the Knowledge is Power and the Ignorance is Bliss class when compared to the Ambivalent class. Additionally, when compared to men, participants who described their gender identity as TGNQ had over three times the odds (OR = 3.39) of residing in the Fearful and Jaded class, and were least likely to reside in the Ignorance is Bliss group (OR = 0.17) when compared to the Ambivalent class. When women were considered the reference group, participants with TGNQ gender identity had a 140% increase in the odds (OR = 2.40) of being in the Fearful and Jaded class, and had a 62% decrease in the odds of being in the Ignorance is Bliss class when compared to the Ambivalent class. In summary, results of the latent class regression revealed that gender identity is a significant predictor of latent class membership, such that being a woman or someone that identifies with a TGNQ gender identity increases the probability of being a member of the Fearful and Jaded class, while men are most likely to reside in the Ignorance is Bliss class.

Table 15

Parameter Estimates and Odds Ratios for Effect of Gender Identity on Latent Class Membership

	Class 1: Ambivalent	Class 2: Knowledge is Power	Class 3: Ignorance is Bliss	Class 4: Fearful and Jaded
Men vs. Women				
Beta	-	-0.686	-0.693	0.347
(SE)		0.018	0.018	0.022
OR	-	0.501	0.500	1.415
[95% CI]		[0.49, 0.52]	[0.48, 0.52]	[1.35, 1.477]
Men vs. TGNQ				
Beta	-	-0.852	-1.77	1.22
(SE)		0.097	0.142	0.078
OR	-	0.427	0.17	3.387
[95% CI]		[0.35, 0.52]	[0.13, 0.22]	[2.91, 3.95]
Women vs. TGNQ				
Beta	-	-0.167	-1.083	0.877
(SE)		0.097	0.141	0.076
OR	-	0.846	0.338	2.40
[95% CI]		[0.70, 1.02]	[0.26, 0.45]	[2.07, 2.79]

Race

Race was entered into the latent class model as a covariate. The Ambivalent class was specified as the reference class in the multinomial logistic regression and White used as the reference group. Race was found to be a statistically significant predictor of latent class membership; results of the latent class regression analysis are presented in Table 16. Specifically, compared to White participants, Black participants had a 17% increase in the odds (OR = 1.17) of being a member of the Fearful and Jaded class when the Ambivalent class was used as the reference class. Additionally, compared to White participants, Black participants had an 18% and 30% decrease in the odds (OR = 0.82;

OR = 0.70) of being a member of the Knowledge is Power class and the Ignorance is Bliss class, respectively, when compared to the Ambivalent class.

When compared to White participants, Asian participants were about as likely to be a member of the Ignorance is Bliss class (OR = 1.08) when using the Ambivalent class as the reference class. Asian participants also had a 40% decrease in the odds (OR = .60) of being in the Knowledge is Power class, as well as a 15% decrease in the odds (OR = .85) of being in the Fearful and Jaded Class when compared to the Ambivalent class. Finally, when compared to White participants, Multiracial participants demonstrated a 23% increase in the odds (OR = 1.23) of being in the Fearful and Jaded class when the Ambivalent class was used as the reference class. Multiracial participants also had about a 20% decrease in the odds (OR = .79) of being in the Knowledge is Power class, and about a 24% decrease in the odds (OR = 0.76) of being in the Ignorance is Bliss group when the Ambivalent class was used as the reference class. In summary, race is a statistically significant predictor of latent class membership, with Black and Multiracial participants being most likely to reside in the Fearful and Jaded class and White and Asian participants being most likely to reside in the Ignorance is Bliss class.

Table 16

Parameter Estimates and Odds Ratios for Effect of Race on Latent Class Membership

	Class 1: Ambivalent	Class 2: Knowledge is Power	Class 3: Ignorance is Bliss	Class 4: Fearful and Jaded
White vs. Black				
Beta	-	-0.200	-0.356	0.158
(SE)		0.040	0.046	0.043
OR	-	0.82	0.700	1.17
[95% CI]		[0.76, 0.89]	[0.64, 0.77]	[1.07, 1.27]
White vs. Asian				
Beta	-	-0.515	0.075	-0.167
(SE)		0.022	0.021	0.024
OR	-	0.60	1.08	0.846
[95% CI]		[0.57, 0.62]	[1.03, 1.12]	[0.81, 0.89]
White vs. Other/Multiracial				
Beta	-	-0.231	-0.272	0.210
(SE)		0.031	0.034	0.033
OR	-	0.794	0.762	1.233
[95% CI]		[0.75, 0.84]	[0.71, 0.81]	[1.16, 1.32]

Disability

Disability status was entered into the latent class model as a covariate. The Ambivalent class was specified as the reference group in the multinomial logistic regression. Results of latent class regression model were found to be statistically significant, and are presented in Table 17. Specifically, when compared to those without a disability, participants with a disability were 62% more likely to reside in the Fearful and Jaded class. Probability of latent class membership based on the levels of the covariate are displayed graphically in Figure 6.

When compared to the reference class, students with a disability had a 65% increase in the odds (OR = 1.65) of being in the Fearful and Jaded class (OR = 1.65), had

when compared to the Ambivalent class. Additionally, students with a disability had a 37% decrease in the odds (OR = 0.63), of being in the Ignorance is Bliss group when compared to the Ambivalent group. Finally, the Knowledge is Power group (OR = 1.05), had about the same odds as having members with a disability when compared to the Ambivalent group. Results of the latent class regression indicate that latent class can be predicted by disability status, and, those with a disability are most likely to be members of the Fearful and Jaded class.

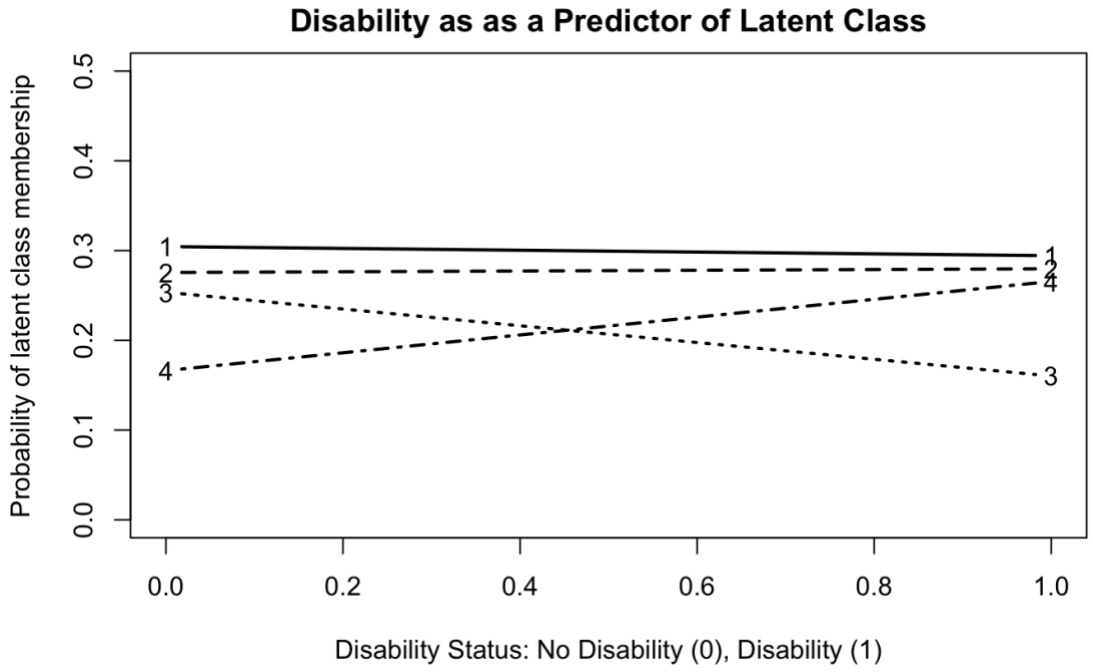
Table 17

Parameter Estimates and Odds Ratios for Effect of Disability Status on Latent Class Membership

	Class 1: Ambivalent	Class 2: Knowledge is Power	Class 3: Ignorance is Bliss	Class 4: Fearful and Jaded
Beta	-	0.049	-0.425	0.502
(SE)		0.045	0.054	0.046
OR	-	1.050	0.634	1.652
[95% CI]		[0.96, 1.15]	[0.59, 0.73]	[1.51, 1.81]

Figure 6

Disability as a Predictor of Latent Class Membership



Sexual orientation

Sexual orientation was coded dichotomously and reflects whether or not a participant identified as being part of the LGBTQ+ community. LGBTQ+ inclusion was entered into the latent class model as a covariate. The Ambivalent class was specified as the reference class in the multinomial logistic regression. Results of the latent class regression model were found to be statistically significant, and are presented in Table 18. Specifically, when compared to those who identify as heterosexual, LGBTQ+ participants were 65% more likely to reside in the Fearful and Jaded class. Probability of latent class membership based on the levels of the covariate are displayed graphically in Figure 7.

Compared to the reference class, the LGBTQ+ students had an 84% increase in the odds (OR = 1.84) of being a member of the Fearful and Jaded class compared to the Ambivalent group. Additionally, LGBTQ+ students had a 53% decrease in the odds(OR = 0.47) of being a member of the Ignorance is Bliss group compared to the Ambivalent group. Finally, the Knowledge is Power group (OR = 0.72), had a 28% decrease in the odds of being LGBTQ+ when compared to the Ambivalent group. Results of the latent class regression indicate that latent class can be predicted by sexual orientation, and, those who identify as LGBTQ+ are most likely to be members of the Fearful and Jaded class.

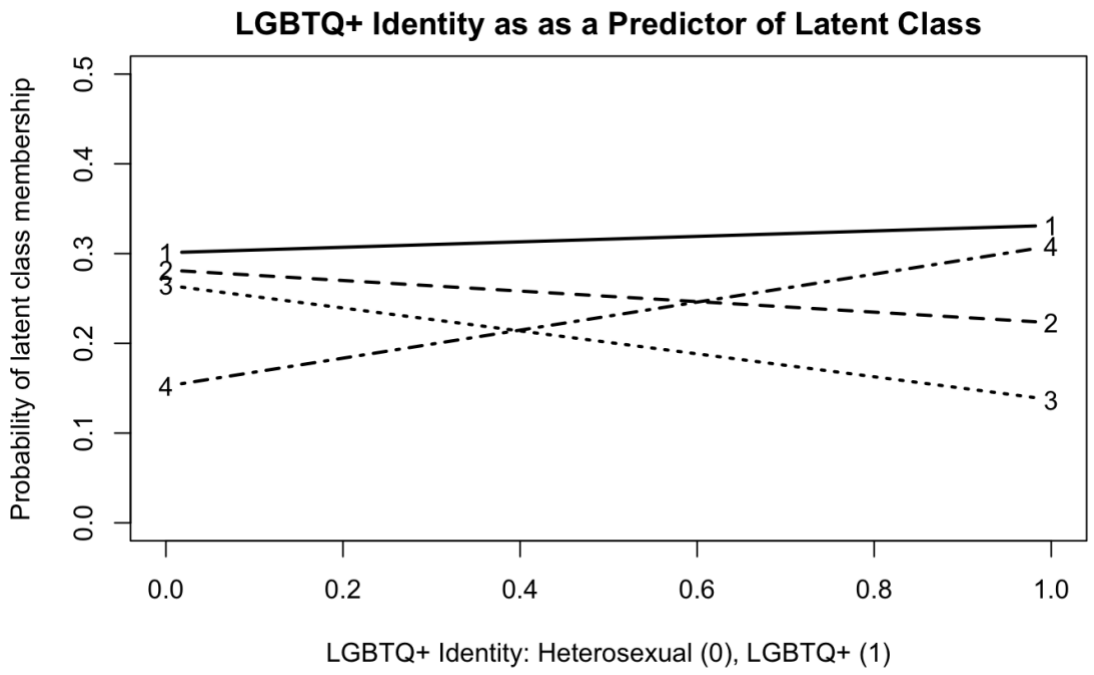
Table 18

Parameter Estimates and Odds Ratios for Effect of Sexual Orientation on Latent Class Membership

	Class 1: Ambivalent	Class 2: Knowledge is Power	Class 3: Ignorance is Bliss	Class 4: Fearful and Jaded
Beta	-	-0.330	-0.754	0.609
(SE)		0.027	0.032	0.026
OR	-	0.718	0.470	1.839
[95% CI]		[0.68, 0.76]	[0.44, 0.50]	[1.74, 1.93]

Figure 7

Sexual Orientation as a Predictor of Latent Class Membership



Research Question 3

Research question 3 set out to determine the predictive capabilities of micro- and mesosystem variables on latent class membership. In order to test Research Question 3, a series of latent class regression analyses were conducted. Prior to analysis, all categorical variables were transformed into dummy variables and each variable was tested individually for ease of interpretation.

Microsystem Level: Relationship Status

Relationship status was coded dichotomously and reflects whether or not a participant reported being in at least one romantic relationship during the academic year. Relationship status was entered into the latent class model as a covariate. The Ambivalent class was specified as the reference group in the multinomial logistic regression. Results of the latent class regression model revealed that relationship status is a statistically significant predictor of membership in the Ignorance is Bliss class, and the Fearful and Jaded class. Results are presented in Table 19. Specifically, when compared to those who are not as opposed those who are in romantic relationship were 56% more likely to reside in the Fearful and Jaded class. Probability of latent class membership based on the levels of the covariate are displayed graphically in Figure 8.

When compared to the reference class, students who reporting being in a romantic relationship had a 27% increase in the odds (OR = 1.27) of being in the Fearful and Jaded class when compared to the Ambivalent class. Additionally, students in romantic relationships had a 21% decrease in the odds (OR = 0.79) of being a member of the Ignorance is Bliss group when compared to the Ambivalent group. Finally, the Knowledge is Power group (OR = 1.04), had about the same odds of being in a romantic

relationship when compared to the Ambivalent group. Results of the latent class regression indicate that latent class can be partially predicted by relationship status, and, those who are in a romantic relationship are most likely to be members of the Fearful and Jaded class.

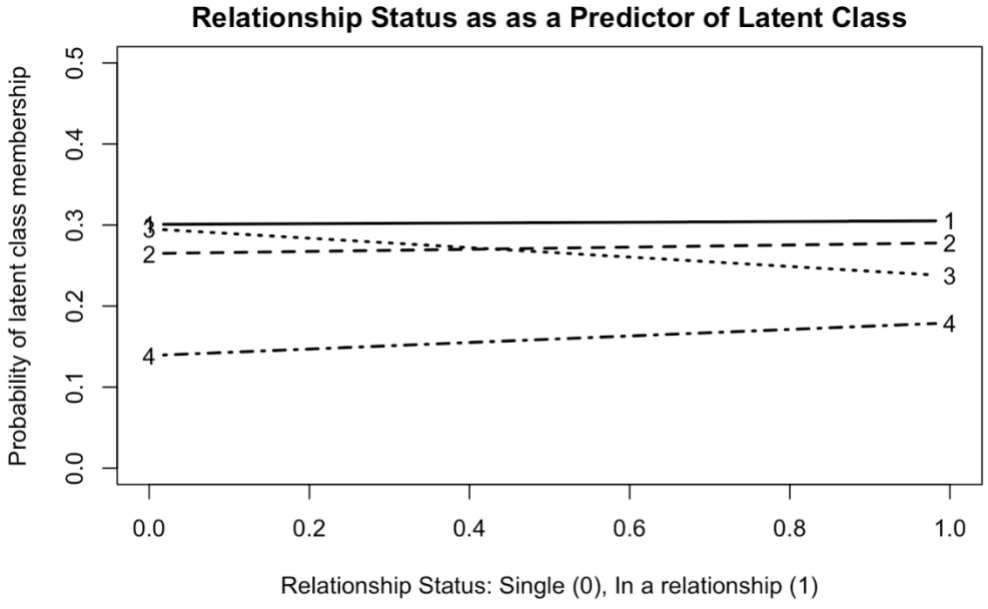
Table 19

Parameter Estimates and Odds Ratios for Effect of Relationship Status on Latent Class Membership

	Class 1: Ambivalent	Class 2: Knowledge is Power	Class 3: Ignorance is Bliss	Class 4: Fearful and Jaded
Beta	-	0.034	-0.234	0.240
(SE)		0.019	0.019	0.023
OR	-	1.035	0.791	1.271
[95% CI]		[1.00, 1.07]	[0.76, 0.82]	[1.22, 1.33]

Figure 8

Relationship Status as a Predictor of Latent Class Membership



Mesosystem Level: Participation in On-Campus Organizations

Participation in on-campus organizations was entered into the latent class model as a covariate. Because specific campus organizations, and type of campus organizations was redacted from the data, the frequency of the number of on-campus organizations was utilized as a proxy covariate. The Ambivalent class was specified as the reference class in the multinomial logistic regression. Results of the latent class regression model were found to be statistically significant, and are presented in Table 20. Probability of latent class membership based on the levels of the covariate are displayed graphically in Figure 9.

For organization membership frequency, a continuous variable, odds ratios are interpreted as the increase in odds of membership in a particular latent class relative to the reference class corresponding to a one-unit increase in the covariate (Linzer, 2007). When odds ratios are less than one, the inverse often can be interpreted more easily (Linzer, 2007). For example, for each one unit increase in organization frequency, participants had a 13% decrease in the odds (OR = 0.87) of being in the Ignorance is Bliss class. Additionally, for each one-unit increase in organization frequency, participants had about a 9% increase in the odds (OR = 1.09) of being in the Knowledge is Power class. Finally, for each one-unit increase in organization frequency, participants had an 8% increase in the odds (OR = 1.08) of being in the Fearful and Jaded Class

Results of the latent class regression found that students who participated in more on-campus organizations were most likely to be a member of the Knowledge is Power class and least likely to be a member of the Ignorance is Bliss class. There was also a

positive relationship between the number of campus organizations and being in the Fearful and Jaded class.

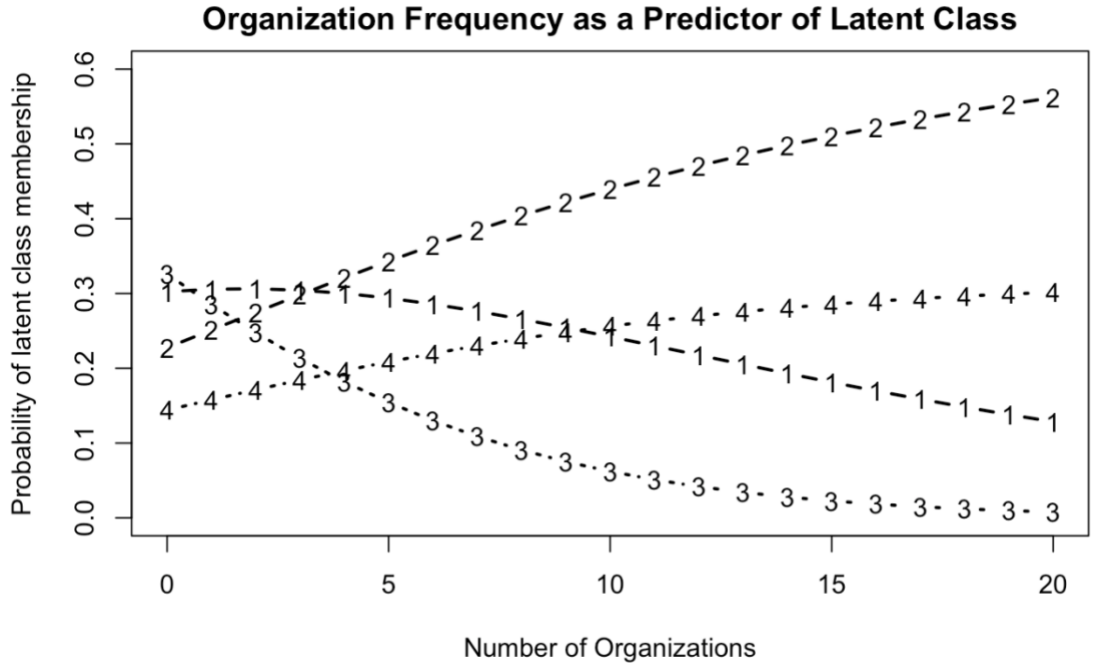
Table 20

Parameter Estimates and Odds Ratios for Effect of Organization Frequency on Latent Class Membership

	Class 1: Ambivalent	Class 2: Knowledge is Power	Class 3: Ignorance is Bliss	Class 4: Fearful and Jaded
Beta	-	0.088	-0.144	0.080
(SE)		0.004	0.005	0.005
OR (inverse for OR < 1)	-	1.091	0.866 (1.134)	1.083
[95% CI]		[1.08, 1.10]	[0.86, 0.87]	[1.07, 1.09]

Figure 9

Organization Frequency as a Predictor of Latent Class Membership



Mesosystem Level: Living Situation

In the initial development of the present study, living situation defined by students living in on-campus versus off-campus housing was proposed to be analyzed. Unfortunately, living situation was a redacted variable in the public use of the dataset. Therefore, online student status was used as a proxy variable for living situation. Online student status was defined by students reporting that they take all of their classes online. Online student status was entered into the latent class model as a covariate. The Ambivalent class was specified as the reference group in the multinomial logistic regression. Results of the latent class regression model revealed that online student status is a statistically significant predictor of the Ignorance is Bliss class and the Fearful and Jaded class. Results of the latent class regression analysis can be found in Table 21. Probability of latent class membership based on the levels of the covariate are displayed graphically in Figure 10.

When compared to the reference class, online students had a 91% increase in the odds (OR = 1.91) of being in the Ignorance is Bliss class when compared to the Ambivalent class. Additionally, online students had about a 35% decrease in the odds (OR = 0.65) of being in the Fearful and Jaded class, compared to the Ambivalent class. Results of the analysis revealed that online students are most likely to reside in the Ignorance is Bliss class, and least likely to reside in the Fearful and Jaded class.

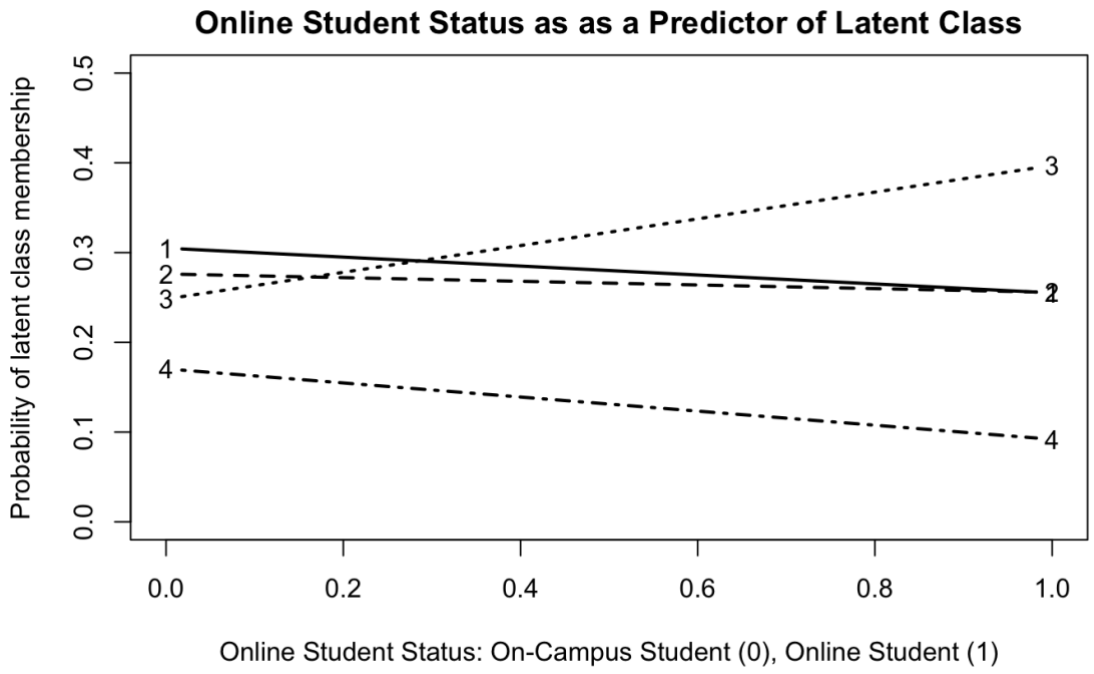
Table 21

Parameter Estimates and Odds Ratios for Effect of Online Student Status on Latent Class Membership

	Class 1: Ambivalent	Class 2: Knowledge is Power	Class 3: Ignorance is Bliss	Class 4: Fearful and Jaded
Beta	-	0.102	0.648	-0.438
(SE)		0.074	0.068	0.102
OR	-	1.107	1.912	0.645
[95% CI]		[0.96, 1.28]	[1.67, 2.18]	[0.53, 0.79]

Figure 10

Online Student Status as a Predictor of Latent Class Membership



Research Question 4

Research Question four set out to determine the predictive capabilities of exo- and macrosystem variables such as university size, university location, and university affiliation, on latent class membership. In order to answer Research Question four, a series of latent class regression analyses were conducted using poLCA in the R statistical computing environment (Linzer & Lewis, 2011; RStudio Team, 2019). Prior to conducting analyses, all categorical variables were transformed into dummy variables and each variable was tested individually for ease of interpretation.

Exosystem Level: University Size

University size was entered into the latent class model as a covariate. University size was categorized into three dummy variables to reflect the three levels of measurement in the study (< 21,000 students, 21,000 – 40,000 students, > 40,000 students), with the largest enrollment category considered the reference class in the analysis. The Ambivalent class was specified as the reference class in the multinomial logistic regression. Results of the latent class regression model revealed that university size is a statistically significant predictor of membership and are presented in Table 22. Specifically, when compared to large universities, students who attend small universities experience nearly a 30% decrease in the odds (OR = 0.71) of being in the Ignorance is Bliss class, a 6% decrease in the odds (OR = 0.94) of being in the Knowledge is Power class, and a 6% increase in the odds (OR = 1.06) of being in the Fearful and Jaded class when the Ambivalent class was used as the reference group. Additionally, when compared to large universities, students who attend medium sized universities had over a 13% increase in the odds (OR = 1.13) of being in the Fearful and Jaded class, a 10%

decrease in the odds (OR = 0.91) of being in the Ignorance is Bliss class, and a 5% increase in the odds (OR = 1.05) of being in the Knowledge is Power class when compared to the Ambivalent class. Results from the latent class regression analysis revealed that university size is a significant predictor of latent class, and that students at small universities are least likely to be in the Ignorance is Bliss class, while students at medium sized universities are most likely to be in the Fearful and Jaded class.

Table 22

Parameter Estimates and Odds Ratios for Effect of University Size on Latent Class Membership

	Class 1: Ambivalent	Class 2: Knowledge is Power	Class 3: Ignorance is Bliss	Class 4: Fearful and Jaded
Large vs. Small				
Beta	-	-0.063	-0.343	0.060
(SE)		0.020	0.021	0.023
OR	-	0.94	0.709	1.062
[95% CI]		[0.90, 0.98]	[0.68, 0.74]	[1.02, 1.11]
Large vs. Medium				
Beta	-	0.049	-0.098	0.124
(SE)		0.019	0.020	0.022
OR	-	1.050	0.906	1.132
[95% CI]		[1.01, 1.09]	[0.87, 0.94]	[1.08, 1.18]

Macrosystem Level: University Location

University location was entered into the latent class model as a covariate. University size was categorized into four dummy variables to reflect the four levels of measurement in the study (Northeast, Midwest, South, West), with the Northeast category considered the reference class in the analysis. The Ambivalent class was specified as the reference group in the multinomial logistic regression. Results of the

latent class regression model revealed that university location is a statistically significant predictor of latent class membership (Table 23). Specifically, compared to students attending Northeastern schools, students attending Midwestern schools had a 52% increase in the odds (OR = 1.52) of being a member of the Knowledge is Power class when the Ambivalent class was used as the reference class. Additionally, compared to students attending Northeastern schools, students attending Midwestern schools had a 29% increase in the odds (OR = 1.29) of being a member of the Ignorance is Bliss class and a 13% decrease in the odds (OR = 0.87) of being in the Fearful and Jaded class compared to the Ambivalent class.

Compared to students attending Northeastern schools, students attending Southern schools had a 31% increase in the odds (OR = 1.31) of being in the Knowledge is Power class, a 20% increase in the odds (OR = 1.20) of being in the Ignorance is Bliss class, and a 14% decrease in the odds (OR = 0.86) of being in the Fearful and Jaded class when the Ambivalent class is used as the reference class. Lastly, when compared to students attending Northeastern universities, students attending Western universities had a 24% increase in the odds (OR = 1.24) of being in the Knowledge is Power class, a 26% increase in the odds (OR = 1.26) of being in the Ignorance is Bliss class, and a 8% increase in the odds (OR = 1.08) of being in the Fearful and Jaded class when the Ambivalent class was used as the reference class. In summary, university location is a significant predictor of latent class membership such that students who attend universities in the Northeast were mostly likely be in the Fearful and Jaded class, while students in the Midwest were most likely to be in the Knowledge is Power class when the Ambivalent class is used as the reference group.

Table 23

Parameter Estimates and Odds Ratios for Effect of University Location on Latent Class Membership

	Class 1: Ambivalent	Class 2: Knowledge is Power	Class 3: Ignorance is Bliss	Class 4: Fearful and Jaded
Northeast vs. Midwest				
Beta	-	0.419	0.257	-0.137
(SE)		0.020	0.020	0.021
OR	-	1.520	1.293	0.872
[95% CI]		[1.46, 1.58]	[1.24, 1.34]	[0.84, 0.91]
Northeast vs. South				
Beta	-	0.267	0.181	-0.148
(SE)		0.024	0.025	0.028
OR	-	1.306	1.198	0.862
[95% CI]		[1.25, 1.37]	[1.14, 1.26]	[0.82, 0.91]
Northeast vs. West				
Beta	-	0.215	0.231	0.074
(SE)		0.030	0.030	0.032
OR	-	1.240	1.260	1.077
[95% CI]		[1.17, 1.31]	[1.19, 1.34]	[1.01, 1.15]

Macrosystem Level: University Affiliation

University affiliation (public vs. private) was entered into the latent class model as a covariate. University affiliation was categorized to consider public university status as being reference class in the analysis. The Ambivalent class was specified as the reference group in the multinomial logistic regression. Results of the latent class regression model revealed that university affiliation is a statistically significant predictor of membership (Table 24). Specifically, attending a private university was associated with a 53% increase in the probability of being in the Fearful and Jaded classes when the

Ambivalent class is considered the reference class. Probability of latent class membership based on the levels of the covariate are displayed graphically in Figure 11.

Compared to attending a public university, those who attended a private university had a 16% increase in the odds (OR = 1.16) of being in the Fearful and Jaded Class compared to the Ambivalent class. Additionally, attending a private university is associated with a 17% decrease in the odds (OR = 0.83) of being in the Knowledge is Power class, and a 20% decrease in the odds (OR = 0.80) of being in the Ignorance is Bliss class compared to the Ambivalent class. In summary, attending a public university is associated with being in the Knowledge is Power class and the Ignorance is Bliss class, while attending a private university is associated with being in the Fearful and Jaded class.

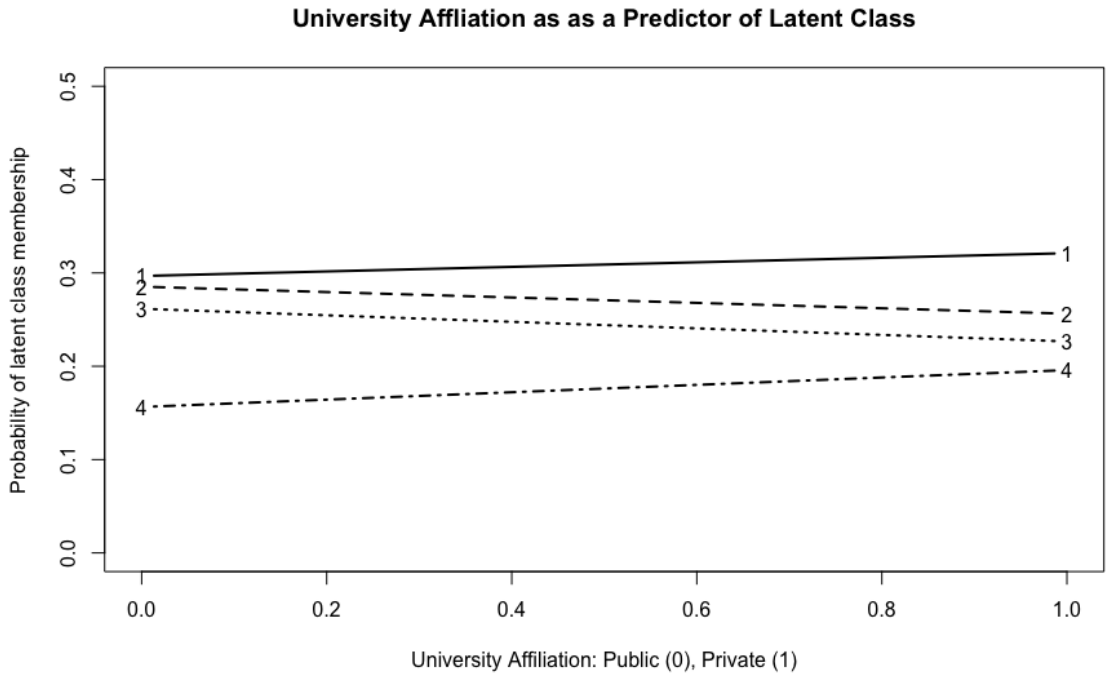
Table 24

Parameter Estimates and Odds Ratios for Effect of University Affiliation on Latent Class Membership

	Class 1: Ambivalent	Class 2: Knowledge is Power	Class 3: Ignorance is Bliss	Class 4: Fearful and Jaded
Beta	-	-0.186	-0.223	0.146
(SE)		0.017	0.018	0.019
OR	-	0.830	0.800	1.157
[95% CI]		[0.80, 0.86]	[0.77, 0.83]	[1.11, 1.20]

Figure 11

University Affiliation as a Predictor of Latent Class Membership



Chapter Five: Discussion

The following chapter will highlight the main results of the study in light of the research questions posed, address methodological limitations, interpret and discuss the findings of each research question, and make recommendations for future research. The purpose of the present study was to determine if there were distinct latent subgroups of students based on measures of campus climate, specifically, perceptions of risk of sexual assault, knowledge of on-campus resources, and perceptions of responses to reporting an incident of sexual assault or misconduct. Additionally, the study set out to determine if those latent subgroups could be predicted by victimization status and variables at the individual, micro-/mesosystem, and exo-/macrosystem levels. Overall, results demonstrated that there are latent subgroups of students that can be identified by their patterns of responses on measures of campus climate, and that membership of those latent subgroups can be predicted by a number of individual, environmental, and institutional variables.

Research question one set out to determine if there are distinct latent subgroups of students based on measures of campus climate. Results showed that among a large sample of college students, there is heterogeneity in response patterns on elements of campus climate. Notably, four latent classes of response patterns emerged which were labeled Ambivalent, Knowledge is Power, Ignorance is Bliss, and Fearful and Jaded. Overall, these results are supported by a breadth of literature highlighting differences in how campus climate is experienced by students (DeKeseredy et al., 2018; Kaczkowski et al., 2016) and seeks to support literature regarding the way that CSA intervention and prevention strategies are tailored depending on students' experiences of campus climate

(Murphy Austin et al, 2016; Gidycz et al., 2011; McMahon et al., 2017). Research question 1.a posited that the latent subgroups found in research question one could be predicted by victimization status. Results highlighted that students who had been victimized were most likely to reside in the Fearful and Jaded class and least likely to reside in the Ignorance is Bliss class. These findings are supported by the literature on negative reporting experiences of survivors and further highlights the increased risk of PTSD, depression, and anxiety symptoms following a mismanaged CSA incident (Pinciotti & Orcutt, 2019).

Research question two set out to determine the predictive capabilities of individual-level measures such as gender identity, age, sexual orientation, race, and disability on latent class membership. Results demonstrated that individual level variables like age, gender identity, sexual orientation, disability, and race predict latent class membership. Specifically, women, gender-nonbinary, members of the LGBTQ+ community, BIPOC students, and students with disabilities were most likely to reside in the Fearful and Jaded class which might indicate institutional disenfranchisement of students with marginalized identities. These results go above and beyond other victimization research that identifies individual variables linked with victimization experiences (Cantor et al., 2015, 2019; Fisher, Cullen, & Turner, 2000; Krebs et al., 2007; Krebs, Lindquist, & Barrick, 2011) and instead highlight how students with marginalized identities experience heterogeneity on elements of campus climate.

Research question three sought to determine the predictive capabilities of micro- and mesosystem measures such as group/club membership, partnered relationship status, and living situation on latent class membership. Results noted that students with larger

micro- and mesosystems who participate in more on-campus organizations are most knowledgeable of on-campus resources, which might indicate that a sense of participation and connectedness on campus is related to how students experience campus climate. Findings from research question three support Bronfenbrenner's (1979) ideas around microsystem size and positive outcomes. Additionally, results from research question three also support findings by Kaczkowski and colleagues (2016) regarding larger, more diverse microsystems and less hostility towards women.

Finally, research question four set out to determine the predictive capabilities of exo- and macrosystem measures such as university affiliation, size of university, and location of university on latent class membership. Results highlighted that region, school size, and school affiliation demonstrated significant prediction of latent class, with students who attend small to medium sized, private institutions being most likely to reside in the Fearful and Jaded class. These results highlight the uneven distribution of CSA prevention resources to differently sized and funded schools and their ability to provide comprehensive and supportive resources for students facing issues of sexual assault and misconduct, which has been documented in the literature in some depth (Paul, 2016; Landreman & Williamson, 2018).

Findings from the present study can inform institutional and federal policies regarding CSA, and help IHEs identify students who are most at risk for experiencing institutional betrayal and poorer outcomes following a victimization experience (Smith & Freyd, 2013). Additionally, the present study helps to identify elements of campus ecology related to students' experiences of campus climate as it relates to on-campus safety and sexual misconduct. The present study is a response to the call to action put out

by Harris et al. (2019) for an increase in action-oriented research initiatives. Results of the present study shed even greater light on the problem of CSA and have the potential to unpack some of the complex dynamics of campus climate and sexual misconduct. The present study also supports a critical examination of the impact of existing institutional initiatives put in place to prevent CSA. Finally, by the inclusion of both victims and nonvictims, the present study invites nuance and highlights disenfranchisement experienced by marginalized populations. Findings of the present study use a unique approach to capture the voices of all survivors and other stakeholders who have been indirectly affected by CSA in an effort to seek a solution.

Restatement of Limitations

Following the analyses in the present study, there are a few limitations that should be noted, specifically as it relates to the dataset and interpretation of the findings. As previously mentioned, the data collection team for the present dataset utilized a census approach with participants self-selecting into the survey. This type of sampling approach may have led to a biased sample. As addressed, there were significant differences in the response rates among certain groups of participants with graduate students being more likely to respond to the survey than undergraduate students, and women being more likely to respond to the survey than men (Cantor et al., 2015). Additionally, there was some evidence suggesting a slight bias in the prevalence rate obtained by Cantor et al. (2015) with survivors of CSA responding at a higher rate than nonvictims. Finally, the sample was not representative in terms of race/ethnicity, sexual orientation, or gender identity.

The survey instrument utilized drew from several existing, reliable and valid scales, in addition to incorporating guidance from the White House Task Force with regards to campus climate surveys. However, the reliability and validity of the measurement instrument was unconfirmed at the outset of the study. A CFA was conducted to confirm the factor structure of the campus climate measures. Results of the CFA identified that one of the 14 campus climate measure items had a negative factor loading, indicating its misfit to the proposed factor. However, this was remedied by considering the misfitting item as its own factor. Additionally, a reliability analysis was conducted to examine evidence for internal consistency, which was upheld. All of the scales in question demonstrated evidence for adequate internal consistency.

One of the biggest limitations of the study was the interpretability of some of the ecological variables included in the secondary analyses. For instance, at the individual level, LGBTQ+ identities needed to be collapsed because the measurement instrument as written only included heterosexual, gay/lesbian, and "other." This categorization of LGBTQ+ identities is problematic because it positions "other" as a nondescript catch-all, and does not reflect the full spectrum of sexual identities. In order to remedy this somewhat, gay/lesbian and "other" were combined. While collapsing LGBTQ+ identities into a dichotomous variable does not represent the complexity associated with more descriptive language, it does enable a more accurate measurement.

At the micro- and mesosystem level, three proxy variables were chosen to approximate the constructs of interest. In the initial development of the present study, it was proposed that Greek organization membership and participation in college athletics would be able to be analyzed to predict latent class membership. Unfortunately, the

public use of the restricted dataset provided by ICPSR did not include such information to protect participant privacy, and all types of organization membership were completely redacted from the data. While the types of organizations that students were members of was unavailable, the frequency of organizations participants were involved in was available. Therefore, as a proxy variable, frequency of organizational membership was used as a micro-/mesosystem factor to predict latent class membership.

Similar to the data available for on-campus organizations, living situation for participants was redacted from the public use dataset. As a proxy variable, online student status was used to predict latent class membership. Online student status included students for whom all of their coursework was online, and likely have very little contact with other students on-campus. Finally, the data collection did not include variables that were able to be used to measure cultural macrosystem factors like adherence to rape myths. Instead, the present study used external factors to the university to approximate the exo-/macrosystem. Initially, the research questions posed sought to understand if urban or rural university location would impact latent class membership as a exo-/macrosystem factor, however the dataset included census location, not whether not the university was located in an urban or rural area. Therefore, census location was used as a proxy variable, although it is not an exact measure of the construct as initially desired.

Interpretation and Discussion of Findings

The proposed research questions were supported by the data and are discussed greater detail hereafter. The results of each major finding is explored in terms of interpretation of the statistical findings and in light of the current research literature on

the topic to highlight the ways in which the present study fits into the context of sexual assault research.

Research Question 1

Research question one confirmed there are four distinct latent subgroups of students based on elements of campus climate and are labeled, Ambivalent, Knowledge is Power, Ignorance is Bliss, and Fearful and Jaded. Results revealed there is heterogeneity among the perceptions of campus climate of college students, specifically as it relates to perceived risk of sexual assault, knowledge of on-campus resources, and perceived responses to reporting an incident of sexual violence. Results from research question one imply that not only do students experience their perception of risk differently, but there seems to be a great deal of difference in the knowledge that students have about available on-campus resources, with some groups of students having very little knowledge on where to get help. Additionally, students also view how their university would treat a survivor with a great deal of variance, meaning that some students have a great deal of faith their IHE would respond to an allegation of CSA with seriousness and fairness, while others feel unsupported by their IHE. The knowledge of the existence latent subgroups can help universities target programming and interventions to support students who might be feeling isolated from their university as well as increase knowledge among students who are lacking the necessary information needed to protect themselves or a peer from CSA. Uncovering latent subgroups of students from the AAU survey tells a more detailed and nuanced story of the differences among how students' experience campus climate, with each latent class telling a unique story of student experiences.

Class 1: Ambivalent Class

With the Ambivalent class having the greatest prevalence comparative to the other latent classes, it highlights a problem in and of itself: some students just don't have a strong opinion about CSA or campus climate. One hypothesis that was discussed in the restatement of limitations is that the method of data collection or the instrument was flawed, and therefore, the validity of the campus climate measures was inhibited. Another hypothesis of this result is the proportion of students inhabiting the Ambivalent class believe the problem of CSA isn't a credible threat on their college campus. This idea is supported by the theory of social norms regarding sexual violence (Berkowitz, 2010). Many students may brush off risky sexual and dating behaviors as "normal" and therefore do not register CSA as being a threat to themselves or their peers. Berkowitz (2010) describes the ways in which college men have difficulty predicting their peers' attitudes and behaviors as it relates to sexual violence. The results hint that students in this class feel a sense of diffused responsibility and anticipate that if an incident of CSA were to occur that other students might take action. These results hint at themes explored earlier such as social group influence on sexual violence. Gwartney-Gibbs and Stockard (1989) long asserted that sexual victimization of college students is engrained into the social fabric of peer groups. Students who are ambivalent to the issue of sexual violence are more likely to endorse rape myths and pro-abuse informational support making them both more likely to perpetrate sexual violence and be victimized (DeKeseredy, Hall-Sanchez, & Nolan, 2018; Kaczkowski, Brennan, & Swartout, 2016).

With the Ambivalent class being observed as the largest latent subgroup, it highlights that students who don't have strong feelings towards CSA risk, knowledge of

on-campus resources, and perceptions of responses to reporting are completely left out of the conversation of CSA. Knowledge of the existence of a potentially large group of students on campus who might experience this type of thinking allows IHEs an opportunity to more thoughtfully engage students in bystander intervention trainings which have shown to be an effective prevention strategy by many other sexual assault researchers (Murphy Austin et al, 2016; Gidycz, Orchowski, & Berkowitz, 2011; McMahon et al., 2017).

Class 2: Knowledge is Power

The Knowledge is Power class is characterized by students having a great deal of knowledge of the on-campus resources and where to get help regarding an incident of sexual misconduct either for themselves or a peer. The Knowledge is Power class also seemed to believe that their IHE would be supportive of someone making a CSA allegation. This result is supported in the existing literature about the impact that comprehensive and well understood CSA policy has on the prevalence of sexual violence on campus. DeLong et al. (2018) found that more comprehensive CSA policies were linked with lower prevalence of CSA, and Potter et al. (2016) found that students who were engaged in comprehensive and interactive CSA prevention programming retained more knowledge of on-campus resources and felt a greater sense of confidence that they would know what to do if they or a friend experienced CSA. Results also suggest that sociopolitical regulations that require IHEs to provide specific types of training to students is helpful in creating a community of students armed with a wealth of knowledge on how to protect themselves or a peer from sexual violence. The timing of the data collection following the implementation of the Campus SaVE Act hints that there is a

trickle-down effect from federal regulations down to student safety, and that federal policies are effective in making college campuses safer for students (McCallion, 2014).

This class of students represents what IHEs should be aiming for. The interpretation of the responses in this latent class highlight the power of giving students meaningful resources so that they can empower themselves to get help, or feel a sense of efficacy to help others. The results of the present study continue this conversation by emphasizing when students know where to get help, they in turn also feel their campus is more supportive. The effort that universities put in to give students the knowledge about CSA and what to do if it happens allows students to have faith that their university is supportive and creates a greater sense of trust in the institution.

Class 3: Ignorance is Bliss

The Ignorance is Bliss class is characterized by low levels of perceived personal risk of CSA, and very low levels of knowledge of on campus resources. Students in this class also reported high levels of agreement that their IHE would support someone making a CSA report. One interpretation of this result is that students in the Ignorance is Bliss class experience a great deal of institutional privilege. As is later discussed, this belief that an institution is universally supportive is based in white, male, cisgender, and able bodied privilege (Campe, 2019; Griner et al., 2020; Seabrook et al., 2018). While this class of respondents highlight a group of students who are trusting of and aligned with their university, it is most concerning that they possess such limited knowledge of on-campus resources and seemingly downplay the risk of CSA. This is problematic because students in this class effectively remove themselves from the problem of CSA on campus.

Previous research by Walsh and colleagues (2010) discussed the dynamics between peer disclosure of CSA experiences and facilitation of on-campus resources. Walsh et al. (2010) discovered that when students' level of knowledge of on-campus resources is low, they are unlikely to encourage a victimized peer to seek assistance and support from their IHE. So while students in the Ignorance is Bliss class might feel supported and have trust in their IHE's ability to handle incidences of CSA fairly and appropriately, these students' complete lack of knowledge of on-campus resources impedes that process by creating a barrier for survivors to also gain knowledge, information, and support from a large group of their peers. These results are also supported by DeKeseredy and colleagues (2018) which examined the level of knowledge and pro-abuse informational support on incidence and prevalence of perpetration and victimization. Students who do not have accurate knowledge about the existence of CSA and knowledge about what to do if they or a peer is sexually victimized presents a barrier to a safe community. This latent subgroup represents an opportunity for IHEs to increase the total amount of knowledge on their campus to include all students, even graduate students, to foster a campus community that is universally supportive of survivors of CSA.

Class 4: Fearful and Jaded

The Fearful and Jaded class is characterized by agreement that CSA is problematic on campus, and very low levels of agreement that their IHE would be supportive of someone making a report. The Fearful and Jaded class is the group of students universities should be working hardest to support and regain their trust. Students in this class have very little faith in an IHE's intention or ability to help, despite adequate

knowledge of on-campus resources. The most alarming result from the interpretation of this latent subgroup is the ways in which this group of students seemingly experience a hostile campus climate with fearfulness that someone accused of CSA might retaliate against their accuser. IHEs should be acutely aware of the existence of this latent subgroup, as this group of students is most at risk for institutional betrayal (Smith & Freyd, 2013). Recall that institutions like college campuses foster a sense of trust and dependency within their students: students rely on their IHE for basic needs and expect their need for a safe environment will be upheld (Smith & Freyd, 2013). When trust is broken by failure to prevent CSA, normalizing dangerous contexts, make the reporting processes unduly difficult or ineffective, and align with the accused over the accuser, students are doubly harmed by institutional betrayal (Smith & Freyd, 2013).

The existence of the Fearful and Jaded latent subgroup highlights that there are groups of students who are already experiencing institutional betrayal at their IHE. With the potential for students to feel isolated, unsupported, and have little faith that their IHE would support someone making a CSA report, members of the Fearful and Jaded class are at an increased risk of worsened mental and physical health outcomes upon victimization (Smidt, Rosenthal, Smith, & Freyd, 2019). This latent class represents a group of students not unlike the late Lizzy Seeberg, who was threatened by her accused perpetrator's friends, unsupported and unbelieved by Notre Dame University, and ultimately succumbed to her trauma by way of suicide (Henneberger, 2012). Tragedies like that of Ms. Seeberg's case can be avoided if IHEs are able to regain the trust of students in the Fearful and Jaded class.

Research Question 1.a

Research question 1.a sought to understand if victimization experience could predict latent class membership. Results of research question 1.a emphasized that generally, victims of CSA view their campus climate differently than nonvictims. Specifically, survivors of CSA are most likely to be in the Fearful and Jaded class. Sexual trauma creates an indelible mark on one's life, and forever changes a student's experience of safety and faith in their IHE for many of the reasons previously discussed. Universities are institutions that students depend on for their safety and well-being, when a student is victimized in the place they depend on, their trust in their institution as being a safe environment is broken. Further, the way in which a university responds to reports of sexual violence matters and impacts the greater campus climate. Following an incident of CSA, survivors turn to their IHE for support, assistance, and justice; when they are met with inaction, mismanagement, or disbelief, survivors are doubly harmed and at increased risk for symptoms of PTSD, depression, anxiety, and other mental health concerns (Pinciotti & Orcutt, 2019). Results also highlight the impact that sexual victimization has on one's Chronosystem and greater ecology (Bronfenbrenner, 1986). Martinello (2020) emphasized that each incidence of sexual violence changes one's interactions within and between their ecosystem, which is highlighted in the present study. Students who experience sexual violence on campus have an altered experience interacting with their college campus environment, forever changing their ecology.

Additionally, as is supported by the data, the students in the Knowledge is Power class were less likely to be victimized, highlighting that the knowledge to detect unsafe situations may protect students from harm. This finding is supported by DeKeseredy and

colleagues' (2018) work that asserts that students who have connections with peers who do not support pro-abuse information are less likely to be victimized. Results of the present study also support the interaction between participation in comprehensive sexual violence prevention programming in keeping students safe from sexual violence as was explored earlier. Specifically, Potter et al. (2016) noted the efficacy of engaging students in open dialogues about sexual assault and consent as a first-line prevention effort against CSA. Students armed with knowledge are safer from being victimized, and are less likely to perpetrate sexual violence against others.

Finally, it is notable that nonvictims are most likely to be in the Ignorance is Bliss class. The privilege of not being victimized allows nonvictims to turn a blind eye to the problem. Students who do not believe that CSA is a problem for them personally are less likely to engage in prosocial bystander behaviors further isolating survivors, especially those who might already feel isolated from their IHE (Murphy Austin et al., 2016). Additionally, nonvictims in the Ignorance is Bliss class might be more likely to endorse rape myths being that they are not as knowledgeable about incidences of sexual violence and what to do if they or a peer is victimized. These results are supported by research explored earlier by O'Connor et al. (2018) that examined the ways in which combating students' endorsement of rape myths is useful in preventing sexual violence on campus.

Research Question 2

Research question two set out to understand the predictive relationship between individual level variables and latent class membership. The purpose of this research question was to bring individual factors into the context of understanding response patterns on measures of campus climate. Results of research question two supported the

idea that individual level variables were adequate predictors of latent class membership. Specifically, students having marginalized identities are more likely to be in the Fearful and Jaded class. Previous CSA research has focused quite a bit of attention on the relationship between individual level variables and risk of victimization in order to paint an accurate picture of who is most likely to be victimized during their time on a college campus (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). The present study takes this idea a step further by looking at how individuals respond to measures of campus climate, and examining the differences in response patterns based on individual characteristics such as age, gender identity, race, sexual orientation, and ability. Results of this research question gave critical information about how students with certain identities and characteristics experience their college campus as it relates to CSA and campus climate. Information gleaned from results of this research question can inform IHEs about who experiences the greatest amount of fear, disenfranchisement, and distrust in their institution. Results from this research question also highlight which students have the greatest amount of knowledge about CSA and where to get help. Finally, results from this research question also highlight which students are least knowledgeable about on-campus resources and might need additional outreach efforts by university Title IX administrators to increase a campus' overall level of knowledge, and therefore, safety.

Gender Identity

It's been widely identified that women experience CSA disproportionately compared to men (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). One of the strengths of the data used in the present study is that the

researchers used a non-binary definition of gender identity by including transgender, genderqueer, nonconforming, questioning (TGNQ) or other gender not listed in the survey. Unsurprisingly, results highlighted that there were gender effects in latent class membership when comparing men and women, with women being much more likely to reside in the Fearful and Jaded class. More interestingly, participants who identified a TGNQ gender identity were even more likely to reside in the Fearful and Jaded class when compared to men or women. This further paints the picture of the Fearful and Jaded class of respondents, and supports the idea that students with a marginalized gender identity might experience institutional disenfranchisement with more intensity than cisgender students. Additionally, TGNQ students were also least likely to reside in the Ignorance is Bliss class, further solidifying the reticence of students who do not identify as cisgender to trust and rely on their IHE. Harris et al. (2019) call for research that uplifts voices of marginalized populations and results of the analysis uplifts the voices of TGNQ students who may experience their college campus as more dangerous and feel a lack of support by their IHE. Additionally, the results of the present study support the findings by Griner et al. (2020), which assert that not only do transgender and gender nonconforming students experience sexual violence disproportionately, but they are often categorically excluded from policies and programming built to reduce CSA. In order to increase safety for TGNQ students, IHEs should take on an inclusive and intersectional approach to understanding the ways that students with minority gender identities are disenfranchised by their university and the programs set up to aid survivors.

Race

Previous studies have shown that White women and women of color experience about the same rate of CSA, with the exception being that Black women attending HBCUs are at slightly less risk than women attending other IHEs (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). While the data supported this idea that there were not significant differences in the rates at which survivors of different races experienced CSA, the results of the present study showed that there are differences in latent class membership based on race, with BIPOC students (with the exception of Asian students) having a greater likelihood of being in the Fearful and Jaded class. Despite not experiencing an increased rate of CSA, BIPOC survivors are less likely to feel supported and believed by their university, possibly leading to a greater sense of disenfranchisement.

Because previous research had largely dismissed race as being a risk factor for increased victimization, the present study uncovers something else altogether: racial and ethnic minority students do not experience campus climate in the same way as their White peers. Within in the context of the current literature, these findings are contrary to those reported by Pinciotti and Orcutt (2019) who found that institutional betrayal was not significantly related to racial identity. While the present study does not measure institutional betrayal, the presence of the relationship between race and latent class membership with BIPOC students being more likely to be in the Fearful and Jaded class, results suggest that racial and ethnic minorities have a more negative experience of campus climate. The present study highlights differences in the experiences of campus climate among students with minority racial identities, which is an important finding in

the context of increasing student safety and garnering increased reporting behaviors among students who have been victimized. This again, highlights the importance of an inclusive and supportive institutional response to CSA for all students.

Disability

Results of the present study found that disability status is a significant predictor of latent class membership with students with disabilities as most likely to be members of the Fearful and Jaded class and least likely to be members of the Ignorance is Bliss class. There is limited data that describes the sexual violence experiences of students with disabilities, however, the few studies that have examined risk of CSA in students with disabilities has identified disability status as a significant risk factor of CSA (Cantor et al., 2015; Campe, 2019). Further, Campe (2019) noted that disability status in women was a predictor of CSA above and beyond other risk factors such as drug use, binge drinking, and Greek organization affiliation. In light of the data and in the context of the present study, students with disabilities are less likely to feel supported by their IHE following CSA than students without disabilities. These results further emphasize the points made earlier: students with marginalized identities are at risk of disenfranchisement by their university and IHEs should take extra considerations to make sure CSA prevention programming and Title IX report responses are inclusive of students with disabilities.

Sexual Orientation

LGBTQ+ identity has long been identified as a risk factor of CSA, with bisexual women being most at risk for experiencing sexual violence (Seabrook et al., 2018). The data supported that LGBTQ+ women were more likely to be victimized than heterosexual

women (Cantor et al., 2015). Results of the present study also highlighted that LGBTQ+ students were most likely to reside in the Fearful and Jaded class. These results put LGBTQ+ students at a great deal of risk for institutional disenfranchisement, and possibly worse outcomes following victimization. In light of the data, LGBTQ+ identity should not only be considered a risk factor for increased victimization, but also a major component of a survivors' feelings of support and trust in their institution. IHEs should be mindful that LGBTQ+ students may feel distrustful of the existing university systems built to aid students who have been victimized, and should work hard to gain their trust and take extra precaution when working to support LGBTQ+ survivors.

Results of the present study also support the results of a mixed methods study examining the perceptions of sexual violence programming by survivors of CSA and LGBTQ+ students (Worthen & Wallace, 2021). Worthen and Wallace (2021) reported that LGBTQ+ students often feel excluded from sexual violence prevention programming because the education and training materials are based on heteronormative relationships and categorically exclude the victimization experiences of LGBTQ+ survivors. The results from the present study are also supported by existing research that identified that lesbian, gay, and bisexual students are less likely to seek support from their IHE out of fear of being mistreated (Piniciotti & Orcutt, 2019). IHEs should look to increase trust of LGBTQ+ students by broadening CSA prevention materials to include non-heterosexual violence and create spaces of inclusion to build an environment of trust of LGBTQ+ students.

Age

Age was considered a significant predictor of latent class membership, but included some results that are somewhat contrary to previous research. Results from previous studies indicate that younger students are more at risk to be victimized than older students (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011). In the present study, older students were much more likely to be in the Ignorance is Bliss class, with responses consistent with considering CSA as being unproblematic on campus, having very limited knowledge of on-campus resources, and strong agreement that the university would be supportive of a student making a CSA report. Additionally, younger students were more likely to be in the Knowledge is Power class, indicating low to moderate agreement that CSA is problematic, a great deal of knowledge of on-campus resources and strong-moderate agreement that the university would be supportive of a student making a report of CSA.

Initially, these results might seem contrary to the existing knowledge that younger, female students are at the highest risk to be assaulted on campus, however, upon examination, the data are consistent with characteristics of the participants, and, the time at which the survey took place. Firstly, Cantor et al.'s (2015) methodology included graduate students in the data collection process. Graduate students are often older than undergraduate students and are much more likely to be removed from campus culture, less likely to attend on-campus parties, or be involved in social groups on campus, therefore, to a graduate student, CSA may not seem like a credible threat. Additionally, graduate students are unlikely to be required to attend Title IX training or programming put on by residence halls and campus organizations. Conversely, the survey took place in

Spring 2014, following the mandatory education and prevention efforts put forth by the Campus SaVE Act in 2013, which required all incoming first-year students to attend programming related to CSA prevention. This result highlights the potential efficacy of education and prevention efforts put on by IHEs. As was previously explored, researchers like DeLong et al. (2018) and Potter et al. (2016) found strong support for the existence of comprehensive prevention programming as a first-line defense against CSA.

Students who are required to attend mandatory Title IX and sexual violence prevention training, especially early on in their college career, feel empowered by the knowledge of the risks of CSA for themselves or a peer, and subsequently where to go if they need help or support. Additionally, when IHEs allocate time and resources to CSA education and prevention programming, they are curating an image of support of survivors, and therefore increasing the level of trust students have in their university. So while freshman students have frequently been thought of as most at risk for CSA, including CSA prevention programming for all incoming freshman students increases their probability of being a part of the Knowledge is Power class, and might decrease their risk of being victimized.

Lastly, there were no significant age effects for the Fearful and Jaded Class, which is contrary to the known age effects of CSA risk (Cantor et al., 2015, 2019; Fisher et al., 2000; Krebs et al., 2007; Krebs et al., 2011), and previous research by Pinciotti and Orcutt (2019) that reported that older age was consistent with experiencing a greater sense of institutional betrayal. In light of the results of the present study in the context of existing literature, it's clear that students at any age or year are universally impacted by distrust in a university's response to reporting behavior, and when students are granted

ample and early opportunities by their university to increase their knowledge of CSA they are more likely to feel empowered with their knowledge.

Research Question 3

The purpose of research question three was to explore the potential impact that micro- and mesosystem level factors has on latent class membership. This research question was guided by Bronfenbrenner's (1994) process-person-context model in his Ecological Systems Theory. Specifically, this research question aimed to answer the ways in which a student's micro- and mesosystem on campus might impact their latent class membership. Results of research question three were supported in that students with varying micro- and mesosystem sizes and connections seem to predict latent class membership.

Relationship Status

Relationship status was found to be a significant predictor of latent class membership, such that, students who reported being in a partnered relationship during their time at the university were most likely to be in the Fearful and Jaded class, and least likely to be in the Ignorance is Bliss class, while students who are not in partnered relationships are most likely to be in the Ignorance is Bliss class.

Interpretation of these results require a bit of unpacking to fully understand their place in the context of EST and current literature. Results of the present study link partnered relationship status to being in the Fearful and Jaded class, which is reminiscent of results by Krebs et al. (2011) and Fisher et al., (2000) who asserted that current or former dating partners are often perpetrators of CSA. These findings are also in alignment with findings by DeKeseredy et al., (2018), which examined the effect of pro-

abuse informational support, or the guidance and advice that encourages and accepts men to sexually, physically, and/or psychologically abuse their dating partners on college peer relationships and sexual assault experiences.

However, these results are contrary to long standing ideas around increased micro-/mesosystem size on developmental potential (Bronfenbrenner, 1994). One might assume that students who are in partnered relationships have expanded micro- and mesosystems, which in light of the present results, are an inaccurate predictor of being in the Knowledge is Power, Ambivalent, or Ignorance is Bliss classes. These results lend themselves to implications around the *quality* of one's microsystem rather than the size. As previously explored, when students are in relationships with others who endorse rape myths, pro-abuse informational support, and hostility towards women are at risk of being victimized (Gwartney-Gibbs & Stockard, 1986; DeKeseredy et al., 2018; Kaczowski et al., 2016). This has particular implications for the students in the Fearful and Jaded class who endorsed fearfulness of retaliation against those accused of sexual violence. Students in relationships with others who are prone to perpetrating sexual violence are also at risk for retaliation for reporting, highlighting an even greater issue that IHEs should address. In light of the present results in combination with previous research indicating that perpetrators of sexual violence are often current or former dating partners, IHEs should broaden CSA prevention to include sexual violence in dating relationships.

Participation in On-Campus Organizations and Groups

Results demonstrated that students who were members of more organizations were most likely to be in the Knowledge is Power class, and least likely to be in the Ignorance is Bliss class or the Ambivalent class. This result is likely attributable to the

level of connectedness students feel to their university when they are a member of several on-campus organizations. Additionally, many university organizations like Greek organizations, athletic teams, and student government often require members to attend or host programming related to campus safety. Therefore, students who are members of many on-campus organizations are exposed to CSA prevention programming at a more consistent rate than students who are not members of on-campus organizations, increasing their reported level of knowledge of on-campus resources. These results support Bronfenbrenner's (1979) theory that the greater number of settings a developing person participates in, with an increased number of positive, enriched settings, the greater their cognitive and emotional ability to adjust between environments, putting them at a greater advantage than those with limited mesosystems. Results also may support findings by Kaczkowski et al. (2016) that men who have larger and more diverse microsystems tend to have less hostility and aggression towards women. These results are further supported in the negative relationship between frequency of organizations and probability of being in the Ignorance is Bliss class, which shows that students who do not participate in on-campus organizations possess lower overall levels of knowledge of on-campus resources.

Overwhelmingly, students who engage in several on-campus resources were at a much higher probability of being in the Knowledge is Power class. One caveat is that there is also a positive relationship between number of organizations and probability of being in the Fearful and Jaded class. This lends itself to the contradictory research regarding Greek membership and risk of CSA. While several studies have linked presence of Greek organizations, and particularly, men's fraternities, with greater

prevalence of CSA (Lasky, Fisher, Henriksen, & Swan, 2017; Martin, 2016; McCray, 2015), there are scholars that view women's sorority membership as being protective against CSA victimization (Radina, 2017). While the results are unable to make specific claims about Greek organizations, the subtext to the current results is that being a member of an on-campus organization has the potential to be both protective and risky. Being a member of many different on-campus organizations expands students' micro- and mesosystems and creates a greater network of support. A greater support network in turn allows students to feel more connected to their university community. However, students who are members of campus organizations that connect them to peers with pro-abuse beliefs is risky (DeKeserdy, Hall-Sanchez, & Nolan, 2018). Not all on-campus organizations are protective, and, connections to men's only organizations in particular (like fraternities and athletic teams), may pose a risk that outweighs the protection of a student's strong social support system. Again, these findings lend themselves to examining the impact of size and quality of micro-/mesosystem factors on sexual violence. Students who have large, diverse micro-/mesosystems full of peers that have supportive views of survivors of sexual violence are more likely to reside in the Knowledge is Power class, and therefore, are safer from sexual violence and experience a more positive campus climate.

Online Student Status

Results indicated that online students were most likely to be in the Ignorance is Bliss class, and least likely to be in the Fearful and Jaded class. Unsurprisingly, online students aren't aware of the on-campus policies and resources available to students who have been victimized on campus. Online students also seem to have a high level of

alignment and faith that their institution would act fairly and appropriately if a CSA case was brought to their IHE. A limitation to using online student status as a proxy variable is that it doesn't corroborate previous research regarding the CSA risk of students living on-campus versus in off-campus housing. These results might have more implications for the present dilemma IHEs are facing during the COVID-19 pandemic. With many first year students attending their first year of college online, their return to campus as second-year students might warrant additional measures by the IHE to increase their knowledge and awareness of CSA.

Research Question 4

Research question four sought to determine the exo- and macrosystem predictive capabilities on latent class membership. This research question was similarly guided by Bronfenbrenner's (1979) EST, with special attention to specific university factors that impact latent class membership. In order to test this research question, university size, location and affiliation (public or private) were used as predictors of latent class membership and revealed that exo- and macrosystem factors do predict latent class membership. Results highlighted that smaller, private, Northeastern institutions are at risk for negatively contributing to a hostile campus climate and increasing the likelihood that students are in the Fearful and Jaded class.

University Size

University size was found to be a significant predictor of latent class membership, such that, students at medium sized universities (20,000 – 40,000 students) were most likely to be in the Fearful and Jaded class when compared to students at large institutions. Further, small institutions (< 20,000 students) also predicted membership of the Fearful

and Jaded class compared to large institutions. Enrollment numbers are important in considering exo-/macrosystem influences as university size is directly related to university funding, endowment, and allocation of resources.

It is well documented that small to medium sized universities are often challenged by maintaining Title IX regulations and supporting survivors of CSA consistently (Paul, 2016; Landreman & Williamson, 2018). Additionally as was detailed earlier, Graham et al. (2017) found that smaller schools tended to have less comprehensive CSA policies compared to larger IHEs. This finding supports the idea that smaller universities who lack adequate funding to maintain holistic and comprehensive CSA responses and preventative efforts contribute to a campus environment that is hostile to students, leaving many students feeling disenfranchised and unsupported by their IHE.

Results emphasize that medium sized universities are especially at risk because they do not have the benefit of a small, close-knit campus community like small universities while still be similarly challenged by budget constraints. Results of the present study should encourage universities to prioritize Title IX funding and on-campus resources that support survivors in order to create a safer and more inclusive campus environment where students feel as though they can rely on their IHE and trust them if an incidence of sexual violence were to occur.

University Location

Surprisingly, there do seem to be regional patterns among students' responses to campus climate. Overwhelmingly, students attending Northeastern universities were most likely to reside in the Fearful and Jaded class, while students attending Midwestern universities were most likely to be in the Knowledge is Power class. Students at

Midwestern, Southern, and Western universities were all more likely to be in the Ignorance is Bliss class when compared to Northeastern university students. These findings have uncovered the potential for a regional, cultural component to campus climate that to my knowledge, has not been discussed previously. Previous research has been inconclusive regarding United States region and CSA risk. Stotzer and MacCartney (2015) found no significant results linking region to CSA victimization. Amin et al. (2015) found that there are geographic clusters of rape especially in Southern states, but the data used was not specific to CSA. The linkage between university location and perceptions of campus climate with students attending Northeastern universities being more likely to embody perceptions in alignment with the Fearful and Jaded class warrants further investigation.

University Affiliation

University affiliation refers to whether the university is a public institution or a private institution. Results of the present study found that university affiliation was a significant predictor of latent class membership. Students at private colleges are more likely to reside in the Fearful and Jaded class than students at public colleges. These results are echoed in the points made earlier regarding university size, resource allocation, and availability of student support resources related to CSA and Title IX.

Previous research by Stotzer and MacCartney (2015) found no significant relationship between private colleges and CSA risk. However, Graham et al. (2017) found that small, private IHEs are less likely to have comprehensive CSA policies that clarify university standards and policies in regards to sexual violence. Additionally, private universities are more likely to have smaller enrollment, which might mean more

limited resources to provide Title IX coordinators with the funds they need to support students holistically. Paul (2016) also found that Title IX coordinators at private institutions have fewer resources at their disposal and often are tasked with multiple roles related to student affairs. Results of the present study help illuminate what limited Title IX resources mean for the student experience and campus climate: schools that do not allocate resources to Title IX coordination create an image of nonsupport of survivors of CSA.

Theoretical Importance

The macro- and exo-systemic factors in the present study described in the above results, also have theoretical implications. In later years, Urie Bronfenbrenner's EST sought to expand his ideas to include a more complex reciprocal interaction between an active, evolving biopsychological human organism, and the persons, objects, and symbols in one's immediate environment over time throughout the life course (Bronfenbrenner, 2001). This idea is commonly referred to as the process-person-context-time model (Bronfenbrenner, 2001). The present study sought to utilize Bronfenbrenner's EST and the process-person-context-time model to frame the research questions and inform a holistic perspective regarding CSA. The results of the present study honor Bronfenbrenner's theory in a number of ways. First, because LCA seeks to uncover patterns of responses among respondents, the methodology does well to examine the interaction between process and person. The present study uncovered latent subgroups of students based on their responses to elements of campus climate. The qualitative descriptions of the latent subgroups help to tell the story about how groups of students experience campus climate. Additionally, the series of latent class regression analyses

which sought to determine the predictive power of factors at the individual, micro-/mesosystem, and exo-/macrosystem level help to uncover context of the experiences of students likely to inhabit each latent subgroup. Thus, there is an interactive process between individuals and the groups to which they belong, that influences study findings.

The Developing Individual

Research question two examined the impact of individual factors such as gender, age, race, sexual orientation, and disability on latent class membership. Bronfenbrenner's (1979) work was inspired by the work of Kurt Lewin and his famous equation $B = f(PE)$, which states that an individual's behavior is a function of both their personal characteristics and their environment (Bronfenbrenner, 1979; Lewin, 1935). In his later work, Bronfenbrenner sought to understand individual characteristics in the greater context of the individual's ecology while also considering the proximal processes of the interactions between personhood and environment (Bronfenbrenner, 2001). The results of the present study describe an interaction between personhood and process by examining the predictive power of individual variables on latent class membership. Of note, women, TGNQ, LGBTQ+ students, and students with disabilities were most likely to reside in the Fearful and Jaded class. These results lend themselves to the process and context of personhood wherein one's individual characteristics interact with their experience of campus climate.

Micro-/Mesosystem Factors

Research question three examined the impact of micro-/mesosystem factors such as relationship status, frequency of membership in on-campus organization, and online student status on latent class membership. According to Bronfenbrenner (1979), the

microsystem includes the pattern of activities, roles, and interpersonal relationships experienced by the individual in any given setting; while the mesosystem is the system of microsystems that an individual participates in. Results of the present study linked micro-/mesosystem influences on latent class membership. Specifically, students who reported having been in romantic partnerships were more likely to be in the Fearful and Jaded class, while students not in romantic relationships were most likely to be in the Ignorance is Bliss class. These results highlight a microsystem impact on the process and context of sexual violence; when students are linked with partners who uphold rape myths, they are at a higher risk of victimization. Results also illuminated the impact of on-campus groups/clubs on latent class membership. Interestingly, there was a positive relationship between frequency of membership in on-campus clubs and being in the Knowledge is Power class as well as the Fearful and Jaded class. These results in particular highlight the impact of the quality of one's micro-/mesosystem on development. Students who have connections with others who have cavalier attitudes about sexual violence are more likely to be victimized and less likely to have knowledge of where to get help if they or a friend are victimized.

Exo-/Macrosystem Factors

Research question four sought to examine the predictive power of exo-/macrosystem influences such as university size, class, and location on latent class membership. The exosystem consists of all indirect environmental influences included in the individual's life while the macrosystem is inclusive of institutional patterns of culture, and economic, social, legal, and political systems of which the exo-, meso-, and micro-systems are affected. Results of the present study illuminated the impact of limited IHE

resources on latent class membership, wherein students who attend smaller, private institutions with have fewer resources at their disposal are most likely to be in the Fearful and Jaded class. These results support Bronfenbrenner's (1979) ideas about the trickle down impact of exo-/macrosystem factors on individual experiences and perceptions as well as the process-person-context-time model (Bronfenbrenner, 2001) wherein the proximal processes in combination with contextual factors impact personhood. Additionally, results also illuminated a possible impact of United States region on latent class membership wherein students attending universities in the Northeast were much more likely to be in the Fearful and Jaded class when compared to students attending IHEs in other areas of the country. IHEs in the Northeast US region are likely to be more in urban settings compared to IHEs in the South, Midwest, or West, lending itself to an interesting conversation around urban and rural college campuses. It could be hypothesized that urban campuses have a weaker sense of community when compared to rural campuses, lending students to feel more disconnected from one another. These results similarly highlight the impact of the exo-/macrosystem on the context and process of individual development in the context of CSA.

In sum, results of the present study utilize EST and process-person-context-time model to understand the complexity and nuance of CSA (Bronfenbrenner 1979; Bronfenbrenner 2001). In his final volume, Bronfenbrenner (2001) called for operational research designs that simultaneously investigate the process-person-context-time impacts on human development. By utilizing a latent variable modeling methodology to uncover response patterns among students as well as utilizing multinomial logistic regression to determine the predictive power of variables at the individual, micro-/mesosystem, and

exo-/macrosystem levels on latent class membership, the present study utilizes Bronfenbrenner's theoretical framework to approach CSA research holistically as recommended by Bronfenbrenner in 2001.

Implications for Practice

The present study invites a novel approach to understanding campus climate and students' patterns of responses on measures of campus climate which lends itself to several implications for administrators at IHEs, Title IX professionals, and policymakers.

Recommendation 1: IHEs should target students with low levels of knowledge of on-campus resources and students who feel unsupported by the IHE

One of the benefits of taking on a latent variable mixture model approach by using LCA to understand response patterns and uncover homogenous subgroups of students, is that information can be used to highlight groups of students who are lacking knowledge of on-campus resources and who might already have low-levels of trust in the IHE. Universities should use this information to gather data about how campus climate is experienced among and between students to target cultural problems on campus. Armed with this knowledge, IHEs can create targeted programming to increase knowledge among campus members and build the support and trust of students who feel as though their IHE wouldn't respond to reports of CSA fairly. There is evidence to support the implementation of CSA prevention programming that includes discussion groups among students, and is gender-specific, allowing members of the same gender identity to speak more candidly and openly about experiences of CSA (Potter et al., 2016). This type of CSA programming has been shown to be most effective in increasing student's knowledge of on-campus policies and resources as it relates to sexual violence and

increasing their confidence that they would be able to help themselves or a peer if an incident of sexual violence occurred (Potter et al., 2016).

Recommendation 2: IHEs should seek to gain the trust of marginalized communities by creating spaces of inclusion and support

The present study illuminates that many students with marginalized identities feel a severe lack of support from their IHE. Universities should create spaces of inclusion and support to regain the trust of marginalized students. Landreman and Williamsen (2019) identified that university administrators who uphold harmful, dominant social narratives such as sexism, racism, homophobia, and normalization of violence creates a campus community that is hostile. IHEs should directly contradict socially unjust narratives and recognize the ways in which oppression and privilege contribute to violence on campus. Social justice and inclusion are core professional competencies for student affairs professionals which necessarily extends into the handlings of Title IX complaints (ACPA/NASPA, 2016). Building trust with marginalized communities will include the use of socially just practices in the responses to CSA cases, and the facilitation of efficacious and inclusive prevention programming where a variety of genders, sexual orientations, races, and ability levels are represented. Universities should seek to challenge the heteronormative narrative that CSA only occurs between heterosexual men and women.

Additionally, Jennifer Freyd (2013), who coined the term institutional betrayal, recommended that IHEs engage in "institutional courage" (Freyd, 2018). A response that inhabits institutional courage cultivates sensitive responding to CSA reports, upholds accountability when cases are mishandled, and cherishes the whistleblower who brought

light to problematic elements of campus climate. Engaging in institutional courage allows students in the Fearful and Jaded class to rebuild trust in their IHE, even if they already have experienced institutional betrayal. Universities should seek to repair relationships with students and make concerted efforts to combat sexism, misogyny, and sexual violence.

Recommendation 3: Universities should allocate adequate resources to their Title IX offices and create structure to support students impacted by CSA

Results of the present study link increased knowledge of on-campus resources with decreased perceptions of risk and increased trust in a IHE to respond effectively and fairly. While at times IHEs can feel burdened by the ever-changing nature of Title IX and the increasing amount of time and effort it takes to put on effective programming, results of the present study show that when universities have accessible resources and commit to providing students with the knowledge they need to remain safe, students feel safer and more confident in their ability to get help. In other words, prevention programming, bystander intervention training and requiring students to engage with campus safety resources is a worthy investment in increasing campus safety and creating a safe and supportive campus culture.

Beyond prevention training, IHEs should create university offices and structures who are solely responsible for the support of survivors, including confidential resources where students are able to speak to licensed clinicians or trained advocates about their experience. Additionally, Freyd (2018) advocates for university leadership to be educated about sexual violence and trauma to cultivate a trauma-informed response. The allocation of resources to structures that serve to solely support survivors further creates a campus

community that demonstrates visible support of survivors to create an environment of trust. Finally, it is recommended that IHEs allocate resources to appoint a sole Title IX coordinator, rather than adding the duties of the Title IX coordinator onto an existing position. Having the singular focus of a Title IX coordinator on the care and support of survivors and on the fair adjudication processes decreases the chance a student will experience institutional betrayal. This recommendation is supported by other scholars like Paul (2016), who focused her dissertation on the experiences of Title IX coordinators at small, private institutions who are often at risk for burnout and ineffectual handlings of Title IX complaints when faced with limited resources.

Recommendation 4: Universities should mandate all students, faculty, and staff to attend comprehensive, mandatory prevention programming

Students who do not possess knowledge of on-campus resources create a barrier to a safe community. A safe community is one that has universal knowledge about on-campus resources, what to do if sexual violence might be occurring, and how to hold campus members accountable. Results of the present study showed that older students, online students, and male students were much more likely to be in the Ignorance is Bliss class. While these students might be at a decreased risk to be victimized, they have an important function in serving as an additional source of information for students who are victimized. Increasing the overall level of knowledge across the entire population of the IHE decreases the overall level of risk and increases a sense of support for survivors within the campus community. While Title IX requires prevention trainings for undergraduate students, IHEs should consider expanding prevention training to include graduate and online students with the intention of creating a safer community. More

specifically, it is recommended that IHEs utilize graduate students particularly in the expansion of prevention programming. Oftentimes, graduate students inhabit a unique role on campus as teaching and research assistants who interact with undergraduate students in a variety of different capacities. Training graduate students as an additional source of knowledge to undergraduate students will help in building a safer campus community.

Additionally, the present study examined perceptions of campus climate according to students and did not include perceptions of campus climate from faculty and staff of IHE, who are included in the effective prevention of CSA. Title IX requires "Designated Reporters" to report any information they learn about CSA to the University Title IX coordinator (Title IX, 1972). It is recommended that all designated reporters and non-designated reporters who interact with students to attend comprehensive Title IX programming and CSA prevention programming with the intention of building a safer university community. This recommendation is supported in previous research by Moylan, Hammock, & Carlson (2020) who found that most higher education personnel believe that appropriate implementation of CSA policies make campus safer and seek to increase fair, victim-centered approaches to handling cases of CSA. Programming for faculty, staff, and administrators should include information above and beyond the Title IX reporting requirements including information for faculty and staff on where to refer students to if they need additional support, and how to respond to students appropriately and effectively to demonstrate support and empathy.

Recommendation 5: CSA Prevention programming should cover a wide variety of topics including definitions and examples of CSA, risky drinking and dating

behaviors, bystander intervention, and knowledge about what to do if CSA does occur

While the present study is unable to discern efficacy of specific interventions or prevention programming topics, the results of the present study within the context of the current literature about CSA prevention programming make it clear that CSA prevention is a function of knowledge that students have at their disposal about CSA, campus policies, and resources. Therefore, the inclusion of comprehensive and inclusive CSA programming increases the overall level of knowledge of a campus community. CSA prevention programming should include realistic information about the risk of CSA, including how many incidences have occurred on campus over the past several years, risk factors and warning signs of CSA, how to intervene effectively as a bystander, and an overview of where to get help if CSA does occur. Freyd (2018) reported that in order for institutions to remedy feelings of institutional betrayal, IHEs should be transparent about current CSA data and their policies and invite public input and scrutiny.

Additionally, as is highlighted by Potter et al. (2016), CSA programming should be interactive, and, if at all possible, include single gender presentations and discussion groups. This allows students to engage in meaningful discussions and conversations about CSA and their on-campus culture so that the entire campus community can come together for a unified goal. Finally, IHEs should double down on their efforts to increase prosocial bystander behaviors. Researchers have long asserted that bystander intervention programs are effective at reducing rape myth acceptance, increasing students' confidence in their ability to intervene, and challenge social norms that prevent students from taking action (Murphy Austin et al., 2016; Banyard et al., 2007; Gidycz et al., 2011).

IHEs that provide comprehensive and interactive prevention programming serve two functional purposes (1) to increase the overall level of knowledge that all students possess about the risk of CSA and where to get support if CSA occurs, and (2) increase positive perceptions to responses of reporting CSA on campus. When time and effort is put forth by IHEs in regards to increasing student safety and decreasing CSA, students are prone to feeling as though their IHE is more supportive, and therefore less likely to feel the impact of institutional betrayal, much like the Fearful and Jaded class.

Recommendation 5: Believe survivors

Believing and supporting survivors of CSA is not antithetical to providing a fair adjudication process. As previously discussed, IHEs that create barriers to survivors being able to make reports of CSA or respond in ways that are not trauma-informed is harmful to the overall campus environment. All faculty, staff, and administrators responsible for the Title IX process should have formal training in trauma-informed care and position themselves in such a way to create environments of trust for survivors. IHEs should respond to survivors considering the basics of trauma-informed care such as (1) increasing safety, (2) empowerment, and (3) helping survivors find their voice (Conley & Griffith, 2014). Mixed-method data collected by Doughty (2018) in her dissertation research revealed that trauma-informed care in education environments is uncommon, and many university educators feel unprepared to implement trauma-informed care to students with trauma. A holistic, trauma-informed response to incidences of sexual violence on campus necessarily requires buy-in and support from IHE leadership and ongoing professional development opportunities where faculty and staff are able to practice trauma-informed responses and how to support students who have been

victimized (Hoch et al., 2015). One model that has shown to be effective the Sanctuary Model developed by Dr. Sandra Bloom, which is a blueprint for organizational change to promote safety and recovery from adversity through the creation of a trauma-informed community (Sanctuary Institute, 2017).

IHEs should also remember that false reports of CSA are very rare, and the way IHEs respond to reports is crucial to building an environment of trust and support (Weiser, 2017). When survivors make a report of sexual violence to their IHE, they are doubly traumatized if their IHE's response is overtly or inadvertently unsupportive of the person making the report (Smith & Freyd, 2013). Additionally, IHEs are systems where all campus members are interconnected and interdependent on one another, when a CSA incident occurs on campus, all campus members are impacted (Hoch et al., 2015). Therefore, it is imperative that IHEs take reports of sexual violence seriously and take a trauma-informed care response in treating the survivor with respect while investigations are ongoing.

Recommendation 6: Create fair, but sensitive, adjudication processes

With the sweeping changes made to Title IX in August 2020 shortly before the election of President Joe Biden, the current state of Title IX includes guidelines that sexual assault advocates deem as harmful to survivors of CSA (Meckler, 2020; Holland et al., 2020). Specifically, the press release on the Title IX changes report that the amended guidelines "Restores fairness on college and university campuses by upholding all students' right to written notice of allegations, the right to an advisor, and the right to submit, cross-examine, and challenge evidence at a live hearing" (US Department of Education, 2020). Two aspects of the current Title IX guidelines, (1) the right of the

accused to cross-examine and (2) the right to challenge evidence at a live hearing are two changes that are thought to be harmful to survivors of sexual assault (Holland et al., 2020). As previously explored, this departure from previous Title IX guidance shifts attention away from survivors and focuses on due process rights for students who have been accused of sexual violence (Butler et al., 2019; Meckler, 2020).

While universities need to create adjudication processes that adhere to Title IX standards, they should do so in such a way that protects the emotional and psychological safety of survivors making the report. The adjudication process of Title IX complaints is often uncomfortable for survivors and IHE administrators should do their part to make the process as supportive of the student making the report as possible. For example, Holland and colleagues (2020) suggest that universities should set policies in place to dictate what types of questions accusers must endure during cross-examination, and setting boundaries for when advisors conducting cross-examination should be removed for inappropriate questioning. Additionally, another suggestion for creating fair adjudication processes is to give survivors a variety of choices in how they would like the case to be handled. Including additional options for a restorative justice approach can be beneficial to both the survivor and the accused party. Research shows that restorative justice approaches require perpetrators to take accountability for the hurt caused, and allow survivors the opportunity to tell their story, observe offender remorse, and have input in the resolution of the violation (Koss et al., 2014; Harper, et al., 2017). When survivors can feel empowered by choices in how they would like their case to be handled, they are more likely to feel supported by the IHE.

Finally, there is room for IHEs, university administers, Title IX professionals, and policymakers to be critical of the current state of Title IX and advocate for an overhaul of legislation. Over the past 50 years, Title IX has been a key piece of legislation in dictating civil rights for women and gender minorities. However, the ways in which Title IX has transformed over the years has increasingly asked IHEs to respond to sexual misconduct as though they are judicial bodies. Universities are not judicial systems, and asking them to behave as such with their role as both judge and jury has become increasingly challenging. IHEs are often not equipped to conduct full-scale investigations and many criminology and legal scholars argue for a complete overhaul of the way in which OCR dictates Title IX. (Butler et al., 2019; Caldwell, 2017; Harper et al., 2017).

Recommendation 7: University counseling centers should be aware of the heterogeneous experiences of campus climate among survivors of CSA and provide comprehensive, trauma-informed care to students

University counseling centers are often the most commonly used confidential resource for survivors of CSA, where they may receive mental health care as they make meaning of their traumatic experience and undergo stressful adjudication processes (Shortway et al., 2020; Yoshimura & Campbell, 2016). Many university counseling centers utilize Solution-Focused Brief Therapy, an approach developed by de Shazer and colleagues (2007) as the primary intervention strategy for working with students with mental health concerns. As is pointed out by Yoshimura and Campbell (2016), this approach may not be appropriate for survivors of CSA due to its short duration, risk of re-traumatization, and lack of an explicit trauma-informed care approach. Additionally, work by Shortway et al. (2020) highlighted the lack of specific trauma-informed training

experiences of counselor and psychology interns at university counseling centers. Further, Artime and Buccholz (2016) found that approximately one-fifth of clients with traumatization experiences were referred out to community providers rather than seen by their university counseling center. These findings indicate that many university counseling centers are ill-equipped to handle CSA cases in providing comprehensive and supportive mental health care to students dealing with sexual trauma.

In order to remedy this somewhat, Yoshimura and Campbell (2016) recommend a brief trauma screening and assessment at the outset of the therapeutic relationship so that university clinicians may follow-up with the client regarding trauma history and the impact on the client's current situation and functioning. Artime and Buccholz (2016) recommend that university counseling centers employ clinicians with specialized, trauma-informed training in evidence based approaches like cognitive processing therapy and trauma-focused cognitive behavioral therapy to respond and support CSA survivor clients. In light of the present study, it is recommended that university counseling centers employ both strategies put forth by Yoshimura and Campbell (2016) and Artime and Buccholz (2016). Additionally, it is recommended that university counseling centers go one step further to not only employ a trauma-focused approach to treating students with CSA experiences, but also to take on an explicitly intersectional trauma-informed approach to care.

With the knowledge that survivors of CSA with marginalized identities experience a more hostile campus climate, it is critical that university counseling centers meet students' unique needs and have tools to begin to repair damage done by institutional betrayal and disenfranchisement. Intersectional approaches to care

underscore the ways in which marginalized identities interact and compound traumatic experiences (Crenshaw, 1991). Kulkarni (2018) proposed an intersectional trauma-informed approach to delivering services to survivors of intimate partner violence which highlighted the importance of power sharing, clinician authenticity, individualized services for survivors, and systems advocacy as the core elements of survivor-centered advocacy and culturally specific, trauma-informed care. I propose that university counseling centers build CSA treatment programming with these elements in mind to deliver intersectional, trauma-informed care to students.

Recommendations for Future Research

The present study is the first of its kind to take a latent variable mixture modeling approach to understand the heterogeneity of student responses to elements of campus climate. The present study uncovered the existence of homogenous subgroups of students that highlight the multitude of ways students might experience their campus climate based on their personhood and ecology. The present study should serve as a continued call to action for future research to continue to seek to understand campus climate and CSA with latent variable modeling and other novel approaches to understanding complex data. While the present study utilized LCA to analyze elements of campus climate, there are implications for future research in the use of LPA to uncover discrete latent subgroups of students based on continuous manifest variables. The use of LPA can assist future researchers in developing typologies to improve theories related to sexual violence and campus climate. Additionally, a multilevel latent class analysis might be used to examine the impact of nested structures on college campuses between individuals and communities or groups of students to understand how campus climate and CSA is

experienced within and between communities. As campus climate surveys are distributed at nearly every IHE, using a latent variable modeling approach to further validate the existence of latent subgroups of students might assist IHEs and federal policymakers in understanding the nuanced experiences of survivors. A specific recommendation for using latent variable modeling in the development of theory to further understand campus climate and sexual victimization is by examining the frequency of responses on a reduced number of items that are most representative of the constructs of interest. This strategy reduces the overall number of possible response patterns, thereby strengthening the consistency among latent subgroups and making it simpler to analyze.

As was explored earlier, CSA victimization research has long been plagued by measurement issues, methodological challenges, and inconclusive predictive designs. Future research should continue to advocate for valid and reliable scales measuring campus climate and sexual victimization. In the present study, a reduced 3-point Likert-style scale was used to increase interpretability of the latent classes. It is recommended in the development of future campus climate surveys that the number of Likert-style scale points be reduced at the inception of surveys, this procedure being justified using psychometric properties and IRT. IRT assumes that latent variables are represented on a continuum and for items to have utility, they must be able to differentiate amongst persons on that continuum (de Ayala, 2009). The use of IRT in the development of campus climate surveys can help to produce precise measurement instruments that provide accurate person estimates on latent variables (de Ayala, 2019). Additionally, campus climate surveys and CSA research should seek to examine additional ecological variables including Greek organization membership, the impact of Division I athletics,

the ways in which Title IX changes impact campus policy and interventions strategies as well as quantifying the impact of macro- and chronosystem influences on rape culture. In conclusion, CSA victimization researchers should use statistical and methodological ingenuity to understand CSA as a complex problem.

The present study revealed that students with marginalized identities are most likely to reside in the Fearful and Jaded class, pointing to experiences of disenfranchisement among students with marginalized identities. Future research should seek to explore this relationship further to understand the ways in which students experience oppression at their IHE. An interesting direction to take future research might to be understand the experiences of students with intersectional identities to determine if there is a multiplicative effect of marginalized identities and feelings of distrust in one's IHE. Additionally, the present study highlighted an additional gap in the research literature regarding CSA which has historically excluded graduate students. Future research should continue to include graduate students in campus climate surveys and seek to explore intervention and prevention strategies with and for graduate students as they constitute an important part of campus communities.

While the present study did examine ecological variables as predictors of latent class membership, it was somewhat limited by the availability of truly ecological variables. Future research should seek to include and expand upon measures of campus ecology to include measures of rape myth acceptance, the existence and pervasiveness of rape culture on campus, and seek to understand how chronosystem influences like the #MeToo movement and others have impacted current college students' experiences of CSA. Urie Bronfenbrenner could not have predicted how pervasive the internet would

become when he developed his ecological systems theory in 1979. Future research should include the ecological impact of online interactions and social media networks on personhood, the interaction between and among persons and their environments and the development of both. In particular, the ecology of sexual violence is greatly impacted by students' use of social media apps and online dating services to meet with and connect with one another. A review by Henry and Powell (2018) revealed very little conclusive or rigorous research on the impact of technology-facilitated sexual violence and called for sexual violence researchers to include the impact of technology when studying sexual violence. Additionally, a study by Andrighetto et al. (2018) found that online dating rejection was related to male hostility towards women and the endorsement of rape myths. As students seek to connect with one another online, future research should include the impact of online dating and social media on the ecology of CSA.

As previously mentioned, new Title IX regulations went into effect in August 2020, and due to the COVID-19 pandemic, many universities have seen a decrease in on-campus enrollment, and therefore, incidences of sexual violence. As the COVID-19 pandemic slowly becomes an event of the past, and IHEs expect the return to campus in the Fall 2021 semester, universities should continue to monitor the ways in which changes to Title IX impact the experiences of students. If IHEs made significant changes to their Title IX procedures, they should continue to use data to inform the efficacy of their procedures and programming.

Finally, there is an argument to be had on the ways in which Title IX, while well intentioned, impacts both accusers and accused parties negatively. Future research efforts should continue to examine the ways that novel approaches can be used to manage

complaints of sexual violence more effectively. For example, many legal scholars have pointed to restorative justice efforts as an effective alternative to the way that most Title IX complaints are handled. Future researchers should continue to examine the efficacy of CSA intervention and prevention efforts in order increase on-campus safety and protect students from sexual violence.

Conclusion

In summary, the present study uncovered latent subgroups of students based on elements of campus climate including perceived risk of CSA, knowledge of on-campus resources, and perceptions of responses to reporting an incident of CSA. Results uncovered four distinct latent classes that were able to be interpreted and understood based on the heterogenous responses of students' experience of campus climate. The latent subgroups enable IHEs to target prevention efforts towards certain groups of students based on their response patterns to help students identify realistic risk of CSA on campus, increase knowledge of resources available to them, and rebuild intuitional trust. IHEs need to provide transparency and education to students on how to prevent CSA and know where to get help if they or a friend might need it. Additionally, the present study amplifies the categorical disenfranchisement of students with marginalized identities. While white, heterosexual, able-bodied cis-men might experience relative safety and trust of the IHE as it relates to CSA, students with marginalized identities are not granted that privilege and are most likely to be in the Fearful and Jaded class. These results begin the discussion of the intersection between how a student's personhood and ecology interact to impact outcomes, with students with marginalized identities being at a much higher

risk to experience institutional disenfranchisement, and subsequently, worsened mental and physical health outcomes.

Additionally, the present study sought to take on an ecological systems theoretical framework to understand the impact of micro- and mesosystem variables on latent class membership and discovered that larger micro- and mesosystems in the participation of on-campus organizations was related to increased knowledge of campus resources and being in the Knowledge is Power class. However, there was also evidence that being in a partnered relationship was related to being in the Fearful and Jaded class. These results highlight the ways in which students use their social support system to feel connected to campus, and represent increased opportunities for students in many on-campus organizations to have increased exposure to prevention programming. Additionally, the results highlight the dangers of dating violence and sexual violence by current or former dating partners, lending the results to call for additional preventative programming regarding dating violence. The present study also discovered exo- and macrosystem factors predict latent class membership with smaller and private universities having students with a greater likelihood of being in the Fearful and Jaded class. These results highlight the need for IHEs to allocate adequate resources towards Title IX coordination and CSA prevention programming. Results from this research question also highlighted regional differences among students, with students at Northeastern universities being more likely to reside in the Fearful and Jaded class, pointing to some novel regional culture implications as it relates to campus climate of US colleges and universities.

In conclusion, the present study utilized a novel approach to understand campus climate by examining patterns of responses in the AAU Campus Climate Survey on

Sexual Assault Sexual Misconduct. Results of the present study seek to inform student affairs professionals, administrators, policymakers to make college campuses safer and more supportive environments for all students.

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Appendix A

Statistical Code for Confirmatory Factor Analysis

All code was adapted from Rosseel (2012)

```{r}
library(haven)
CFA_Variables <- read_sav("datafile.sav")
View(CFA_Variables)
library(lavaan)
```

Model 1 = orthogonal model, three factors, all items.##
```{r}
Model1 <- '
f1 =~ B1 + B2 + B3
f2 =~ C2A + C2B + C2C + C2D
f3 =~ I1 + I2 + I3 + I4 + I5 + I6 + I7'
fitm1 <- cfa(Model1, data = CFA_Variables, orthogonal = TRUE, estimator = "MLM",
mimic = "Mplus")
```

##parameter estimation of model 1##
```{r}
partable(fitm1)
```

##Fit statistics of model 1##
```{r}
summary(fitm1, standardized = TRUE, fit.measures = TRUE)
```

##Model 2 = oblique model, three factors, all items##
```{r}
Model2 <- '
f1 =~ B1 + B2 + B3
f2 =~ C2A + C2B + C2C + C2D
f3 =~ I1 + I2 + I3 + I4 + I5 + I6 + I7

f1 ~~ f2 + f3
f2 ~~ f3'
fitm2 <- cfa(Model2, data = CFA_Variables, estimator = "MLM", mimic = "Mplus")
```

##parameter estimation of model 2##

```{r}
partable(fitm2)
parameterestimates(fitm2)
```

##fit statistics of model 2##
```{r}
summary(fitm2, standardized = TRUE, fit.measures = TRUE)
```

##Model 3 = single factor model##
```{r}
Model3 <- '
f1 =~ B1 + B2 + B3 + C2A + C2B + C2C + C2D + I1 + I2 + I3 + I4 + I5 + I6 + I7'
fitm3 <- cfa(Model3, data = CFA_Variables, estimator = "MLM", mimic = "Mplus")
```

##parameter estimation of model 3##
```{r}
partable(fitm3)
```

##fit statistics of model 3##
```{r}
summary(fitm3, standardized = TRUE, fit.measures = TRUE)
```

##Model 4 = oblique model, three factors, removing item I2##
```{r}
Model4 <- '
f1 =~ B1 + B2 + B3
f2 =~ C2A + C2B + C2C + C2D
f3 =~ I1 + I3 + I4 + I5 + I6 + I7

f1 ~~ f2 + f3
f2 ~~ f3'
fitm4 <- cfa(Model4, data = CFA_Variables, estimator = "MLM", mimic = "Mplus")
```

##parameter estimation of model 4##
```{r}
partable(fitm4)
```

##fit statistics of model 4##
```{r}
```

```
summary(fitm4, standardized = TRUE, fit.measures = TRUE)
```

##Model 5 = using item I2 as its own factor
```{r}
Model5 <- '
f1 =~ B1 + B2 + B3
f2 =~ C2A + C2B + C2C + C2D
f3 =~ I1 + I3 + I4 + I5 + I6 + I7
f4 =~ I2

f1 ~~ f2 + f3 + f4
f2 ~~ f3 + f4
f3 ~~ f4'
fitm5 <- cfa(Model5, data = CFA_Variables, estimator = "MLM", mimic = "Mplus")
summary(fitm5, standardized = TRUE, estimates = TRUE, fit.measures = TRUE)
```
##comparing Model 2 which includes I2 in F3 to model 5 which makes I2 it's own factor
```{r}
anova(fitm2, fitm1)
anova(fitm2,fitm3)
anova(fitm5,fitm2)
```

Appendix B

Statistical Code For Latent Class Analysis

Code was adapted from Linzer and Lewis (2011) with additional code from Ohlsen (2015) and DeSante and Sparks (2012)

##File source
```{r}
tempfile(tmpdir="filedirectory ")
LCA_Data <- read_sav("datafile.sav")
```

##libraries
```{r}
library(haven)
library("reshape2")
library("plyr")
library("dplyr")
library("poLCA")
library("ggplot2")
library("ggparallel")
library("igraph")
library("tidyr")
library("knitr")
library("forcats")
library("effects")
```

##Latent class formula
```{r}
formula1 <- cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R, I2_R, I3_R, I4_R, I5_R, I6_R, I7_R) ~ 1
```

##run a sequence of models with 1-10 classes and print out the model with the lowest BIC
```{r}
max_II <- -100000
min_bic <- 100000
for(i in 2:10)
  lc <- poLCA(formula1, LCA_Data, nclass=i, maxiter=3000,
              tol=1e-5, na.rm=FALSE,
              nrep=10, verbose=TRUE, calc.se=TRUE)
```

```{r}
  if(lc$bic <- min_bic)
    {min_bic <- lc$bic
    LCA_best_model <- lc}
LCA_best_model
```

##Run series of latent class models 1-9
```{r}
set.seed(01012)
lc1<-poLCA(formula1, data=LCA_Data, nclass=1, na.rm = FALSE, nrep=10,
maxiter=3000) #Loglinear independence model.
lc2<-poLCA(formula1, data=LCA_Data, nclass=2, na.rm = FALSE, nrep=10,
maxiter=3000)
lc3<-poLCA(formula1, data=LCA_Data, nclass=3, na.rm = FALSE, nrep=10,
maxiter=3000)
lc4<-poLCA(formula1, data=LCA_Data, nclass=4, na.rm = FALSE, nrep=10,
maxiter=3000)
lc5<-poLCA(formula1, data=LCA_Data, nclass=5, na.rm = FALSE, nrep=10,
maxiter=3000)
lc6<-poLCA(formula1, data=LCA_Data, nclass=6, na.rm = FALSE, nrep=10,
maxiter=3000)
lc7<-poLCA(formula1, data=LCA_Data, nclass=7, na.rm = FALSE, nrep=10,
maxiter=3000)
lc8<-poLCA(formula1, data=LCA_Data, nclass=8, na.rm = FALSE, nrep=10,
maxiter=3000)
lc9<-poLCA(formula1, data=LCA_Data, nclass=9, na.rm = FALSE, nrep=10,
maxiter=3000)
```

##Fit value data for class models 1-9
```{r}
# generate dataframe with fit-values

results <- data.frame(Model=c("Model 1"),
                      LL=lc1$llik,
                      df = lc1$resid.df,
                      BIC=lc1$bic,
                      ABIC=  (-2*lc1$llik) + ((log((lc1$N + 2)/24)) * lc1$npar),
                      CAIC = (-2*lc1$llik) + lc1$npar * (1 + log(lc1$N)),
                      LLR=lc1$Gsq)
results$Model<-as.integer(results$Model)
results[1,1]<-c("Model 1")
results[2,1]<-c("Model 2")
results[3,1]<-c("Model 3")
results[4,1]<-c("Model 4")
```

```
results[5,1]<-c("Model 5")
results[6,1]<-c("Model 6")
results[7,1]<-c("Model 7")
results[8,1]<-c("Model 8")
results[9,1]<-c("Model 9")


results[2,2]<-lc2$llik
results[3,2]<-lc3$llik
results[4,2]<-lc4$llik
results[5,2]<-lc5$llik
results[6,2]<-lc6$llik
results[7,2]<-lc7$llik
results[8,2]<-lc8$llik
results[9,2]<-lc9$llik


results[2,3]<-lc2$resid.df
results[3,3]<-lc3$resid.df
results[4,3]<-lc4$resid.df
results[5,3]<-lc5$resid.df
results[6,3]<-lc6$resid.df
results[7,3]<-lc7$resid.df
results[8,3]<-lc8$resid.df
results[9,3]<-lc9$resid.df


results[2,4]<-lc2$bic
results[3,4]<-lc3$bic
results[4,4]<-lc4$bic
results[5,4]<-lc5$bic
results[6,4]<-lc6$bic
results[7,4]<-lc7$bic
results[8,4]<-lc8$bic
results[9,4]<-lc9$bic


results[2,5]<-(-2*lc2$llik) + ((log((lc2$N + 2)/24)) * lc2$npar) #abic
results[3,5]<-(-2*lc3$llik) + ((log((lc3$N + 2)/24)) * lc3$npar)
results[4,5]<-(-2*lc4$llik) + ((log((lc4$N + 2)/24)) * lc4$npar)
results[5,5]<-(-2*lc5$llik) + ((log((lc5$N + 2)/24)) * lc5$npar)
results[6,5]<-(-2*lc6$llik) + ((log((lc6$N + 2)/24)) * lc6$npar)
results[7,5]<-(-2*lc7$llik) + ((log((lc7$N + 2)/24)) * lc7$npar)
results[8,5]<-(-2*lc8$llik) + ((log((lc8$N + 2)/24)) * lc8$npar)
results[9,5]<-(-2*lc9$llik) + ((log((lc9$N + 2)/24)) * lc9$npar)
```

```
results[2,6]<- (-2*lc2$llik) + lc2$npar * (1 + log(lc2$N)) #caic
results[3,6]<- (-2*lc3$llik) + lc3$npar * (1 + log(lc3$N))
results[4,6]<- (-2*lc4$llik) + lc4$npar * (1 + log(lc4$N))
results[5,6]<- (-2*lc5$llik) + lc5$npar * (1 + log(lc5$N))
results[6,6]<- (-2*lc6$llik) + lc6$npar * (1 + log(lc6$N))
results[7,6]<- (-2*lc7$llik) + lc7$npar * (1 + log(lc7$N))
results[8,6]<- (-2*lc8$llik) + lc8$npar * (1 + log(lc8$N))
results[9,6]<- (-2*lc9$llik) + lc9$npar * (1 + log(lc9$N))


results[2,7]<-lc2$Gsq
results[3,7]<-lc3$Gsq
results[4,7]<-lc4$Gsq
results[5,7]<-lc5$Gsq
results[6,7]<-lc6$Gsq
results[7,7]<-lc7$Gsq
results[8,7]<-lc8$Gsq
results[9,7]<-lc9$Gsq
```

```
##Calculating Entropy
```{r}
entropy<-function (p) sum(-p*log(p))

results$R2_entropy
results[1,8]<-c("-")

error_prior<-entropy(lc2$P) # class proportions model 2
error_post<-mean(apply(lc2$posterior,1, entropy),na.rm = TRUE)
results[2,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(lc3$P) # class proportions model 3
error_post<-mean(apply(lc3$posterior,1, entropy),na.rm = TRUE)
results[3,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(lc4$P) # class proportions model 4
error_post<-mean(apply(lc4$posterior,1, entropy),na.rm = TRUE)
results[4,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(lc5$P) # class proportions model 5
error_post<-mean(apply(lc5$posterior,1, entropy),na.rm = TRUE)
results[5,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(lc6$P) # class proportions model 6
error_post<-mean(apply(lc6$posterior,1, entropy),na.rm = TRUE)
```
```

```
results[6,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(lc7$P) # class proportions model 7
error_post<-mean(apply(lc7$posterior,1, entropy),na.rm = TRUE)
results[7,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(lc8$P) # class proportions model 8
error_post<-mean(apply(lc8$posterior,1, entropy),na.rm = TRUE)
results[8,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(lc9$P) # class proportions model 9
error_post<-mean(apply(lc9$posterior,1, entropy),na.rm = TRUE)
results[9,8]<-round(((error_prior-error_post) / error_prior),3)

# combining results to a dataframe
colnames(results)<-c("Model","log-likelihood","resid.
df","BIC","aBIC","cAIC","likelihood-ratio","Entropy")
lca_results<-results

```

##Scree plot with fit statistics code adapted from Ohlson (2015)
```{r}

#convert to long format
results2 <- tidyr::gather(results,Kriterium,Guete,4:7)
results2

#plot
fit.plot <- ggplot(results2) +
  geom_point(aes(x=Model,y=Guete),size=3) +
  geom_line(aes(Model, Guete, group = 1)) +
  theme_bw()+
  labs(x = "", y="", title = "") +
  facet_grid(Kriterium ~. ,scales = "free") +
  theme_bw(base_size = 12, base_family = "") +
  theme(panel.grid.major.x = element_blank() ,
        panel.grid.major.y = element_line(colour="grey", size=0.5),
        legend.title = element_text(size = 8, face = 'bold'),
        axis.text = element_text(size = 8),
        axis.title = element_text(size = 8),
        legend.text=  element_text(size=8),
        axis.line = element_line(colour = "black")) # Achsen etwas dicker

# save 650 x 800
fit.plot
```

```

### 4 class model plot with class names - cleaned up. Code adapted from DeSante & Sparks 2012
```{r}
lcModelProbs <- melt(vvlc4$probs)

zp1 <- ggplot(lcModelProbs,
          aes(x = L1, y = value, fill = Var2))
zp1 <- zp1 + geom_bar(stat = "identity", position = "stack")
zp1 <- zp1 + facet_wrap(~Var1, labeller = as_labeller(
  c(`class 1: ` = "Class 1: Ambivalent", `class 2: ` = "Class 2: Knowledge is Power",
    `class 3: ` = "Class 3: Ignorance is Bliss",
    `class 4: ` = "Class 4: Fearful and Jaded")))
zp1 <- zp1 + scale_fill_discrete(name = "Response", labels = c("Disagree (1)", "Neutral (2)", "Agree (3)"))
zp1 <- zp1 + scale_x_discrete(breaks=c("B1_r", "B2_r",
                          "B3_r", "C2A_R", "C2B_R",
                          "C2C_R", "C2D_R", "I1_R", "I2_R",
                          "I3_R", "I4_R", "I5_R", "I6_R", "I7_R"),
                   labels=c("B1", "B2",
                          "B3", "C2A", "C2B",
                          "C2C", "C2D", "I1", "I2",
                          "I3", "I4", "I5", "I6", "I7"))
zp1 <- zp1 + labs(title = "Latent Classes of Students on Measures of Campus Climate",
                subtitle = "Four-class model",
                x = "Item", y = "Conditional Item Response Probabilities")


print (zp1)
```

##Validation of the model by splitting the data randomly
```{r}
splitdata1 <- read_sav("/Volumes/Scratch/splitfile1.sav")

split1.1<-poLCA(formula1, data=splitdata1, nclass=1, na.rm = FALSE, nrep=10, maxiter=3000) #Loglinear independence model.
split1.2<-poLCA(formula1, data=splitdata1, nclass=2, na.rm = FALSE, nrep=10, maxiter=3000)
split1.3<-poLCA(formula1, data=splitdata1, nclass=3, na.rm = FALSE, nrep=10, maxiter=3000)
split1.4<-poLCA(formula1, data=splitdata1, nclass=4, na.rm = FALSE, nrep=10, maxiter=3000)
split1.5<-poLCA(formula1, data=splitdata1, nclass=5, na.rm = FALSE, nrep=10, maxiter=3000)

```
split1.6<-poLCA(formula1, data=splitdata1, nclass=6, na.rm = FALSE, nrep=10,
maxiter=3000)
split1.7<-poLCA(formula1, data=splitdata1, nclass=7, na.rm = FALSE, nrep=10,
maxiter=3000)
split1.8<-poLCA(formula1, data=splitdata1, nclass=8, na.rm = FALSE, nrep=10,
maxiter=3000)
split1.9<-poLCA(formula1, data=splitdata1, nclass=9, na.rm = FALSE, nrep=10,
maxiter=3000)
```

```{r}
split1results <- data.frame(Model=c("Model 1"),
                log_likelihood=split1.1$llik,
                df = split1.1$resid.df,
                BIC=split1.1$bic,
                ABIC=  (-2*split1.1$llik) + ((log((split1.1$N + 2)/24)) * split1.1$npar),
                CAIC = (-2*split1.1$llik) + split1.1$npar * (1 + log(split1.1$N)),
                likelihood_ratio=split1.1$Gsq)
split1results$Model<-as.integer(split1results$Model)
split1results[1,1]<-c("Model 1")
split1results[2,1]<-c("Model 2")
split1results[3,1]<-c("Model 3")
split1results[4,1]<-c("Model 4")
split1results[5,1]<-c("Model 5")
split1results[6,1]<-c("Model 6")
split1results[7,1]<-c("Model 7")
split1results[8,1]<-c("Model 8")
split1results[9,1]<-c("Model 9")


split1results[2,2]<-split1.2$llik
split1results[3,2]<-split1.3$llik
split1results[4,2]<-split1.4$llik
split1results[5,2]<-split1.5$llik
split1results[6,2]<-split1.6$llik
split1results[7,2]<-split1.7$llik
split1results[8,2]<-split1.8$llik
split1results[9,2]<-split1.9$llik


split1results[2,3]<-split1.2$resid.df
split1results[3,3]<-split1.3$resid.df
split1results[4,3]<-split1.4$resid.df
split1results[5,3]<-split1.5$resid.df
split1results[6,3]<-split1.6$resid.df
```

```
split1results[7,3]<-split1.7$resid.df
split1results[8,3]<-split1.8$resid.df
split1results[9,3]<-split1.9$resid.df


split1results[2,4]<-split1.2$bic
split1results[3,4]<-split1.3$bic
split1results[4,4]<-split1.4$bic
split1results[5,4]<-split1.5$bic
split1results[6,4]<-split1.6$bic
split1results[7,4]<-split1.7$bic
split1results[8,4]<-split1.8$bic
split1results[9,4]<-split1.9$bic


split1results[2,5]<-(-2*split1.2$llik) + ((log((split1.2$N + 2)/24)) * split1.2$npar) #abic
split1results[3,5]<-(-2*split1.3$llik) + ((log((split1.3$N + 2)/24)) * split1.3$npar)
split1results[4,5]<-(-2*split1.4$llik) + ((log((split1.4$N + 2)/24)) * split1.4$npar)
split1results[5,5]<-(-2*split1.5$llik) + ((log((split1.5$N + 2)/24)) * split1.5$npar)
split1results[6,5]<-(-2*split1.6$llik) + ((log((split1.6$N + 2)/24)) * split1.6$npar)
split1results[7,5]<-(-2*split1.7$llik) + ((log((split1.7$N + 2)/24)) * split1.7$npar)
split1results[8,5]<-(-2*split1.8$llik) + ((log((split1.8$N + 2)/24)) * split1.8$npar)
split1results[9,5]<-(-2*split1.9$llik) + ((log((split1.9$N + 2)/24)) * split1.9$npar)


split1results[2,6]<- (-2*split1.2$llik) + split1.2$npar * (1 + log(split1.2$N)) #caic
split1results[3,6]<- (-2*split1.3$llik) + split1.3$npar * (1 + log(split1.3$N))
split1results[4,6]<- (-2*split1.4$llik) + split1.4$npar * (1 + log(split1.4$N))
split1results[5,6]<- (-2*split1.5$llik) + split1.5$npar * (1 + log(split1.5$N))
split1results[6,6]<- (-2*split1.6$llik) + split1.6$npar * (1 + log(split1.6$N))
split1results[7,6]<- (-2*split1.7$llik) + split1.7$npar * (1 + log(split1.7$N))
split1results[8,6]<- (-2*split1.8$llik) + split1.8$npar * (1 + log(split1.8$N))
split1results[9,6]<- (-2*split1.9$llik) + split1.9$npar * (1 + log(split1.9$N))


split1results[2,7]<-split1.2$Gsq
split1results[3,7]<-split1.3$Gsq
split1results[4,7]<-split1.4$Gsq
split1results[5,7]<-split1.5$Gsq
split1results[6,7]<-split1.6$Gsq
split1results[7,7]<-split1.7$Gsq
split1results[8,7]<-split1.8$Gsq
split1results[9,7]<-split1.9$Gsq
```

```{r}
```

```
entropy<-function (p) sum(-p*log(p))

split1results$R2_entropy
split1results[1,8]<-c("-")

error_prior<-entropy(split1.2$P) # class proportions model 2
error_post<-mean(apply(split1.2$posterior,1, entropy),na.rm = TRUE)
split1results[2,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(split1.3$P) # class proportions model 3
error_post<-mean(apply(split1.3$posterior,1, entropy),na.rm = TRUE)
split1results[3,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(split1.4$P) # class proportions model 4
error_post<-mean(apply(split1.4$posterior,1, entropy),na.rm = TRUE)
split1results[4,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(split1.5$P) # class proportions model 5
error_post<-mean(apply(split1.5$posterior,1, entropy),na.rm = TRUE)
split1results[5,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(split1.6$P) # class proportions model 6
error_post<-mean(apply(split1.6$posterior,1, entropy),na.rm = TRUE)
split1results[6,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(split1.7$P) # class proportions model 7
error_post<-mean(apply(split1.7$posterior,1, entropy),na.rm = TRUE)
split1results[7,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(split1.8$P) # class proportions model 8
error_post<-mean(apply(split1.8$posterior,1, entropy),na.rm = TRUE)
split1results[8,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(split1.9$P) # class proportions model 9
error_post<-mean(apply(split1.8$posterior,1, entropy),na.rm = TRUE)
split1results[9,8]<-round(((error_prior-error_post) / error_prior),3)

# combining results to a dataframe
colnames(results)<-c("Model","log-likelihood","resid.
df","BIC","aBIC","cAIC","likelihood-ratio","Entropy")
split1.lca_results<-split1results
```

```{r}
#convert to long format
splitresults2 <- tidyr::gather(split1results,Kriterium,Guete,4:7)
```

```
splitresults2

#plot
fit.plot <- ggplot(splitresults2) +
  geom_point(aes(x=Model,y=Guete),size=3) +
  geom_line(aes(Model, Guete, group = 1)) +
  theme_bw()+
  labs(x = "", y="", title = "") +
  facet_grid(Kriterium ~. ,scales = "free") +
  theme_bw(base_size = 12, base_family = "") +
  theme(panel.grid.major.x = element_blank() ,
        panel.grid.major.y = element_line(colour="grey", size=0.5),
        legend.title = element_text(size = 8, face = 'bold'),
        axis.text = element_text(size = 8),
        axis.title = element_text(size = 8),
        legend.text=  element_text(size=8),
        axis.line = element_line(colour = "black")) # Achsen etwas dicker
# save 650 x 800
fit.plot
```

```{r}
splitdata2 <- read_sav("/Volumes/Scratch/splitfile2.sav")

split2.1<-poLCA(formula1, data=splitdata2, nclass=1, na.rm = FALSE, nrep=10,
maxiter=3000) #Loglinear independence model.
split2.2<-poLCA(formula1, data=splitdata2, nclass=2, na.rm = FALSE, nrep=10,
maxiter=3000)
split2.3<-poLCA(formula1, data=splitdata2, nclass=3, na.rm = FALSE, nrep=10,
maxiter=3000)
split2.4<-poLCA(formula1, data=splitdata2, nclass=4, na.rm = FALSE, nrep=10,
maxiter=3000)
split2.5<-poLCA(formula1, data=splitdata2, nclass=5, na.rm = FALSE, nrep=10,
maxiter=3000)
split2.6<-poLCA(formula1, data=splitdata2, nclass=6, na.rm = FALSE, nrep=10,
maxiter=3000)
split2.7<-poLCA(formula1, data=splitdata2, nclass=7, na.rm = FALSE, nrep=10,
maxiter=3000)
split2.8<-poLCA(formula1, data=splitdata2, nclass=8, na.rm = FALSE, nrep=10,
maxiter=3000)
split2.9<-poLCA(formula1, data=splitdata2, nclass=9, na.rm = FALSE, nrep=10,
maxiter=3000)
```

```{r}
```

```
split2results <- data.frame(Model=c("Model 1"),
                log_likelihood=split2.1$llik,
                df = split2.1$resid.df,
                BIC=split2.1$bic,
                ABIC=  (-2*split2.1$llik) + ((log((split2.1$N + 2)/24)) * split2.1$npar),
                CAIC = (-2*split2.1$llik) + split2.1$npar * (1 + log(split2.1$N)),
                likelihood_ratio=split2.1$Gsq)
split2results$Model<-as.integer(split2results$Model)
split2results[1,1]<-c("Model 1")
split2results[2,1]<-c("Model 2")
split2results[3,1]<-c("Model 3")
split2results[4,1]<-c("Model 4")
split2results[5,1]<-c("Model 5")
split2results[6,1]<-c("Model 6")
split2results[7,1]<-c("Model 7")
split2results[8,1]<-c("Model 8")
split2results[9,1]<-c("Model 9")


split2results[2,2]<-split2.2$llik
split2results[3,2]<-split2.3$llik
split2results[4,2]<-split2.4$llik
split2results[5,2]<-split2.5$llik
split2results[6,2]<-split2.6$llik
split2results[7,2]<-split2.7$llik
split2results[8,2]<-split2.8$llik
split2results[9,2]<-split2.9$llik


split2results[2,3]<-split2.2$resid.df
split2results[3,3]<-split2.3$resid.df
split2results[4,3]<-split2.4$resid.df
split2results[5,3]<-split2.5$resid.df
split2results[6,3]<-split2.6$resid.df
split2results[7,3]<-split2.7$resid.df
split2results[8,3]<-split2.8$resid.df
split2results[9,3]<-split2.9$resid.df


split2results[2,4]<-split2.2$bic
split2results[3,4]<-split2.3$bic
split2results[4,4]<-split2.4$bic
split2results[5,4]<-split2.5$bic
split2results[6,4]<-split2.6$bic
split2results[7,4]<-split2.7$bic
split2results[8,4]<-split2.8$bic
```

```
split2results[9,4]<-split2.9$bic


split2results[2,5]<-(-2*split2.2$llik) + ((log((split2.2$N + 2)/24)) * split2.2$npar) #abic
split2results[3,5]<-(-2*split2.3$llik) + ((log((split2.3$N + 2)/24)) * split2.3$npar)
split2results[4,5]<-(-2*split2.4$llik) + ((log((split2.4$N + 2)/24)) * split2.4$npar)
split2results[5,5]<-(-2*split2.5$llik) + ((log((split2.5$N + 2)/24)) * split2.5$npar)
split2results[6,5]<-(-2*split2.6$llik) + ((log((split2.6$N + 2)/24)) * split2.6$npar)
split2results[7,5]<-(-2*split2.7$llik) + ((log((split2.7$N + 2)/24)) * split2.7$npar)
split2results[8,5]<-(-2*split2.8$llik) + ((log((split2.8$N + 2)/24)) * split2.8$npar)
split2results[9,5]<-(-2*split2.9$llik) + ((log((split2.9$N + 2)/24)) * split2.9$npar)


split2results[2,6]<- (-2*split2.2$llik) + split2.2$npar * (1 + log(split2.2$N)) #caic
split2results[3,6]<- (-2*split2.3$llik) + split2.3$npar * (1 + log(split2.3$N))
split2results[4,6]<- (-2*split2.4$llik) + split2.4$npar * (1 + log(split2.4$N))
split2results[5,6]<- (-2*split2.5$llik) + split2.5$npar * (1 + log(split2.5$N))
split2results[6,6]<- (-2*split2.6$llik) + split2.6$npar * (1 + log(split2.6$N))
split2results[7,6]<- (-2*split2.7$llik) + split2.7$npar * (1 + log(split2.7$N))
split2results[8,6]<- (-2*split2.8$llik) + split2.8$npar * (1 + log(split2.8$N))
split2results[9,6]<- (-2*split2.9$llik) + split2.9$npar * (1 + log(split2.9$N))


split2results[2,7]<-split2.2$Gsq
split2results[3,7]<-split2.3$Gsq
split2results[4,7]<-split2.4$Gsq
split2results[5,7]<-split2.5$Gsq
split2results[6,7]<-split2.6$Gsq
split2results[7,7]<-split2.7$Gsq
split2results[8,7]<-split2.8$Gsq
split2results[9,7]<-split2.9$Gsq
```

```{r}
entropy<-function (p) sum(-p*log(p))

split2results$R2_entropy
split2results[1,8]<-c("-")

error_prior<-entropy(split2.2$P) # class proportions model 2
error_post<-mean(apply(split2.2$posterior,1, entropy),na.rm = TRUE)
split2results[2,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(split2.3$P) # class proportions model 3
error_post<-mean(apply(split2.3$posterior,1, entropy),na.rm = TRUE)
split2results[3,8]<-round(((error_prior-error_post) / error_prior),3)
```

```
error_prior<-entropy(split2.4$P) # class proportions model 4
error_post<-mean(apply(split2.4$posterior,1, entropy),na.rm = TRUE)
split2results[4,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(split2.5$P) # class proportions model 5
error_post<-mean(apply(split2.5$posterior,1, entropy),na.rm = TRUE)
split2results[5,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(split2.6$P) # class proportions model 6
error_post<-mean(apply(split2.6$posterior,1, entropy),na.rm = TRUE)
split2results[6,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(split2.7$P) # class proportions model 7
error_post<-mean(apply(split2.7$posterior,1, entropy),na.rm = TRUE)
split2results[7,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(split2.8$P) # class proportions model 8
error_post<-mean(apply(split2.8$posterior,1, entropy),na.rm = TRUE)
split2results[8,8]<-round(((error_prior-error_post) / error_prior),3)

error_prior<-entropy(split2.9$P) # class proportions model 9
error_post<-mean(apply(split2.8$posterior,1, entropy),na.rm = TRUE)
split2results[9,8]<-round(((error_prior-error_post) / error_prior),3)

# combining results to a dataframe
colnames(results)<-c("Model","log-likelihood","resid.
df","BIC","aBIC","cAIC","likelihood-ratio","Entropy")
split2.lca_results<-split2results
```

Appendix C

Statistical Code for Latent Class Regression Analyses

Code was adapted from Linzer and Lewis (2011)

##RQ 1.a - Victimization status as covariate including plot - need to add key for publication

```{r}
formula3 <-cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R, I2_R, I3_R, I4_R, I5_R, I6_R, I7_R) ~ Victimization_Status
vvlc4 <-poLCA(formula3, data=LCA_Data, nclass=4, na.rm = FALSE, nrep=10, maxiter=3000)
probs.start <- poLCA.reorder(vvlc4$probs.start, order (vvlc4$P, decreasing = T))
vvlc4 <-poLCA(formula3, data=LCA_Data, nclass=4, probs.start = probs.start)
vvlc4
```

```{r}
plot(allEffects(vvlc4))
```

```{r}
pidmat <- cbind(1,c(0:1))
exb <- exp(pidmat %*% vvlc4$coeff)
matplot(c(0:1),(cbind(1,exb)/(1+rowSums(exb))),ylim=c(0,.5),type="b",
   main="Victimization Status as as a Predictor of Latent Class",
   xlab="Victimization Status: Non-victim (0), Victim (1)",
   ylab="Probability of latent class membership",lwd=2,col=1)
```

##RQ 2: Gender identity as covariate - men as reference class

```{r}
gender.formula <-cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R, I2_R, I3_R, I4_R, I5_R, I6_R, I7_R) ~ gender_2 * gender_3
gender.lcr<-poLCA(gender.formula, data=LCA_Data, nclass=4, probs.start = probs.start)
```

women as reference class

```{r}
gender2.formula <-cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R, I2_R, I3_R, I4_R, I5_R, I6_R, I7_R) ~ gender_1 *  gender_3
gender2.lcr<-poLCA(gender2.formula, data=LCA_Data, nclass=4, probs.start = probs.start)
```

```{r}

strdems <- cbind(1, 1, c(0:1), (c(0:1) * 1))
exb.strdems <- exp(strdems %*% gender.lcr$coeff)
matplot(c(0:1), (cbind(1, exb.strdems)/(1+rowSums(exb.strdems))),
   main = "Age and candidate affinity for strong Democrats",
    xlab = "Age", ylab = "Probability of latent class membership",
 ylim = c(0, 1), type = "l", col = 1, lwd = 3)
strreps <- cbind(1, 7, c(0:1), (c(0:1) * 7))
exb.strreps <- exp(strreps %*% gender.lcr$coeff)
matplot(c(0:1), (cbind(1, exb.strreps) / (1 + rowSums(exb.strreps))),
    main = "Age and candidate affinity for strong Republicans",
   xlab = "Age", ylab = "Probability of latent class membership",
   ylim = c(0, 1), type = "l", col = 1, lwd = 3)
```

##RQ 2 - disability as covariate.
```{r}
dis.formula <-cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R, I2_R,
I3_R, I4_R, I5_R, I6_R, I7_R) ~ disability2
dis.lcr<-poLCA(dis.formula, data=LCA_Data, nclass=4, probs.start = probs.start)
```

```{r}
pidmat <- cbind(1,c(0:1))
exb <- exp(pidmat %*% dis.lcr$coeff)
matplot(c(0:1),(cbind(1,exb)/(1+rowSums(exb))),ylim=c(0,.5),type="b",
    main="Disability as as a Predictor of Latent Class",
    xlab="Disability Status: No Disability (0), Disability (1)",
    ylab="Probability of latent class membership",lwd=2,col=1)
```

##RQ 2 - sexual orientation as covariate
```{r}
lgbtq.formula <-cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R, I2_R,
I3_R, I4_R, I5_R, I6_R, I7_R) ~ LGBTQ
lgbtq.lcr<-poLCA(lgbtq.formula, data=LCA_Data, nclass=4, probs.start = probs.start)
```

```{r}
pidmat <- cbind(1,c(0:1))
exb <- exp(pidmat %*% lgbtq.lcr$coeff)
matplot(c(0:1),(cbind(1,exb)/(1+rowSums(exb))),ylim=c(0,.5),type="b",
    main="LGBTQ+ Identity as as a Predictor of Latent Class",
```

```
   xlab="LGBTQ+ Identity: Heterosexual (0), LGBTQ+ (1)",
   ylab="Probability of latent class membership",lwd=2,col=1)
```

##RQ 2 - race as covariate white as reference class
```{r}
race.formula <-cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R, I2_R,
I3_R, I4_R, I5_R, I6_R, I7_R) ~ race_2 * race_3 * race_4
race.lcr<-poLCA(race.formula, data=LCA_Data, nclass=4, probs.start = probs.start)
```

##RQ 2 - age as covariate
```{r}
age.formula <-cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R, I2_R,
I3_R, I4_R, I5_R, I6_R, I7_R) ~ AGE
age.lcr<-poLCA(age.formula, data=LCA_Data, nclass=4, probs.start = probs.start)
```
Needs labels
```{r}
pidmat <- cbind(1,c(15:30))
exb <- exp(pidmat %*% age.lcr$coeff)
matplot(c(15:30),(cbind(1,exb)/(1+rowSums(exb))),ylim=c(0,0.5),type="b",
   main="Age as as a Predictor of Latent Class",
   xlab="Age",
   ylab="Probability of latent class membership",lwd=2,col=1)
```

##RQ 3 - relationship status as covariate
```{r}
relationship.formula <-cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R,
I2_R, I3_R, I4_R, I5_R, I6_R, I7_R) ~ RELATIONSHIP
relationship.lcr<-poLCA(relationship.formula, data=LCA_Data, nclass=4, probs.start =
probs.start)
```

```{r}
pidmat <- cbind(1,c(0:1))
exb <- exp(pidmat %*% relationship.lcr$coeff)
matplot(c(0:1),(cbind(1,exb)/(1+rowSums(exb))),ylim=c(0,0.5),type="b",
   main="Relationship Status as as a Predictor of Latent Class",
   xlab="Relationship Status: Single (0), In a relationship (1)",
   ylab="Probability of latent class membership",lwd=2,col=1)
```

##RQ 3 - organization freq as covariate
```{r}
```

```
org.formula <-cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R, I2_R,
I3_R, I4_R, I5_R, I6_R, I7_R) ~ ORG_FREQ
org.lcr<-poLCA(org.formula, data=LCA_Data, nclass=4, probs.start = probs.start)
```
```{r}
pidmat <- cbind(1,c(0:20))
exb <- exp(pidmat %*% org.lcr$coeff)
matplot(c(0:20),(cbind(1,exb)/(1+rowSums(exb))),ylim=c(0,0.6),type="b",
   main="Organization Frequency as a Predictor of Latent Class",
   xlab="Number of Organizations",
   ylab="Probability of latent class membership",lwd=2,col=1)
```

##RQ 3 - online student status as covariate
```{r}
online.formula <-cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R, I2_R,
I3_R, I4_R, I5_R, I6_R, I7_R) ~ ONLINE
online.lcr<-poLCA(online.formula, data=LCA_Data, nclass=4, probs.start = probs.start)
```

```{r}
pidmat <- cbind(1,c(0:1))
exb <- exp(pidmat %*% online.lcr$coeff)
matplot(c(0:1),(cbind(1,exb)/(1+rowSums(exb))),ylim=c(0,0.5),type="b",
   main="Online Student Status as as a Predictor of Latent Class",
   xlab="Online Student Status: On-Campus Student (0), Online Student (1)",
   ylab="Probability of latent class membership",lwd=2,col=1)
```

##RQ 4 - public vs private, public as reference class
```{r}
priv.formula <-cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R, I2_R,
I3_R, I4_R, I5_R, I6_R, I7_R) ~ private1
priv.lcr<-poLCA(priv.formula, data=LCA_Data, nclass=4, probs.start = probs.start)
```
```{r}
pidmat <- cbind(1,c(0:1))
exb <- exp(pidmat %*% priv.lcr$coeff)
matplot(c(0:1),(cbind(1,exb)/(1+rowSums(exb))),ylim=c(0,0.5),type="b",
   main="University Affliation as as a Predictor of Latent Class",
   xlab="University Affiliation: Public (0), Private (1)",
   ylab="Probability of latent class membership",lwd=2,col=1)
```

##RQ4 - size as covariate with large as reference class

```{r}
size.formula <-cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R, I2_R, I3_R, I4_R, I5_R, I6_R, I7_R) ~ size_1 * size_2
size.lcr<-poLCA(size.formula, data=LCA_Data, nclass=4, probs.start = probs.start)
```

##RQ4 - region as covariate with north east as reference class
```{r}
region.formula <-cbind(B1_r, B2_r, B3_r, C2A_R, C2B_R, C2C_R, C2D_R, I1_R, I2_R, I3_R, I4_R, I5_R, I6_R, I7_R) ~ region_1 * region_3 * region_4
region.lcr<-poLCA(region.formula, data=LCA_Data, nclass=4, probs.start = probs.start)
```