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A CRITICAL EXAMINATION OF THE IMPACT OF SOCIAL STRATIFICATION AND THE ENVIRONMENT ON BRAIN DEVELOPMENT AND MENTAL HEALTH

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The journey to complete this document has been arduous, enlightening, but most importantly, extremely humbling. To say that it takes a village is an extreme understatement. Anyone who knows me understands that although I am the greatest cheerleader to those around me, I often fail to return myself the favor. One important hack I've learned over the years, or perhaps subconsciously knew the whole time, is to surround myself with individuals that find some element of myself worthy of support, and it is all of these people that I have to thank. Much like *Avengers: Infinity War*, it is extremely overwhelming when you realize how many characters have contributed to making this project happen. The least I can do is honor them here, in what has been promised to be an immortalized piece of academic history. In the *Harry Potter* universe, this would definitely be one of my horcruxes. I am a part of it as much as it is a part of me.

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ABSTRACT

Unprecedented economic inequality has motivated scholarly work in disciplines as diverse as sociology, public health, psychology, and economics. In doing so, much of this research has converged on what may be considered optimal indicators of socioeconomic status (SES), such as educational attainment, income, and occupation. However, a much less considered aspect of this research and the use of these indicators has been the notion that although this research has the opportunity for widespread impact, without critically acknowledging its impact within a social and cultural context, this research may contribute to existing narratives that perpetuate and support the marginalization of historically underrepresented groups and further reinforce structural inequality. This dissertation will review a few frameworks that aim to address the multi-level factors related to social stratification that may impact health, behavior, and development beyond the traditional indicators of SES. Here I propose a new modified framework that includes considerations for scientific research as a values-laden and situated endeavor that should avoid interpretations that foster biosocial determinism, and examines the impact of the social, built, and natural environment.

Guided by the interpretive frameworks of social epidemiology, environmental neuroscience, critical race theory, and critical neuroscience, this dissertation will outline my framework and apply it as an interpretative lens for psychology and neuroscience research (Chapter 2). I will then present two studies that illustrate the effects of social stratification: One in which social, built, and environmental factors explain variations in cognitive performance and cortical morphometry in a sample of 8-10 year olds from the first Annual Curated Release of the Adolescent Brain Cognitive Development (ABCD) dataset (Chapter 3). In the next chapter I examine social, natural/built, and community factors, including health care utilization, and how they are related to variations in mental health outcomes using data from the Chicago Community Adult Health Study (CCAHS; Chapter 4). Together, these chapters illustrate a framework through which future interdisciplinary research endeavors

can characterize elements of an individuals social and physical environment while maintaining a critical perspective that minimizes the harm done to marginalized groups which should benefit from this research.

CHAPTER 1
INTRODUCTION

Numerous economic, social, and political events in the past decade, such as the Occupy movement, and the focus on class warfare in the most recent US Presidential election, have brought social stratification, and its resulting inequalities, to the forefront of the national conversation. According to the Stanford Center for Poverty and Inequality, wealth and income inequality has only increased in recent years, currently at a national highest, such that while the poverty level has decreased by a tiny amount (a drop from 15.1% in 2010 to 13.5% in 2015), those at the highest level have dramatically increased in wealth.

Inequality based on social stratification has motivated scholarly work in disciplines as diverse as sociology, public health, psychology, and economics. This multi-disciplinary interest has yielded a great amount of literature on the definitions, the causes, and the downstream effects of socioeconomic social stratification. While methodologies and definitions may vary by field, most studies converge on a very similar finding: lower social status is consistently associated with greater morbidity, less social power, and less well-being.

With the advent of big data and large-scale collaborative investigations, researchers investigating social stratification and its relevance to important outcomes, such as academic achievement, health outcomes, and cognitive performance, have used a number of strategies and approaches to integrate relevant information across a number of important scales, so as to characterize determinants in a number of important domains (e.g. social, economic/political, natural/built environment). The development of these frameworks has presented unique challenges, such as the need for statistical/analyses methods that can incorporate data of various types and sources, and the need to harmonize language from a wide range of academic domains, from the qualitative to the quantitative. While the synergy of these cross-disciplinary coalitions have resulted in many important developments in the field of minority health and health disparities that wouldnt be possible within just one discipline, these collaborations have also highlighted each of those fields shortcomings or blind spots, sometimes creating as many new questions and problems than were obvious at first.

Particularly within the fields of psychology and neuroscience, the history and development of studies focused on the impact of poverty and adversity on the brain is marked by controversy. As reported in a recent ethnography by Kasia Tolwinski in which she interviewed at least thirty cognitive and developmental neuroscientists focusing on this particular topic, researchers in the late 90s and early 2000s faced extreme opposition from funding agencies and fellow scientists that characterized their research programs, and the scientists themselves, as "racist" and "eugenicist" (Tolwinski, 2019). Over time, many critics came around and saw the value of such research such that the idea that social and environmental processes may result in "biological embedding" that may impact development, cognition, and behavior (Hertzman, 1999). However, this has not changed the fact that researchers researching the negative impacts of social stratification must engage in constant controversy management, either with media sources, funding agencies, and fellow members of the scientific community.

In recent years, a number of articles have emerged in popular media that have activated a number of concerns of early critics regarding the field's promotion of deterministic and essentialist ideals with headlines such as: "New brain science shows poor kids have smaller brains than affluent kids" (Layton, 2015), "Poverty shrinks brains from birth" (Reardon, Reardon), and the more recent headline "The real advantage the rich have in getting into college is biological" (Sapolsky, 2019). While the scientists interviewed by Tolwinski might respond by saying that "the work is misunderstood," instead focusing on the plastic properties of the brain, and what Tolwinski (2019) calls the "sociological imagination", where individual (biological) problems can only be understood within the context of greater societal structures, it is clear that all present efforts to investigate the role of social stratification on individual biology must actively and continuously consider the practical and social complexities that may arise.

1.1 Complexities of Researching Social Stratification: Definitions and Operationalization

One huge issue that quickly emerges in the collaborative study of social stratification and its downstream effects on health, cognition and behavior is a definitional one. While social class, which can be generally understood as a broad construct that describes a person or a groups position within a social-economic-power hierarchy (Diemer et al., 2013), this definition does not provide any more information about the qualities or metrics through which researchers may quantify and evaluate social stratification and its impact. Although social stratification can occur based on any number of dimensions, most studies have focused on socioeconomic stratification by focusing on a few select measures that may be considered to be "traditional indicators" and include individual/household income, educational attainment, and occupational prestige. Although these indicators have been used for many years, the usage of these indicators to explicitly index socioeconomic inequality and its connection to health seems to have come about in the United States in the the mid-90s, as a number of practitioners and scientists raised concerns regarding the use of "racial indicators" as crude proxies for economic inequality (Williams, 1997), in addition to a large push for universal health insurance to remedy observed health inequalities (Adler et al., 1993). The three "traditional indicators" seemed to be a good compromise for what a number of governmental agencies and disease registries may have been collecting at the time, and became the established norms, as per recommendations from the National Institutes of Health (Syme, Moss, & Krieger, 1996). These particular measures tap into a particular definition of social class known as Socioeconomic Status (SES) and refers to an individuals access to economic and social resources (Diemer et al., 2013). The operationalization of social class using these SES measures has led to a large number of findings that highlight the impact of higher (or lower) SES on health outcomes and overall well-being.

One of the greatest contributions in the consideration of SES factors in studies of health, psychological, and neural function has been the notion that low socioeconomic status is associated with a number of negative environmental factors that may get under the skin and impact development and function via large number of pathways, including those in the behavioral, sociocultural, biological and environmental realm. The wide association between these SES factors and a number of other outcomes and environmental conditions has widely served to leverage the popularity and prominence of these measures in psychological and neuroscience research.

That being said, this has also underscored the importance of not only considering SES as being composed of only these traditional factors. As noted by early advocates for the inclusion of these traditional measures in governmental and medical surveys, although the measures have been around for many years, the underlying factors constituting these constructs may have radically shifted though the years, such that status could have been attributed to mere survival in times of acute infections (such as the Great Plague of London in 1665) (Adler et al., 1993). A review of the literature indicates that the growing interest in socioeconomic status and its relationship to a number of outcomes has resulted in two very broad schools of thought regarding SES that highlight its complexity: those that have focused on understanding social stratification and the impacts of low-SES and its nuances, and those who are interested in SES so as to rule out its effects on an outcome or process of interest. Several studies have begun to use multivariate approaches that not only use commonly-used indicators of SES but also include their relationship to other variables, such as those related to individuals physical and sociocultural environment, which help to provide a better and fuller picture (a better approximator) of the underlying multi-dimensional construct.

In summary, one major element of future frameworks addressing the impact of social stratification should be **to use measures from multiple levels of organization, including those related to the social, built, and natural environment, instead of only the traditional approximators of socioeconomic status (SES).** After all, to use the words of David Blane, one of the strongest advocates for consistent SES indicators in public health research in hte 90s, SES factors are useful in that they "encapsulate complex information about a person's life"(Blane, 1995). As such, traditional operationalizations of SES should be revisited to enhance existing models.

1.2 Complexities of Researching Social Stratification: Unintended Consequences

The growth and popularity of SES and social stratification in psychology and neuroscience has been extremely important due to the possible applications to policy and education. However, the growth of popularity of SES and social stratification as a prominent and important topic has identified a number of possibly unintended consequences. This has become an even more relevant issue as evidence including neuroscience or brain images has been shown to be evaluated as more compelling or alluring (Farah, 2018), raising a number of important points concerning the impact of neuroscience and psychology research surrounding SES, and social stratification more broadly.

One large issue is that discussing and addressing issues related to social stratification while only focusing on strictly financial socioeconomic status is that it may eclipse other elements of identity for which there is structural inequality, such as race, ethnicity, and gender, reducing a multi-dimensional construct to a very narrow set of indicators.

A second issue is that the operationalization of these structural variables to individual analyses has in some cases led to a fundamental attribution of environmental conditions to individual choices and states, in many ways placing the blame on those that are impacted by belonging to a low social class position, and in some cases asserting an essentialist narrative that attributes inferiority to anyone belonging to a social category associated with lower social status. Another unintended consequence is that many studies investigating the impact of social stratification on a number of outcomes such as development, may, in trying to identify the critical point of intervention, promote a the idea that people are supposed to be optimized so as to be the maximally useful within a capitalist economic context (Pitts-Taylor, 2019). Similarly, this includes assumptions that all individuals are motivated in their actions by the promise of upwards social mobility, aiming to always increase the amount of income they may be making, improving their educational attainment, and gaining occupations with greater prestige. While this assumption research may hold for those in higher positions of the social class strata, recent evidence has shown that these motivational factors may not be present in groups that have been historically marginalized, due to the higher probability of having feelings of disenfranchisement from the existing sociopolitical social structure (Shaked et al., 2016). This stance, of course, is one that researchers are free to take, but one that may be focusing more on developing more productive members of society than it is on promoting well-being.

Yet another issue is the agnostic stance that researchers or communicators of science may take (or ignorance they may hold) to the impact that their science may make, by assuming that the adoption of these broad SES indicators automatically communicates the complexity of the underlying constructs which these proxies are meant to approximate. A similar issue that has been brought up is that with the adoption of more data-driven methods may similarly obscure the values that drive and motivate a number of research projects hoping to characterize and mitigate the negative impacts of social stratification and improve well-being. A suggestion that has emerged in much of this research has been for researchers to take a closer look at the values that are driving their research endeavors, and identify how their research contributes to conversations in society.

In summary, one critical element of future frameworks addressing the impact of social stratification is **to consider scientific research as a "values-laden and situated" endeavor that occurs in a particular cultural and historical context, and should avoid interpretations and study conceptualizations that promote notions of bi-**

ological and social essentialism, and adopt an intersectional approach to demographics when possible.

1.3 Goals and Scope of This Dissertation

The purpose of this dissertation is to provide an example of a research approach/framework through which to evaluate and predict the impact of social stratification that addresses the following two goals: to integrate determinants/factors across a wide range of dimensions to incorporate elements of the social, cultural, built, and natural environment; and to critically identify and evaluate the historical and cultural context in which a given project is occurring in order to avoid reductionist or deterministic interpretations, and to mitigate the possibility to perpetuate and support narratives of oppression that further stigmatize and marginalize particular groups in society.

The structure of this dissertation will include one chapter that will specify the elements of the proposed framework here, and illustrate existing frameworks that have been invaluable in developing the perspective proposed in this dissertation (Chapter 2), closing by revisiting "traditional" indicators of socioeconomic status and providing recommendations for researchers that may use their variables in their research. The following chapters will describe two studies that illustrate the effects of social stratification using the framework and guidelines proposed so far. The first of these chapters (Chapter 3), will use data from the first Annual Release of the Adolescent Brain Cognitive Development (ABCD) dataset to illustrate how social, built, and environmental factors explain variations in cortical morphometry and cognitive performance during childhood (ages 8-10). This dataset was chosen for this analysis due to the narrow age range of the children in the dataset (8-10 years of age), the large size and diversity of the sample, the wide range of variables contained in the dataset, which include measures collected from children and caregivers, in addition to a number of measures related to their residential neighborhood. The following chapter, Chapter 4, illustrates a very different implementation of the same framework in evaluating the impact of environmental determinants and social stratification by using data from the Chicago Community Adult Health Study (CCAHS) to examine the relationship of social, natural/built, and community factors to various health-behaviors and psychosocial attitudes and examine how they explain variations in mental health outcomes (depression and anxiety). This dataset was chosen for analysis due to the large, older age range of participants (ages 18-83), and because it used a representative probabilistic sampling procedure to allow representation of all neighborhoods within Cook County, IL, which allowed for the inclusion of many more measures of participants neighborhood conditions, including satellite land cover measures, and estimates from the US Census Bureau. Finally, this dissertation will conclude with conclusions and future directions for the use of this framework in characterizing elements of an individuals social and physical environment while maintaining a critical perspective that minimizes the harm done to marginalized groups which should benefit from this research.

Although this will be discussed specifically within the different chapters, it is important to note that this dissertation is focused on highlighting the importance of multi-factor analyses in the study of the impact of social stratification in a multi-ethnic US urban context. While this may present some limitations to the study's generalizability as it does not consider rural and/or regions outside of the US, this should not diminish the importance of researchers explicitly assessing the manner in which their research may perpetuate or create additional marginalization, either through the way they communicate their research, or through the operationalization of their constructs. Although very important as well, this dissertation will not be discussing how the adoption of this framework operates within the incentive structures of academic publishing and funding applications to private and governmental funding agencies, as the values and priorities of these may be highly variable and subject to their own restrictions. In addition, while of utmost importance, this dissertation will not discuss structural inequality as it impacts researchers themselves, and the stresses, barriers and additional labor this poses for researchers belonging to marginalized groups, such as having to justify their interest in research projects at higher rates when research is related to their own identity ("me-search" versus "research"), and the greater burden of having to become content experts in research related to their identity as this is often underrepresented in the literature.

Finally, this dissertation will not specifically focus on neurobehavioral decision-making models that have been proposed to describe the actions of people experiencing financial hardship, such as those relating to the Scarcity Hypothesis (Huijsmans et al., 2019; Shah et al., 2012). While these dual-process models provide substantial insights on processes occurring at a very immediate time scale, the time-scale of focus in this dissertation will be how these experiences accrue over the life-course.

CHAPTER 2
FRAMEWORKS TO EVALUATE THE IMPACT OF SOCIAL STRATIFICATION

The proper examination of the impact of social stratification on well-being, psychological and neural function requires an interdisciplinary set of tools that can address a complex topic that spans across a number of scales and modalities. Over the years, a large number of disciplines have tackled this topic using the tools available in their field. In this chapter, I present four interpretive perspectives that have proved invaluable for the work presented in this dissertation (See Figure 2.1): Social Epidemiology, Environmental Neuroscience, Critical Neuroscience, and Intersectional Critical Race Theory. These fields have been identified due to their methods and goals which, as discussed in Chapter 1, address two key components needed in a strong framework that will address the impact social stratification in a manner responsible manner: the need to incorporate measures from various levels of organization that extend beyond traditional measures of SES, and a critical self-analytic component that holds researchers accountable for the narratives and values they promote through their research. Two of these frameworks, Social Epidemiology and Environmental Neuroscience, each integrate data from multiple levels to make inferences on about how elements of the environment impact individual level functions, while the other two, Critical Neuroscience and Intersectional Critical Race Theory, provide strong considerations when providing explanatory accounts of human behavior and outcomes.

Following the discussion of the contribution of these frameworks, this chapter will reintroduce traditional measures of socioeconomic status considering the recommendations of these frameworks, as they will be used in the following chapters. Finally, this chapter will summarize key recommendations for researchers in psychological and neural sciences interested in investigating the impact of social stratification.

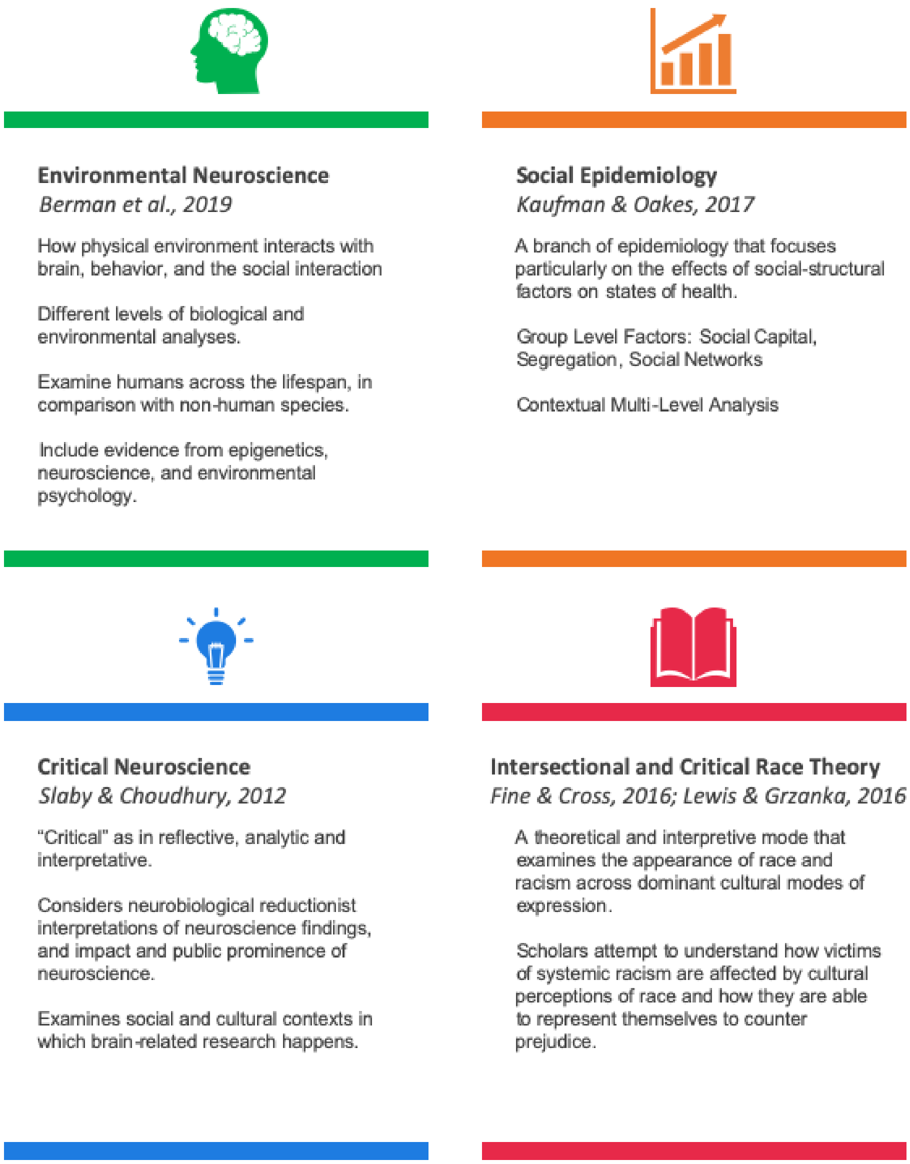


Figure 2.1: Summary of Frameworks influencing this Dissertation

2.1 Bringing in Social Structures: Social Epidemiology

For many years, epidemiologists have focused on identifying and analyzing the incidence, distribution, and control of diseases and various health states. Although the particular definition of the field has changed throughout the years (Oakes & Kaufman, 2017), this field has been integral in developing a number of methods in public health sciences and various biological sciences. These studies may focus on a wide number of factors that may include the often cited "social determinants of health", which include social and economic factors that may contribute to health. Epidemiological studies may focus on disaggregations between groups for which there are documented differences, such as differences in socioeconomic status, race/ethnicity, and gender.

Social epidemiology, as a more focused subfield, focuses particularly on how social and structural factors may contribute to states of health, rather than specific diseases. Similar to epidemiology, this subfield also uses detailed methods to infer a causal relationship between any given two items, such as the *Bradford Hill criteria* for causation (temporal relationship, strength, dose-response relationship, consistency, plausibility, consideration of alternate explanations, specificity, and coherence)(Oakes & Kaufman, 2017). However, due to the complexity introduced by social structures, this is much more difficult. These social and structural factors can be summarized in three principles that, although interrelated, tap into a separate qualities of social structures and their impact on health (often referred to as social cohesion): *Social Capital*, *Social Support*, and *Social Networks*.

The term *social capital* was first introduced by Pierre Bourdieu, a French sociologist, and was defined as "the sum of resources, actual or virtual, that accrue to an individual or group by virtue of possessing a durable network of more or less institutionalized relationships of mutual acquaintance and recognition." Social capital is related not only to the number of resources that an individual may possess, but also access to amenities, such as transportation, health, and recreational resources (Oakes & Kaufman, 2017). Communities with high social capital may employ social control over abnormal behaviors (depending on the community), and thus is often related to crime levels and associated levels of stress. These variables are often measured at the individual or are aggregated to the group-level.

The next principle, *social networks*, refers to social structures involving a set of social participants and the ties between them, whether they are individuals or organizations(Oakes

& Kaufman, 2017). Often leading to positive outcomes, strong quality of social interactions are often measured based on number of close kin/friends, degree of reciprocal exchanges with community members, community involvement.

Finally, *social support*, is closely related to social capital and social networks, and is related to factors that may exacerbate or mitigate the stressors that may arise based on individual social capital, or social ties. For example, segregation, a characteristic of a region in which population subgroups are unevenly distributed throughout a region. Another element that is often discussed with this principle is that of institutional trust, and feelings of anomie, a condition in which society provides little moral guidance for individuals.

A very strong element of social epidemiology is that it is a perspective in which social interactions and social structures, and their experience, have a lasting impact on health and well-being. Social epidemiology approaches often incorporate developmental and life course approaches, which allows for the consideration of transgenerational accounts of experiential stress, which helps to incorporate elements that may have accrued over time, as is the case with segregation. This approach elevates existing studies in public health and biological studies that have proposed that the way in which the "environment" may get "under the skin" as has been proposed by models of "allostatic load", "oxidative stress," and "experiential stress. To clarify, a social epidemiology perspective underscores that inadequate levels of social capital, social support, and/or social networks are characterized by high levels of stress, which then has an impact on health and wellbeing.

One such model in describing the biological mechanisms of how socioeconomic conditions may get under the skin has been the life course perspective of childhood poverty, which suggests that the duration and time in which one experiences disadvantage may shape long-term health trajectories of individuals in ways that are difficult to change by upward social mobility later in life (Evans, 2016). The life course perspective on poverty describes conditions of disadvantage as conditions of chronic physiological stress that may be influenced by any number of environmental or experiential factors, with long-term effects on the sympathetic nervous system, the hypothalamic-pituitary-adrenal (HPA) axis, and metabolic processes (Evans et al., 2012, see).

In summary, social epidemiology is an extremely useful network in that it provides an interpretive lens through which to interpret social structural elements and how they may have an impact on health and wellness.

2.2 Translation and the Measurable Environment: Environmental Neuroscience

Environmental neuroscience focuses on how the physical environment interacts with brain, behavior, and the environment, and is extremely valuable as an interpretive lens for the study of how processes at multiple levels have an impact on an individual level.

As stated by Marc Berman and colleagues (2019), environmental neuroscience has five goals: (1) To place the physical and social environment at the forefront as an opportunity to create inter-disciplinary connections between environmental psychology and neuroscience; (2) To identify quantitative and qualitative relationships across different levels of analyses, so as to develop and apply new predictive models; (3) To incorporate analyses at different time-points and time-scales, to highlight the accumulation of experiences across the lifespan; (4) To highlight translatability in research design and interpretation of human physical and natural environments to non-human species; and (5) To take a generative theoretical approach to improve human psychological functioning (Berman et al., 2019).

A strong component of environmental neuroscience is that it places such a strong emphasis on the the physical and natural environment and its impact on an individual, which compliments the social epidemiology perspective, and allows for the modeling of several toxic environmental exposures. In addition, the field of neuroscience provides strong theory behind why certain built or natural elements of the environment may be beneficial (or hurtful), which strengthens the inferences we can make in our analyses. Particularly for the study of social stratification, environmental neuroscientists provide multiple perspectives and findings in the study of enriched environments (or the converse, deprived environments) in non-human species, and has generated many hypotheses related to how the natural and built environment may impact perception and decision-making processes.

2.3 Keeping The Research Accountable: Critical Neuroscience and Intersectional Critical Race Theory

In contrast to the two previous perspectives presented, the following two fields of inspiration, critical neuroscience and intersectional critical race theory, are theoretical and interpretive models that focus on the context in which scholarly discourse and communication occurs, and provide very important tools to ensure the second goal of a responsible social stratification analysis framework, to be aware of the values and messages communicated by the research so as to mitigate the negative impact on marginalized groups.

According to scholars in the critical neuroscience discipline (Choudhury & Slaby, 2016), the goals of this field are: (1) To advocate for the demonstration of alternative possibilities of results by modifying technical parameters or comparing and re(de)fining categories; (2) To explore routes to empirically investigate social and cultural phenomena without assuming universal neural mechanisms from the outset; (3) To enrich behavioral theories by allowing for pluralistic viewpoints and methodologies to result in layered explanations of complex phenomena; and (4) To examine the subtle relationship and feedback loops between popular opinion or ideologies about the brain and findings in neuroscience.

Critical race theory is a theoretical and interpretive mode that examines the appearance of race and racism across dominant cultural modes of expression (Crenshaw, 2010). Scholars in this discipline attempt to understand how victims of systemic racism are affected by cultural perceptions of race and how they are able to represent themselves to counter prejudice.

Key points within critical race theory are that "race" is a socially constructed category and that "racial difference" is invented, perpetuated, and reinforced by society (Peller, 1995; Delgado & Stefancic, 2012; Taylor et al., 2016). More recent definitions of critical race theory also include the term intersectionality, first coined by Kimberlé Crenshaw in 1995, who defined it as "the question of how multiple forms of inequality and identity inter-relate in different contexts and over time, for example, the inter-connectedness of race, class, gender, disability, [etc]" (Crenshaw, 2010). Intersectional critical race theory have been instrumental as interpretive lenses that frame race, not as a variable of "essential difference," but one that is embedded and associated with a number of cultural and historical factors, many of which have a strong impact individual experience. Furthermore, the adoption of an intersectional framework when studying social stratification is extremely important, particularly when focusing on the United States, as many factors that may be considered "independent" may actually be co-occurring, such as race and SES.

A strong critique that these fields have pointed out particularly for research focusing on SES and race and their effects on biological function is that they may promote "biosocial determinism," which elevates biological explanations for social problems while attributing biological conditions to social causes (Pitts-Taylor, 2019). By using the individual as the explanatory variable, certain causes may be attributed to individual factors, when really they should be attributed to structural or sociocultural factors. Critical Neuroscientists have warned that this may lead to "neurocorrections", such that the take-home message is to target "at-risk" children, so that these children will be able to contribute best to society in a neoliberal market model. In this view, "classification and entrenchment" are reinforced in order for proposed intervention models to be sustainable.

Another element that is shared by these interpretive frameworks is that they echo recommendations that have been previously made in fields examining patient-centered and media-based communications (Penner et al., 2014; Ramasubramanian, 2007): that in order to reduce misinformed communication of findings, researchers should adopt one of several types of strategies–(1) *research-centered* solutions that focus on how researchers may identify and reduce their own biases; (2) *audience-centered* solutions in which researchers explicitly instruct audiences to be critical consumers of their scientific content within their communications; and (3) *message-centered* solutions which highlight stereotype-disconfirming, or counter-stereotypical examples for research where negative stereotypes may be activated.

Together, these theoretical frameworks advocate for a way of doing science in which researchers identify that research endeavors are "value-laden and situated" within existing historical and cultural contexts (Pitts-Taylor, 2017), and that particular and intentional care should be taken by researchers so as to avoid reinforcing narratives that may perpetuate negative conditions for already marginalized populations.

2.4 Bringing It All Together: How Do we Measure Social Stratification?

2.4.1 Proposed framework

As described in the previous sections, many frameworks and perspectives are necessary to encapsulate the complex dynamics of the factors that drive and result from social stratification. Based on these frameworks, this dissertation proposes a framework for conducting research on social stratification with the following principles:

1. In order to avoid reductionist and biosocial essentialist interpretations in study design and communication, studies should adopt a multi-level approach that in its operationalizations considers:
    (a) Social structures and social dynamics
    (b) Local, built, and natural environment and neighborhood context
2. Researchers should consider studies as a "values-laden" endeavor that occurs within a particular historical and social context, and evaluate the motivation of their research, so as to avoid narratives that perpetuate negative stigmas or stereotypes of marginalized groups.
    (a) Researchers should adopt an intersectional approach that considers the effects of multiple aspects of identity/group membership
    (b) Research should aim to provide positive and/or counterstereotypical portrayals and examples of marginalized groups when possible in study reporting and description. Furthermore, Researchers should use a "strengths-based" approach (instead of a deficit-based approach) in these descriptions and portrayals.
3. Researchers should aim to include qualitative accounts that allows members of marginalized groups to report and communicate their own strengths and experiences when possible.

These recommendations encompass the scope of variables utilized in the environmental neuroscience and social epidemiology frameworks necessary to describe the complex biological, social, structural, and interpersonal dynamics of an individual's environment, while also striving to address the challenges that arise in doing research tackling complex, and at times controversial, social issues identified by adopting the critical lenses of intersectional critical race theory and critical neuroscience.

2.4.2 Framework in action: This Dissertation

As an example of these proposed recommendations in action drawing from these various frameworks, the following two chapters will use a model illustrated in Figure 2.2. As discussed in the previous section, this model incorporates elements that highlight individual factors that may signal structural advantage or disadvantage (Demographics and Socio Economic Positioning), various elements of the local, built, and natural environment (Greenspace, Neighhborhood and Home Conditions, City Sensors), and individual-level factors (Psychosocial and Biological Factors). Not illustrated in the figure are interpretive elements that place the definition and interpretation of these variables into a historical and cultural context.

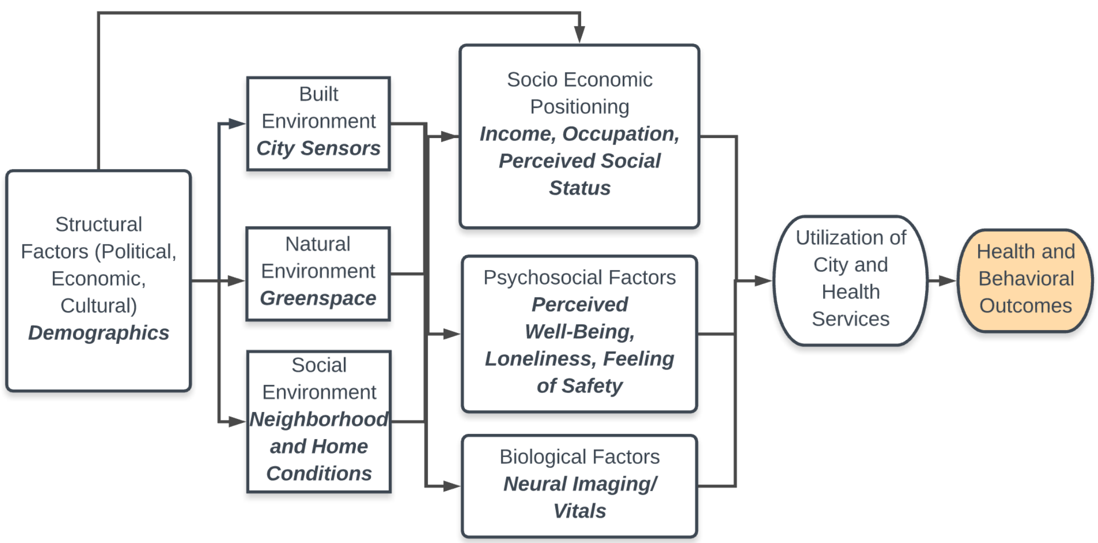


Figure 2.2: Model for this dissertation using framework recommendations

2.4.3 Revisiting Traditional SES Measures: What are we measuring?

Within psychology and other behavioral sciences, a considerable number of researchers have investigated how social status may shape the daily lives of people, although the consideration of social status as a social environmental variable in psychological research, as opposed to a demographic variable to be controlled for, has only been introduced within the past few decades (Evans et al., 2012; Liu, 2013). In this literature, the social status of an individual refers to their rank on a socially valued dimension, usually determined and valued by all members within a society, although the operationalization of social status varies significantly across studies (Fiske, 2010; Magee & Galinsky, 2008; Ridgeway & Walker, 1995). The rank, or social status, of an individual often determines the access to material and social resources, such as healthcare, financial assets, social networks, and certain class-related values, and may be associated with status-specific benefits and costs.

Social Status

Social status is often measured in terms of ones socioeconomic status, or SES. Socioeconomic status typically refers to an individuals access to economic and social resources and is therefore considered a multi-dimensional construct (Brito & Noble, 2014). As such, researchers investigating the link between SES and any outcome must make a number of careful decisions when defining SES. Borrowing from Social Class Theory in sociology, most studies adopt a distributional model of social class (also called functional or gradational"), in which social class is viewed as a hierarchical continuum of income and/or prestige, as opposed to a relational model of social class (also called order or conflict), which views social classes as mutually dependent and inherently conflictual. The distributional model is more commonly used as it allows researchers to treat socioeconomic variables as continuous, while the relational model is more common in impression formation and intergroup relations paradigms. Research on SES often relies on a number of proxies to operationalize complex environmental factors. The most common factors selected by researchers to measure SES include income, educational attainment, occupational prestige, and information regarding an individuals neighborhood SES. In some circumstances, for instance, depending on the age of the individual, these factors may be assessed in terms of both the individual and his/her parents. Although many of these factors may be correlated, they should not be thought of as interchangeable as, for example, they may deferentially impact developmental outcomes (Brito & Noble, 2014).

Income

Income may be calculated using household, familial, or parental income in studies with child populations, or solely by the income of the individual when studying adult populations (Duncan & Magnuson, 2012; Hanson et al., 2013; Lawson et al., 2013). While income has been used widely as a marker for SES, and therefore social status in general, in recent years it has fallen out of favor as a reliable measure due to the unreliability of self-report data from participants and the marked fluctuations of income over time at both an individual and familial level (Brito & Noble, 2014). More recent studies have instead begun to use the Income-to-Needs (ITN) ratio. This ratio divides total family income by the official federal poverty threshold for a family of that size (US Census Bureau, 2004). The ITN ratio now allows researchers to assess family income while also taking into account other important factors, such as national norms, family size, and cost of living, thereby providing a clearer measure of a familys financial standing.

Educational Attainment

Educational attainment, defined simply as the highest level of education completed by either the parents or the individual, is another component of SES that is often used to assess social status. In studies focusing on children, educational attainment is commonly used as a proxy for a number of factors related to cognitive stimulation in ones home environment, educational attainment is thought to measure the qualitative aspects of relationship between caregiver and child, such as exposure to complex language, parent-child interactions, and the quality of guardian caregiving practices (Bradley & Corwin, 2002; Duncan & Brooks-Gunn, 1994; Evans & English, 2002). The results of a number of studies focusing on maternal educational attainment, which is believed to be associated with better cognitive stimulation in the home environment, suggest that education may be the best predictor of a number of developmental outcomes (Aubret, 1977; Haverman & Wolfe, 1995; Smith & Brooks-Gunn,

& Klebanov, 1997). In studies focusing on adult populations, educational attainment is also commonly used as a proxy for greater social capital and exposure to traditions and knowledge considered to convey higher social status, especially in middle- and upper-class environments (Snibbe & Markus, 2005).

Occupational Prestige

Occupational prestige is another common indicator of objective social status since the differing occupations may carry a different set of psychological experiences. High-prestige occupations (e.g. professional or white collar) are usually accompanied by varying tasks, and more freedom of choice in the workplace, whereas low-prestige (working-class or blue collar) occupations may often be accompanied by high levels of supervision and limited choice and control (Kohn & Schoenbach, 1983; Kohn & Schooler, 1983). This indicator is less used by researchers, as it is more difficult to define status on a continuum, since it reflects a number of potential variables: social standing and network, intellect, access to resources, earning power, stress and psychological demands, sense of autonomy, and toxic exposures in the work environment (Galobardes et al., 2006; Warren & Kuo, 2003).

Composite measures of SES

Given the wide variety of measures used to define social status, many researchers prefer to use composite measures of SES including a combination of two or more of the previously mentioned factors. Composite measures of SES commonly used include the Hollingshead scale, which combines occupation and education (Two-Factor Index), or education, occupation, marital status, and employment status (Four-Factor Index). Although common in the literature, many researchers have advocated against the use of composite measures of SES, as it obscures the contributions from the component variables. Even though the various measures of SES may be somewhat correlated, they are proxies for different aspects of social status (Brito & Noble, 2014; Liu et al., 2013).

Subjective/Perceived measures of SES

Another measure commonly used by researchers is subjective social status: a self-report index which refers to an individuals perception of his or her own social rank relative to others within a defined group. Subjective social status is typically measured using the MacArthur Scale of Subjective Social Status. This scale requires individuals to indicate their place on a ten-rung ladder said to represent their larger community and has been found to predict a number of physical and mental health outcomes, above and beyond other, possibly more objective, measures of SES (Adler et al., 2000; Demakkos et al., 2008). Furthermore, theoretical models have posited that SSS captures class standing, including dimensions of social rank, and the experience of social inequalities and inequities (Adler et al., 2000; Franzini & Fernandez-Esquer, 2006; Pieterse, et al., 2013).

2.5 Recommendations for Researchers

As an additional tool for researchers that are interested in adopting many of the recommendations of Critical Neuroscience and Intersectional Critical Race Theory in their own projects, Table 2.1 is a checklist that outlines recommendations for each step of the research process. These have been adapted from Intersectional Critical Race Theory models initially presented in Lewis & Grzanka (2016).

Table 2.1: Checklist for Research on Social Stratification in Psychology and Neuroscience (adapted from Lewis & Grzanka, 2016)

Generating the Research Question

☑ **History**: Have I attended to the historical processes that shaped these peoples lives and the terms of my research? What are the historical-structural phenomena (e.g. educational policy, housing, labor) that have contributed to the research question or problem under investigation?

☑ **Literature**: In developing my question(s), have I attended to the foundational literature on intersectionality that will inform my research design? Have I considered interdisciplinarity and may it enhance my research?

☑ **Context**: Have I considered the context-specific factors, including unique cultural practices, beliefs, and ideologies, that influence the lives of the individuals in my research? Where is this psychological problem or issue manifesting, and why does it matter?

Methodology and Data Collection

☑ **Standpoint**: Have I accounted for my own standpoint in relation to the people who are the subject of my research? Where are my own beliefs manifesting in my research design, data collection, and analyses? Can I name and defend these choices?

☑ **Methods**: Have I chosen my methods based on my research question, or the other way around? Have I considered nontraditional, mixed methods, and interdisciplinary approaches that might be better suited to my questions?

☑ **Measurements/constructs**: How did I arrive at my variables? Are my participants experiences of the extant research guiding the selection of my variables or constructs under investigation? Have I taken the time to adequately critique the extant research that typically is not intersectional? Do I need to theorize and/or develop new measurement tools to adequately address my research questions?

☑ **Sampling**: Have I selected a sample based on convenience or my research questions? Have I considered the multiple identities of my participants and how other samples might be more representative? Do I have theoretical and scientific reasons for choosing to include or not include a control group?

☑ **Hypotheses**: How might my hypotheses be imposing a single-axis, comparative, additive, or interactional approach on my data? Are hypotheses even necessary or appropriate to my study, given the intersectional nature of the research question? If so, do they enable intersectional dynamics to emerge in data analysis?

Data Analysis

☑ **Power Dynamics**: Where is power manifesting in the lives of my participants? Have I considered how power might be operating in ways that are typically invisible? What strategies can I use to see power at work in my data?

☑ **Analytic Strategies**: Why am I using these particular analytic approaches to my data? How might my data be pointing me toward unfamiliar or nontradititonal approaches? How might my analytic tools be constraining my potential findings?

☑ **Relationships**: Have I foregrounded the relationships among the social categories and group memberships in my study? Rather than merely include people who occupy multiple positions of subordinations, marginality, and/or privilege, have I focused on how these categories co-construct one another and are not discrete aspects of lived experience?

Conclusions and Implications

☑ **Action**: What work is my research intended to do in the world? Does my research adequately attend to issues of social justice and the potential for research to catalyze social change, or does my research just generate knowledge for the sake of knowledge? Do the implications of my research extend beyond my own research program?

☑ **Community**: How does my work involve and contribute to the communities or groups under investigation? Have I sufficiently involved them in the development of my conclusion and my steps for future research?

2.6 Conclusions

The aim of this chapter was to introduce a framework that provides recommendations on how to approach research focusing on social stratification while accomplishing two goals: to incorporate measures in research extending beyond traditional measures of Socioeconomic Status in order to properly capture the dynamic properties of individual's social, local, and personal environment; and to provide recommendations that enable scientists to engage in rigorous and critical reflection of their research values and forms of communication to minimize the possibility of perpetuating or creating stigmas that may may impact the very people they aim to benefit. This chapter sets the stage for the following two chapters which illustrate this framework in action as applied to two empirical studies.

CHAPTER 3
SOCIOECONOMIC STATUS, MINORITY STATUS, AND NEIGHBORHOOD DEPRIVATION EFFECTS ON BRAIN STRUCTURE AND COGNITIVE PERFORMANCE: A MULTIVARIATE ANALYSIS OF THE ABCD DATASET

3.1 Introduction

The purpose of this chapter is to investigate how childhood socioeconomic stress (and minority stress) may be correlated with differences in brain structure and function, and how these factors may explain cognitive performance in the Adolescent Brain Cognitive Development (ABCD) dataset. Childhood low socioeconomic status (SES), widely associated with increased psychosocial and environmental stress, has been previously associated with differences in brain morphometry and cognitive function (Noble et al., 2014). Results from a study by Kim Noble and colleagues (2014) on a sample of 1,099 typically-developing individuals ages 3-20 found a positive relationship between surface area in regions related to executive function and spatial skills and household income. Interestingly, the increase in surface area was found to be logarithmic, such that a subtle increase in income for lower-SES individuals resulted in a relatively large increase in surface area, suggesting that extremely disadvantaged children are the most negatively impacted. When using these brain volume measures to explain cognitive performance, they found that left hippocampal volume partially mediated the relationship between income and flanker task performance.

For this study, we would like to also look at reported race/ethnicity in addition to childhood SES in the ABCD dataset, since there is evidence indicating that even at a young age, children belonging to an underrepresented minority group in the US may be experiencing greater social stress as a result of perceived discrimination (Cooke, et al., 2014). Instead of using reported race/ethnicity, the Noble et al. (2014) study used a Genetic Ancestry Factor (GAF) using saliva samples from the family in order to control for generic ancestry. We are also interested in seeing how race/ethnicity and childhood SES together (along with brain morphometry) may help to explain differences in cognitive behavior, given the ample research suggesting that greater experiential stress is associated with differences in areas supporting memory, executive function, and language processing (Raizada et al., 2008; Eckert et al., 2001; Luby et al, 2013).

3.2 Materials and Methods

3.2.1 Dataset

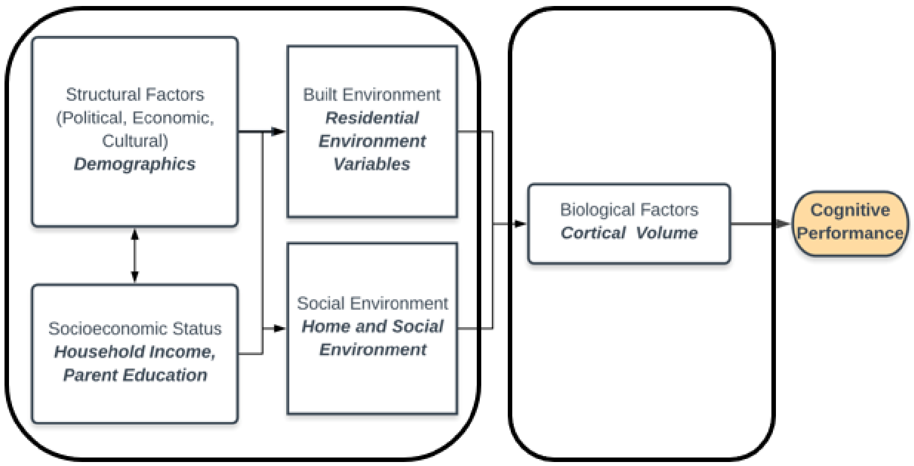
The Adolescent Brain and Cognitive Development Study (ABCD) is a multi-site, longitudinal neuroimaging study following 9-10 year-old youth through adolescence. The ABCD study team employed a rigorous epidemiologically informed school-based recruitment strategy, designed with consideration of the demographic composition of the 21 ABCD sites and the US as a whole (Volkow et al., 2017). The total sample size for the ABCD Study is projected to be 11,500; the first data release (February 2018) included 4534 youth who completed the baseline protocol before September 2017, and is the basis for these analyses.

Information regarding funding agencies, recruitment sites, investigators, and project organization can be obtained at http://abcdstudy.org. A baseline cohort of 11,872 children between the ages of 911 (and their parents/guardians) has been recruited across 21 data collection sites (see Garavan et al., 2018) and will be followed for at least ten years. The study closely matches the US population of 910 year-old children on several key demographic variables, including gender, race/ethnicity, household income, and parental education and marital status.

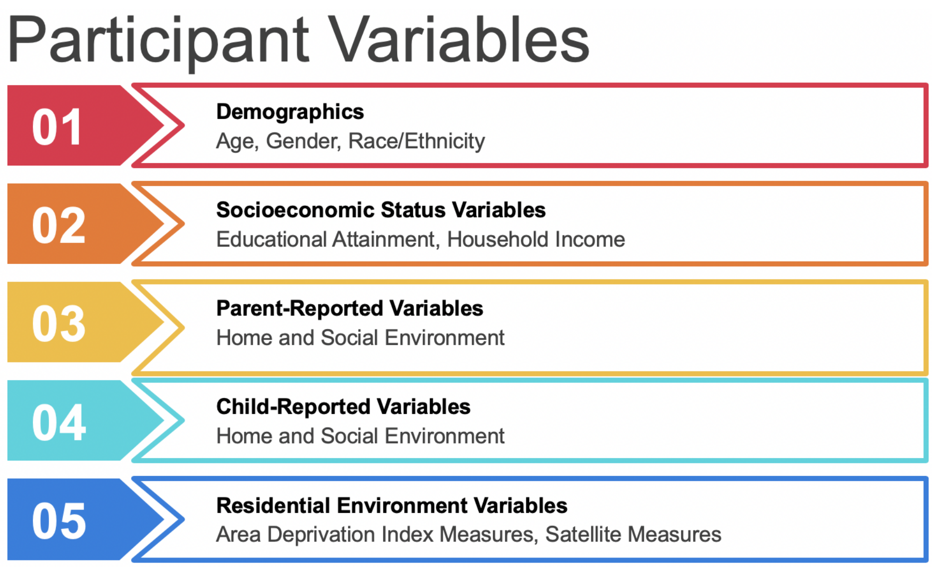
At each ABCD data-collection site, participants were predominantly recruited through local elementary and charter schools (Garavan et al., 2018). ABCD employed a probability sampling strategy to identify schools within the 21 areas as the primary method for contacting and recruiting eligible children and their parents. A minority of participants were recruited through non-school-based community outreach and word-of-mouth referrals. Across recruitment sites, inclusion criteria included being in the desired age range (910 years of age) and able to provide informed consent (parents) and assent (child). Exclusions were minimal and were limited to lack of English language proficiency in the children, the presence of severe sensory, intellectual, medical or neurological issues that would impact the validity of collected data or the childs ability to comply with the protocol, and contraindications to MRI scanning. Parents must be fluent in either English or Spanish.

3.2.2 Behavioral and Subject-Reported Measures

The ABCD Dataset Annual Release 1.1 has a large number of variables for each participant. For the analysis in this chapter, measures were collected in 5 categories corresponding to different elements of the participant's environment: *Demographics, Socioeconomic Status, Family/School Environment* (as reported by Parents or Child), and *Neighborhood/Community Environment*. For each category, measures from the ABCD study were included unless: there was a large amount of missing data not at random, or data were coded in open-text format or were not part of a standardized measure. A full table of the included measures can be found in Table 3.1, and are discussed in detail in the following sections.



(a) Schematic model for this study



(b) Description of variable categories for environmental variables

Figure 3.1: Structural model for this study and variable categories. **(a)** The schematic model of the theorized relationships between variables in this study are shown here. The black ovals indicate how these variables will be entered into the Canonical Correlations and Mediation analyses. Variables indicating elements of an individuals' (and their families') environment are shown in the left oval, while the right oval contains Cortical Volume measures. Also depicted in the figure are the Cognitive Scores which will be modeled as being the result of the previous two factors. **(b)** Shown in this figure are the five categories of variables that will be used for analysis in this chapter. The colors used in this figure will be used as a visual aid in the results for the Canonical Correlations and Mediation analyses.

Table 3.1: Measures from the ABCD dataset, Annual Release 1.1.

Demographics
Age, Gender, and Race/Ethnicity
Socioeconomic Status
Household Income
Highest Level of Parent Education
Family/Home Environment (Parent-reported)
Mexican American Cultural Values Scale (MACV)
Religion Subscale
Family as a Referent
Independence & Self-Reliance Subscale
Family Obligation Subscale
Family Support Subscale
Multi-group Ethnic Identity Measure (MEIM)
Commitment & Attachment Subscale
Exploration Subscale
Family Environment Scale, *Family Conflict Subscale*
Perceived Neighborhood Safety
Perceived Child Prosocial Behavior
Home/School Environment (Child-reported)
Parental Monitoring Survey
Family Environment Scale, *Family Conflict Subscale*
Prosocial Behavior
Child Report of Behavior Inventory (CRPBI)
Acceptance Subscale, for Parent and Caregivers
Reported Physical Activity
School Risk and Protective Factors Survey (SRPF)
School Environment Subscale
School Involvement Subscale
School Disengagement Subscale
Residential/Neighborhood Measures
Area Deprivation Index (Neighborhood Percentile)
Neighborhood Walkability
Amount of Crime (Derived from Census Tract Crime)
Population Density
Levels of NO2 and PM 2.5
Proximity of Home to Roads
NIH Cognition ToolBox Measures
Used composite measure (age-corrected) derived from these tasks:
Flanker Inhibitory Control and Attention Task
List Sorting Working Memory Test
Picture Vocabulary Test
Picture Sequence Memory
Oral Reading Recognition Test
Dimensional Change Card Sort Task
Pattern Comparison Processing Speed Task

Demographic Variables

In order to determine the relationship of participants to their environment and how this could change based on demographic factors, we included the variables of age (in months), gender, and reported race and ethnicity in our analysis. For a participant's race/ethnicity, the ABCD Study followed conventions used by the US Decennial Census, in which participants are first asked if identify as Latino/Hispanic, before asking if they identify with any of the following "racial" groups: White, Black/African-American, American Indian, Asian, Pacific Islander, or another race that was not listed. For this analysis, we imposed a mutually exclusive categorization of race/ethnicity on this multiracial/multiethnic data structure which consisted of the following categories: Hispanic, which includes all people who reported being of Latino/Hispanic origin, regardless of their identification with any other racial groups, non-Hispanic Black, non-Hispanic White, non-Hispanic Asian, and non-Hispanic Other, which included those that may have identified as Pacific Islander, American Indian, or another race. A breakdown of participant demographics for this study is shown in Table 3.2.

Table 3.2: Participant Demographics for ABCD Annual Release 1.1.

N		3284
Age in months	M=120.09	SD=7.2
Gender		
Female	1548	47.1%
Male	1736	52.9%
Race/Ethnicity		
Hispanic	641	19.5%
Non-Hispanic White	1987	60.5%
Non-Hispanic Black	290	8.8%
Non-Hispanic Asian	69	2.1%
Other	297	9.0%
Household Income		
Less than $50K	788	24.0%
Between $50−100K	978	29.8%
Greater than $100K	1518	46.2%
Parental Education		
Less than High School	99	3.0%
High School Diploma/GED	207	6.3%
Some College	793	24.1%
Bachelor's Degree	898	27.3%
Higher	1287	39.2%

Socioeconomic Status Variables

To assess the contribution of Socioeconomic Status (SES), we included measures of household income and parental educational attainment as reported by families involved in the ABCD study. The sample was the stratified using dummy variables to fit into one of three categories: Household income of less than $50,000 per year, between $50,000 and $100,000 per year, and greater than $100,000 per year. Parental educational attainment was determined as the highest level of education held by a child's parent or caregiver. The sample was stratified using dummy variables to fit into one of the following five categories: less than a high school diploma, having obtained a high school diploma or an equivalent (such as a GED), having attended college for some time, having received a bachelor's degree, or having received additional education. A breakdown of participant demographics for this study is shown in

Table 3.2.

Parent-Reported Variables

Measures reported by the parents of participants were used to approximate family and home environment. From the ABCD Annual Release 1.1 database, we used the following subscales from the *Mexican American Cultural Values Scale (MACV)*: Religion, Family as a referent, Independence and self-reliance, Family obligation, and Family subscales. We also included the Commitment and Attachment, and Exploration subscales of the *Multi-Group Ethnic Identity Measure (MEIM)*. The inclusion of the MEIM and MACV subscales was inspired by several study that highlight the inclusion of culture-related variables in research, as this may be extremely important, particularly for non-White participants. We also included the Family conflict subscale of the *Family Environment Scale*,which assessed the amount of openly expressed conflict among family members and a measure of *Perceived Child Prosocial Behavior*. To evaluate feelings about safety and presence of crime in respondent's neighborhood, we also used the *Perceived Neighborhood Safety* questions from the ABCD Annual Release Database.

Youth-Reported Variables

In addition to those measures reported by participant's parents, we also chose to include a number of measures related to the home, school, and social environment from the perpective of the participants. These measures included a version of the Family Conflict subscale of the *Family Environment Scale*, and a measure of *Prosocial Behavior* that were very similar to those completed by parents/caregivers. We also included measures related to parent attitudes from the perspective of the child, such as the *Parental Monitoring Survey*, which consisted of questions assessing a parent's active efforts to keep track of a child whereabouts when at home and outside the home, and the acceptance subscale of the *Child Report of*

Behavior Inventory (CRPBI). So as to also include measures that approximated the youth's perceptions of the school climate and school engagement, we included three subscales of the *School Risk and Protective Factors Survey (SRPF)*: School environment, School Involvement, and School Disengagement, and *Reported Physical Activity*.

Neighborhood/Community Variables

A number of variables approximating neighborhood conditions and elements of the built environment were also included from the ABCD Annual Release.

Area Deprivation Index (ADI) The Area Deprivation Index (ADI) is calculated based on a published study for the socioeconomic inequality impact on health (Kind et al., 2014). The ADI used here is based on a query of the 2011-2015 American Community Survey 5-year summary at the census tract-level for each participant. The ADI is a composite score of 18 different subscores that include: percentage of population aged $\geq$25 years with $<$9 years of education, percentage of population aged $\geq$25 years with at least a high school diploma, percentage of employed persons aged $\geq$16 years in white collar occupations, median family income, income disparity, median home value, median gross rent, median monthly mortgage, home ownership rate, unemployment rate, percentage of families below the poverty level, percentage of the population below 150% if the poverty threshold, percentage of single-parent households with children aged less than 18 years, percentage of occupied housing units without a motor vehicle, percentage of occupied housing units without a telephone, log percentage of occupied housing units without complete plumbing, and percentage of occupied housing units with less more than one person per room (crowding). For this analysis, we will be using the national percentiles of the ADI scores, where greater number denote greater deprivation.

Satellite Measures and Smart Location Mapping Measures Using the Smart Location Database from the Environmental Protection Agency at the census tract level, we included measures of *Residential Density* (log transformed) and *Walkability Index* for each participant (https://www.epa.gov/smartgrowth/smart-location-mapping#walkability).
In addition, we included available satellite measures of *PM 2.5* and *NO2 levels* provided from the NASA Socioeconomic Data and Applications Center (SEDAC), at a resolution of 100 km^2. These estimates were three-year average estimates, spanning from 2010 to 2012 (https://sedac.ciesin.columbia.edu/).

Amount of Crime In order to include information regarding the amount of crime in a participant's environment, we used measures provided in the dataset that were drawn from the Uniform Crime Reporting Program Data at the county level available through the Inter-University Consortium for Political and Social Research (ICPSR) at the Institute for Social Research at the University of Michigan (https://www.icpsr.umich.edu/ icpsrweb/NACJD/studies/33523). To maintain a stability on the crime estimates, three-year estimates were used from years 2010-2012.
Due to the wide range of crime types available, we conducted a principal component analysis (PCA) to reduce the total number of variables while preserve the interrelated nature of these variables. We entered the following variables into our PCA:total number of violent crimes, number of drug abuse crimes, drug sale crimes, drug possession crimes, and DUI crimes. The PCA analysis revealed a first component that explained 97.80% of all variables, and so for the rest of this analysis, we used this compoennt as our measure of *Residential Crime*.

Cognitive Performance

The NIH Toolbox cognition measures were used by ABCD to foster harmonization of common data elements across federally funded studies and were developed as part of the NIH

Blueprint for Neuroscience Research (http://www.nihtoolbox.org). The battery consists of seven different tasks that cover episodic memory, executive function, attention, working memory, processing speed, and language abilities: The Picture Vocabulary Task, the Oral Reading Recognition Task, the Pattern Comparison Processing Speed Test, the List Sorting Working Memory Test, the Picture Sequence Memory Test, the Flanker Task, and the Dimensional Change Card Sort Task. Each of the Toolbox tasks produces a number of scores, some of which are adjusted based on participant demographics. All tasks provide raw scores, uncorrected standard scores, and age-corrected standard scores. Age-corrected standard task scores were used in our analyses. For the purpose of our analyses, we used a composite score of all seven tasks.

3.2.3 Structural Image Processing

All structural neuroimaging processing as completed using FreeSurfer version 5.3.0 according to standardized processing pipelines (Casey et al., 2018). The only participants that were included in this analysis were participants for which there was an entire set of structurals, demographics, and measures of interest, which left a sample of N=3284. Cortical reconstruction and volumetric segmentation was performed by the ABCD Data Acquisition and Integration Core using the FreeSurfer image analysis suite (http://surfer.nmr.mgh.harvard.edu/). Details of these procedures are described in prior publications (Dale et al., 1999; Fischl et al., 1999). Preprocessed images using the Freesurfer pipeline were registered to a spherical atlas, which is based on individual cortical folding patterns to match cortical geometry across subjects and the cerebral cortex was parcellated into 34 regions per hemisphere based on the gyral and sulcal structure (Desikan et al., 2006). Cortical volume measures available from the NIMH Data Archive were used for this analysis.

3.2.4 Statistical Analysis

The ABCD Study's Curated Annual Release 1.1 was made publicly available on November 2, 2018, and can be accessed through the NIMH Data Archive (NDA, https://data-archive.nimh.nih.gov/abcd/query/abcd-annual-releases.html). This release contains baseline data from 4521 subjects. After obtaining permissions as described there, data files can be downloaded in csv format; R scripts for merging these files and including some initial processing (e.g., computing the demographic categories used in this paper) can be found at https://github.com/ABCD-STUDY/analysis-nda17. These scripts produce an. Rds file which can then be used with the R, stan, and R Markdown scripts available online at https://github.com/ABCD-STUDY/ to reproduce these results.

Canonical Correlations Analysis

In a canonical correlation analysis, first, the weights that maximize the correlation of the two weighted sums (linear composites) of each set of variables (called canonical roots) are calculated. Then the first root is extracted and the weights that produce the second largest correlation between sum scores is calculated, subject to the constraint that the next set of sum scores is orthogonal to the previous one. Each successive root will explain a unique additional proportion of variability in the two sets of variables. There can be as many canonical roots as the minimum number of variables in the two sets, which is thirty-eight in this analysis. Therefore, we obtain thirty-eight sets of canonical weights for each set of variables, and each of these thirty-eight canonical roots have a canonical correlation coefficient which is the square root of the explained variability between the two weighted sums (canonical roots).

To obtain unbiased canonical weights for variables and canonical correlation coefficients, we performed canonical correlation analysis on the z-scores of the averaged data using MATLAB (MATLAB and Statistics Toolbox Release 2019a, The MathWorks, Inc., Natick, Massachusetts, United States). For a more straight-forward interpretation and better characterization of the underlying latent variable, instead of using the canonical weights, we calculated the Pearson correlation coefficient (canonical loading) of each observed variable in the set with the weighted sum scores for each of the four linear composites. This way, each canonical root (linear composite) could be interpreted as an underlying latent variable whose degree of relationship with each of the observed variables in the set (how much the observed variable contributes to the canonical variate) is represented by the loading of the observed variable and its errorbar (see canonical correlation results).

To estimate the standard errors of the canonical loadings, we bootstrapped z-scores from the data (2000 simulations for each) and performed canonical correlation analysis 2000 times using MATLAB. Then, we calculated the variances of the set of loadings, which were calculated as explained above.

Mediations Analysis

The mediations were implemented using R package mediation (Tingley et al., 2014) with quasi-Bayesian confidence intervals. This method offers a more robust test of the model, as it uses a bootstrapping procedure (10,000 iterations) and is not as conservatively biased as the Sobel test for medation. Running moderation analyses using this package allows us to evaluate the the Average Direct Effects (ADE) of the model, traditionally called the **c'** path in Baron-Kenney mediation models, in addition to the Average Causal Mediation Effect, (ACME), traditionally called the **a*b** or indirect effect in Baron-Kenney mediation models.

3.3 Results

3.3.1 Canonical Correlations Analysis

Although the canonical correlations analysis yielded 38 latent variables, we will only interpret and focus on those latent variables that included at least one reliable variable based on the canonical correlation bootstrap analysis. That is, that the standard error calculated for the variable loading did not include zero. For this analysis, this yielded four latent variables which we will characterize and interpret below. Together, these three latent variables accounted for 40% of both sets of variables. The loadings for each of the variables within the CCA Latent Variables are listed in Tables 3.3 and 3.4, where values in bold indicate that values as reliable based on a bootstrap analysis.

Results of Canonical Correlations Analysis for Latent Variable 1– Affluence and Advantage.

In the canonical correlations analysis, the linear composites that make up the first canonical root, which we will hereto refer to as the first Latent Variable, accounts for 37% of the variance of the two samples. The weighted canonical scores, or loadings, which indicate the correlation between the original variables and the latent variable scores, are shown in Figure 3.2. The correlation of the Cortical Volume scores and the Environment Scores to each other (r = 0.59, $p < 0.001$) is shown in Figure 3.4. The Cortical Volume scores, shown in Figure 3.3, indicate positive loadings across the entire cerebral cortex. The Environment scores for this LV show positive loadings with being male, being White, having high educational attainment, having high household income, reporting living in a safe neighborhood, showing high scores in MEIM Exploration, and Communication and Attachment scores, having high physical activity, high school disengagement, and high residential proximity to roads. This LV indicated negative loadings for being female, being Black, being Asian, having parents with a high school diploma or some college, having low household income (less than $50,000), all subscales of the MACV (religiosity, family obligations, family as referent, independence and self-reliance, family support), school environment and involvement, population density, residential crime, and Area Deprivation Index (indicating low Area Deprivation). Together, this Latent Variable seems to encapsulate the relationship between Cortical Volume and Environmental factors associated with affluence, and positive residential neighborhood characteristics. As such, for the remainder of our results we will characterize this Latent Variable as indexing **Affluence and Advantage**.

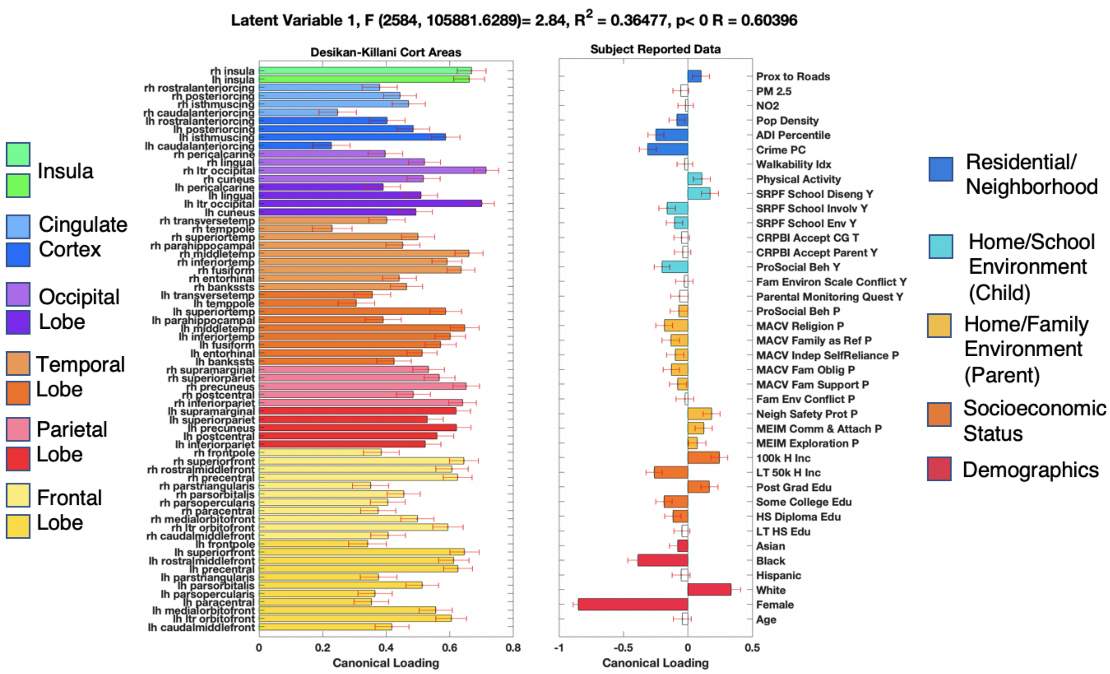


Figure 3.2: Canonical correlation results for Latent Variable 1. Bars show correlation of each variable with the first set of weighted canonical scores (loadings). Error bars show ±2 standard errors. The bars on the left represent loadings of Cortical Volume scores, while the bars on the right represent loadings on Environment scores. This pair of linear composites represents an overall pattern of greater cortical volume associated with being White, of higher SES, and lower neighborhood adversity and crime. For the rest of the results, this LV will be characterized as indexing **Affluence and Advantage**.

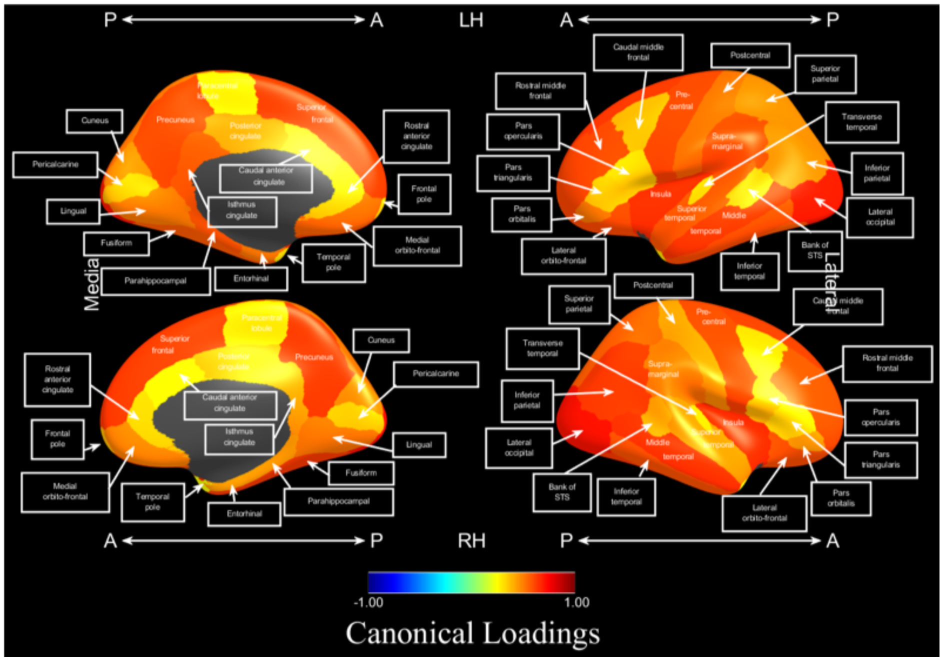


Figure 3.3: Cortical volume loadings for canonical correlation, Latent Variable 1. Cortical volume loadings are shown projected on an inflated Desikan-Killiany parcellation scheme. Warmer colors indicate greater correlation between the weighted canonical scores and each region. The scores indicate a homogeneous positive across all regions of the cerebral cortex, with strong associations with high affluence and low disadvantage (See Figure 3.2).

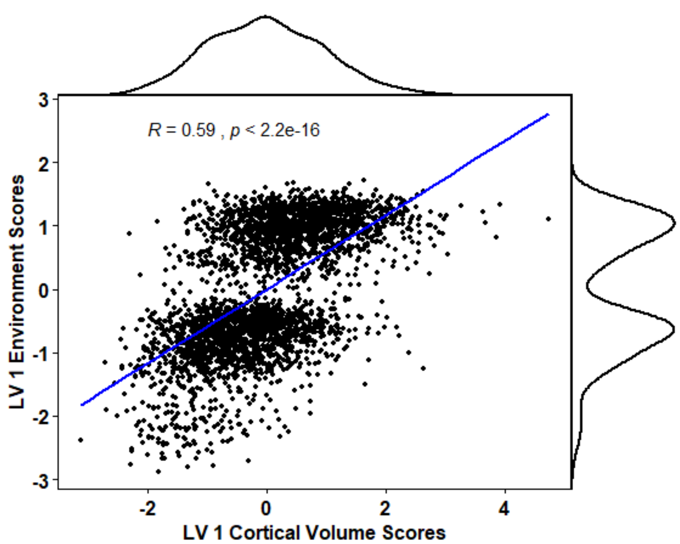


Figure 3.4: Correlation of canonical correlation scores, Latent Variable 1. The distribution and correlation between the Cortical Volume and Environmental scores are shown here. At the top is the density function for the Cortical Volume scores, and at the right is the density function for the Environment scores.

Results of canonical correlations analysis for LV 2 – Disadvantage, Familialism, and Urbanicity

The second Latent Variable that emerges in the canonical correlation analysis between Cortical Volume scores and Environment scores accounts for 16.8% of the remaining variance. The weighted canonical scores, or loadings, which indicate the correlation between the original variables and the latent variable scores, are shown in Figure 3.5. The correlation of the Cortical Volume scores and the Environment Scores to each other (r = 0.37, $p < 0.001$) is shown in Figure 3.7. The Cortical Volume scores, are shown in Figure 3.6.

As opposed to the homogeneous effect of Latent Variable 1, this Latent Variable shows positive and negative loadings at various spots throughout the cortex (see Table 3.3 for all values). Cortical Volume areas indicating significant positive loadings include left medial orbitofrontal cortex, bilateral pars triangularis, bilateral rostral middle frontal cortex, bilateral inferior parietal cortex, bilateral insula, left posterior cingulate cortex, and right isthmus cingulate cortex. Cortical Volume areas with significant negative loadings include lateral orbitofrontal cortex, left postcentral cortex, bilateral superior parietal cortex, bilateral middle temporal cortex, left parahippocampal cortex, right entorhinal cortex, bilateral lingual cortex, and right lateral occipital cortex.

The Environmental scores for this LV (see Table 3.4) show positive loadings with being Black, having some college education, having a household income of less than $50,000, all subscales of the MACV, which indexes familialism (religiosity, family obligations, family as referent, independence and self-reliance, family support), residential walkability, residential crime, Area Deprivation Index (indicating high Area Deprivation), and population density. This LV indicated negative loadings for being female, being White, having high household income (more than $100,000 a year), all subscales of the MEIM which indexes parenting style (Community & attachment, Exploration subscales), reported neighborhood safety, lower reported prosocial behavior, lower reported parental monitoring, and proximity to roads.

Together, this Latent Variable seems to encapsulate the relationship between Cortical Volume and Environmental factors associated with disadvantage and familialism, and negative residential neighborhood characteristics. In addition, separately from Latent Variable 1, this Latent Variable seems to capture more factors associated with non-White and non-affluent participants, highlighting strong contributions from cultural variables, as the MEIM, and variables that may be associated with dense urban environments. As such, for the remainder of our results we will characterize this Latent Variable as indexing **Disadvantage, Familialism, and Urbanicity**.

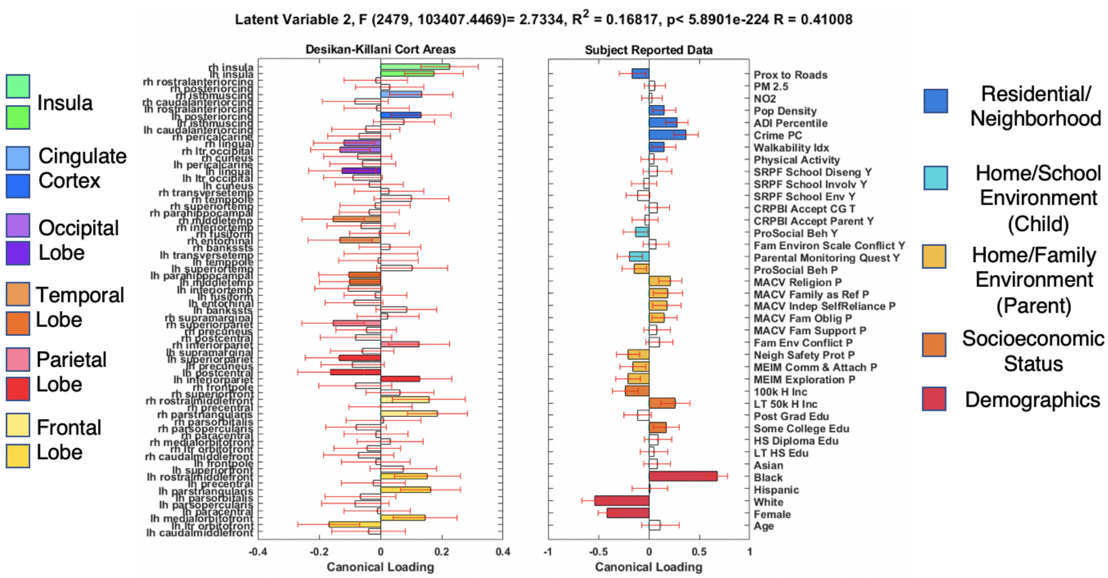


Figure 3.5: Canonical correlation results for Latent Variable 2. Bars show correlation of each variable with the second set of weighted canonical scores (loadings). Error bars show ± 2 standard errors. The bars on the left represent loadings of Cortical Volume scores, while the bars on the right represent loadings on Environment scores. This pair of linear composites represents an a pattern that loads positively with high neighborhood adversity, high familialism values, low SES, and being Black. For the rest of this analysis, this LV will be characterized as indexing **Disadvantage, Familialism, and Urbanism**.

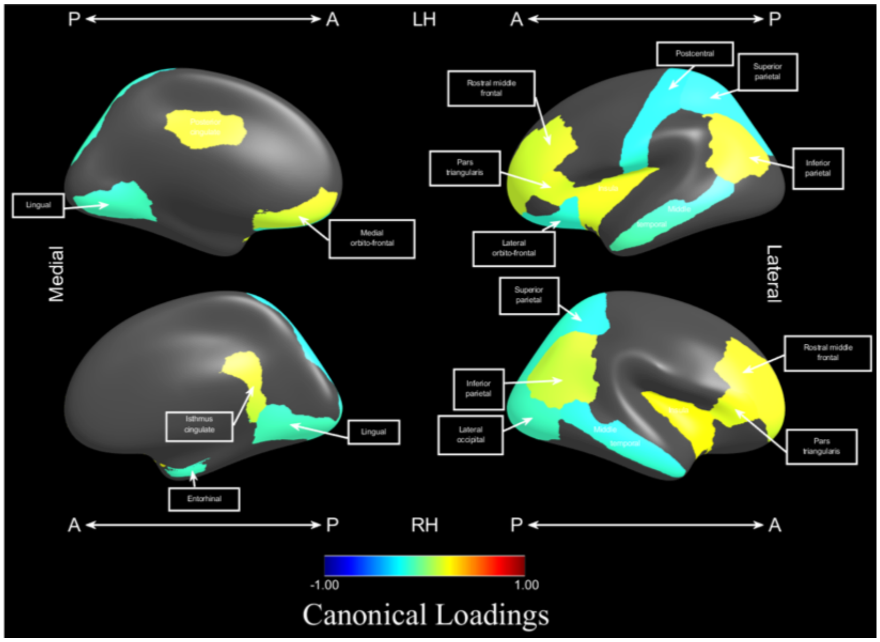


Figure 3.6: Cortical volume loadings for canonical correlation, Latent Variable 2. Cortical volume loadings are shown projected on an inflated Desikan-Killiany parcellation scheme. Only loadings that showed a reliable relationship after bootstrapping (error bars did not cross zero) are shown. Loading values here indicate the degree of correlation with environmental loadings shown in Figure 3.5, indexing **Disadvantage, Familialism, and Urbanism**. Warmer colors indicate positive loadings, a positive correlation, while cooler colors indicate more negative loadings with this latent variable.

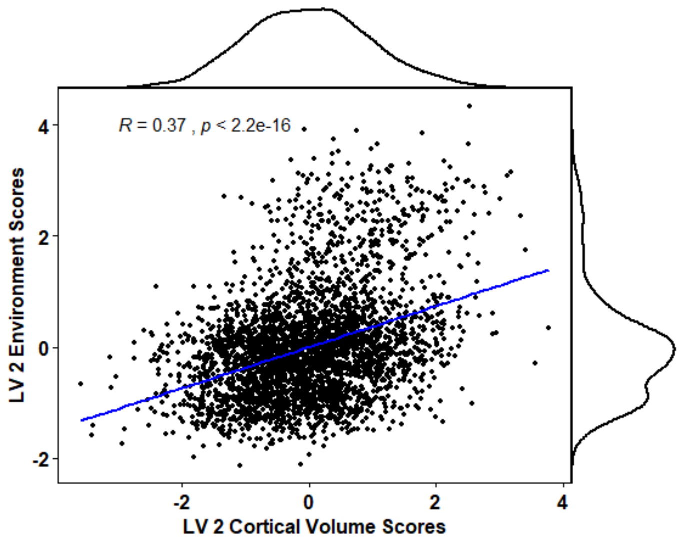


Figure 3.7: Correlation of canonical correlation scores, Latent Variable 2. The distribution and correlation between the Cortical Volume and Environment scores are shown here. At the top is the density function for the Cortical Volume scores, and at the right is the density function for the Environment scores.

Results of Canonical Correlations Analysis for LV 3–Low SES and Hispanic

The third Latent Variable that emerges in the canonical correlation analysis between Cortical Volume scores and Environment scores accounts for 12.0% of the remaining variance. The weighted canonical scores, or loadings, which indicate the correlation between the original variables and the latent variable scores, are shown in Figure 3.8. The correlation of the Cortical Volume scores and the Environment Scores to each other (r = 0.28, $p < 0.001$) is shown in Figure 3.10. The Cortical Volume scores, are shown in Figure 3.9.

As opposed to the homogeneous effect of Latent Variable 1 and the broad effect of Latent Variable 2, this Latent Variable highlights a significant relationship between specific areas and environmental factors. As seen in 3.8, with signs changed for ease of interpretation, this latent variable indicates a strong relationship between Cortical Volume in the left temporal pole and left caudal middle frontal cortex, and being Hispanic, having less than a high school education, and having a household income of less than $50,000 a year. As such, for the remainder of our results we will characterize this Latent Variable as indexing being **Low SES, and Hispanic**.

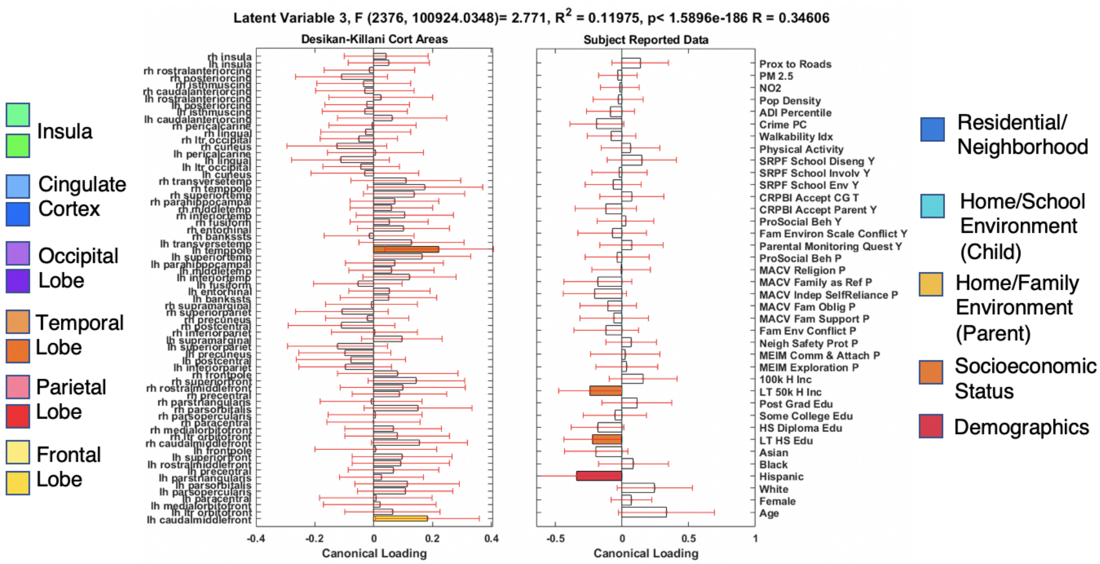


Figure 3.8: Canonical correlation results for Latent Variable 3. Bars show correlation of each variable with the first set of weighted canonical scores (loadings). Error bars show ± 2 standard errors. The bars on the left represent loadings of cortical volume scores, while the bars on the right represent loadings on environment scores. This pair of linear composites represents a pattern that shows a negative correlation between left caudal medial frontal and left temporal pole areas and household income and parental education and being Hispanic.

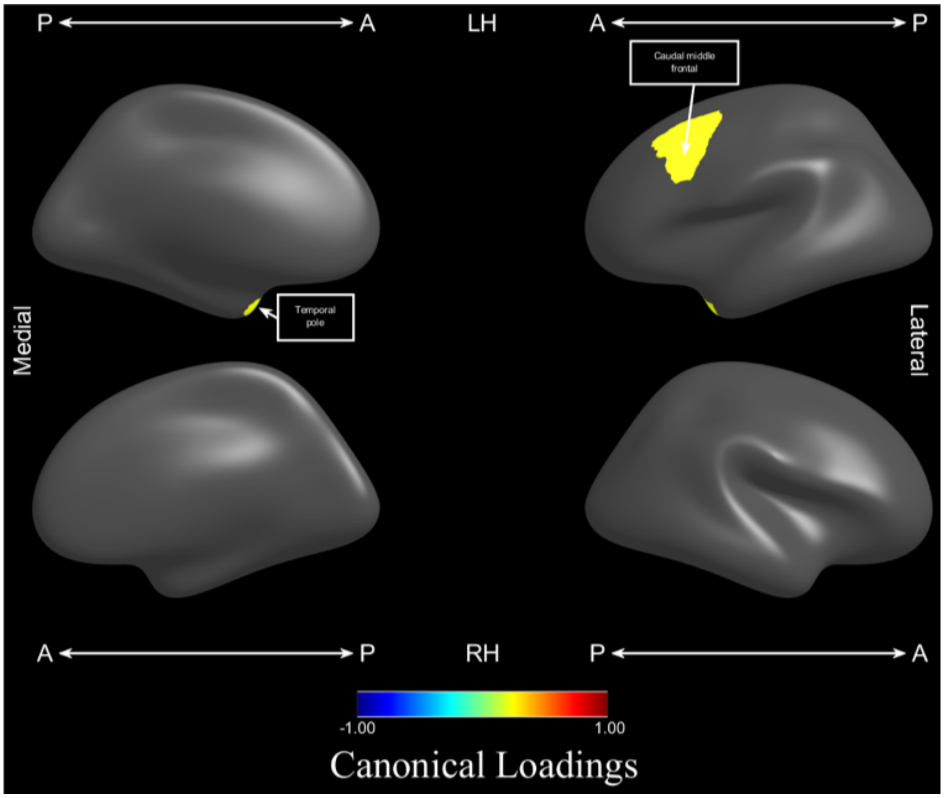


Figure 3.9: Cortical volume loadings for canonical correlation, Latent Variable 3. Cortical volume loadings are shown projected on an inflated Desikan-Killiany parcellation scheme. Only loadings that showed a reliable relationship after bootstrapping (error bars did not cross zero) are shown. While loading values are positive, they indicate the degree of negative correlation with environmental loadings shown in Figure 3.5, indexing being low SES and identifying as Hispanic.

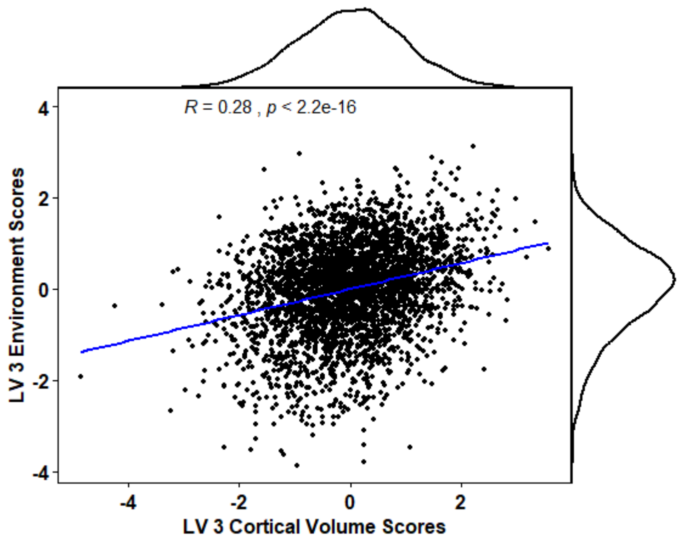


Figure 3.10: Correlation of canonical correlation scores, Latent Variable 3. The distribution and correlation between the Cortical Volume and Environmental scores are shown here. At the top is the density function for the Cortical Volume scores, and at the right is the density function for the Environment scores.

Table 3.3: Canonical correlation Latent Variable loadings for Cortical Volume Areas (Desikan-Killiany)

Lobe	Variable	LV1	LV2	LV3	Lobe	Variable	LV1	LV2	LV3
Frontal	Left Caudal Middle Frontal	**0.418**	-0.039	**0.182**	Temporal	Left Bank of Superior Temporal	**0.425**	0.085	0.050
	Left Lateral Orbitofrontal	**0.605**	**-0.168**	0.064		Left Entorhinal	**0.513**	-0.086	0.053
	Left Medial Orbitofrontal	**0.556**	**0.146**	0.021		Left Fusiform	**0.572**	-0.016	-0.054
	Left Paracentral	**0.353**	-0.010	0.007		Left Inferior Temporal	**0.602**	-0.105	0.121
	Left Pars Opercularis	**0.365**	-0.083	0.107		Left Middle Temporal	**0.647**	**-0.101**	0.060
	Left Pars Orbitalis	**0.514**	-0.065	0.113		Left Parahippocampal	**0.391**	**-0.103**	0.071
	Left Pars Triangularis	**0.377**	**0.164**	0.026		Left Superior Temporal	**0.588**	0.104	0.164
	Left Precentral	**0.626**	-0.024	0.067		Left Temporal Pole	**0.306**	-0.007	**0.221**
	Left Rostral Middle Frontal	**0.613**	**0.153**	0.092		Left Transverse Temporal	**0.356**	0.001	0.128
	Left Superior Frontal	**0.647**	0.074	0.096		Right Bank of Superior Temporal	**0.464**	0.031	-0.015
	Left Frontal Pole	**0.341**	-0.015	0.007		Right Entorhinal	**0.441**	**-0.132**	0.101
	Right Caudal Middle Frontal	**0.406**	-0.072	0.155		Right Fusiform	**0.636**	-0.003	0.053
	Right Lateral Orbitofrontal	**0.594**	-0.044	0.079		Right Inferior Temporal	**0.592**	-0.063	0.104
	Right Medial Orbitofrontal	**0.498**	0.031	0.066		Right Middle Temporal	**0.660**	**-0.154**	0.060
	Right Paracentral	**0.375**	-0.015	-0.002		Right Parahippocampal	**0.453**	-0.037	0.070
	Right Pars Opercularis	**0.405**	-0.079	0.005		Right Superior Temporal	**0.500**	-0.018	0.137
	Right Pars Orbitalis	**0.455**	0.010	0.150		Right Temporal Pole	**0.230**	0.101	0.174
	Right Pars Triangularis	**0.351**	**0.185**	-0.008		Right Transverse Temporal	**0.402**	0.028	0.109
	Right Precentral	**0.625**	0.000	0.087	Occipital	Left Cuneus	**0.494**	-0.037	-0.031
	Right Rostral Middle Frontal	**0.607**	**0.158**	0.098		Left Lateral Occipital	**0.702**	-0.089	-0.043
	Right Superior Frontal	**0.645**	0.064	0.145		Left Lingual	**0.510**	**-0.125**	-0.113
	Right Frontal Pole	**0.385**	-0.082	0.081		Left Pericalcarine	**0.391**	-0.058	0.006
Parietal	Left Inferior Parietal	**0.523**	**0.128**	-0.096		Right Cuneus	**0.518**	-0.074	-0.125
	Left Postcentral	**0.560**	**-0.162**	-0.077		Right Lateral Occipital	**0.715**	**-0.131**	-0.051
	Left Precuneus	**0.621**	-0.091	-0.098		Right Lingual	**0.521**	**-0.119**	-0.027
	Left Superior Parietal	**0.530**	**-0.135**	-0.123		Right Pericalcarine	**0.398**	-0.070	-0.005
	Left Supramarginal	**0.620**	-0.060	0.095	Cingulate	Left Caudal Anterior	**0.228**	-0.048	0.063
	Right Inferior Parietal	**0.641**	**0.125**	0.003		Left Isthmus	**0.588**	0.076	-0.030
	Right Postcentral	**0.486**	-0.081	-0.110		Left Posterior	**0.485**	**0.133**	-0.023
	Right Precuneus	**0.652**	-0.046	-0.022		Left Caudal Anterior	**0.404**	-0.013	0.024
	Right Superior Parietal	**0.568**	**-0.154**	-0.108		Right Caudal Anterior	**0.248**	-0.083	-0.030
	Right Supramarginal	**0.534**	0.024	-0.007		Right Isthmus	**0.471**	**0.134**	-0.035
Insula	Left Insula	**0.661**	**0.174**	0.051		Right Posterior	**0.444**	0.030	-0.109
	Right Insula	**0.669**	**0.225**	0.042		Right Caudal Anterior	**0.379**	-0.015	-0.015

Note: Numbers in bold indicate reliable loadings based on bootstrap analysis

Table 3.4: Canonical correlation Latent Variable loadings for Environment variables

Category	**Variable**	**LV1**	**LV2**	**LV3**
Demographics	Age	-0.042	0.113	0.333
	Female	**-0.849**	**-0.414**	0.070
	White	**0.335**	**-0.535**	0.245
	Hispanic	-0.052	0.011	**-0.342**
	Black	**-0.388**	**0.676**	0.085
	Asian	**-0.078**	0.083	-0.195
Socioeconomic Status	Less than High School, Education	-0.046	0.050	**-0.220**
	HS Diploma, Education	**-0.115**	0.090	-0.184
	Some College, Education	**-0.184**	**0.171**	-0.054
	Post Grad, Education	**0.166**	-0.111	0.111
	Less Than $50K, Income	**-0.261**	**0.263**	**-0.240**
	More than $100K, Income	**0.244**	**-0.233**	0.156
Family/Home Environment (Parent-Reported)	MEIM Exploration Subscale	**0.072**	**-0.207**	0.035
	MEIM Commitment and Attachment Subscale	**0.123**	**-0.157**	0.025
	Perceived Neighborhood Safety	**0.184**	**-0.205**	0.068
	Family Environment, Family Conflict Subscale	-0.023	0.104	-0.121
	MACV Family Support	**-0.078**	0.080	-0.060
	MACV Family Obligation	**-0.128**	**0.155**	-0.105
	MACV Indepependence & Self-Reliance	**-0.097**	**0.180**	-0.205
	MACV Family as a Referent	**-0.132**	**0.188**	-0.183
	MACV Religion	**-0.182**	**0.213**	-0.007
	Perceived Child ProSocial Behavior	**-0.069**	**-0.144**	-0.037
Home/School Environment (Child-Reported)	Parental Monitoring Survey	-0.065	**-0.192**	0.070
	Family Environment, Family Conflict Subscale	-0.027	0.070	-0.073
	Prosocial Behavior	**-0.200**	**-0.132**	0.027
	CRPBI Parental Acceptance	-0.039	-0.039	-0.122
	CRPBI Caregiver Acceptance	-0.049	0.082	0.073
	SRPF School Environment	**-0.103**	-0.110	-0.067
	SRPF School Involvement	**-0.160**	-0.049	-0.021
	SRPF School Disengagement	**0.173**	0.082	0.148
	Physical Activity	**0.109**	0.049	0.064
Residential/Neighborhood Measures	Neighborhood Walkability	-0.025	**0.150**	-0.080
	Amount of Neighborhood Crime	**-0.311**	**0.366**	-0.190
	Area Deprivation Index Percentile	**-0.248**	**0.277**	-0.087
	Population Density	**-0.084**	**0.151**	-0.029
	NO2 Levels	-0.018	0.030	-0.017
	PM 2.5 Levels	-0.055	0.058	-0.032
	Proximity of Home to Roads	**0.102**	**-0.164**	0.137

Note: Numbers in bold indicate reliable loadings based on bootstrap analysis

3.3.2 Mediation Analysis

Latent Variable 1– Affluence and Advantage

This purpose of this mediation model was to test the hypothesis that Environment Scores of Latent Variable 1, which in this case are characterized as highlighting **Affluence and Advantage**, mediate the relationship between Cortical Volume scores and Cognitive scores (see Figure 3.11 for a structural representation of the model, and Figure 3.2 for the individual variable loadings of this latent variable). A mediation regression analysis (results shown in Table 3.5a) revealed that Cortical Volume scores, while ignoring the mediator, were a significant predictor of Cognitive scores (β = 2.269, $SE(\beta)$ = 0.303, t(3282)= 7.493, p < 0.001 (**c path**)). Once controlling for Environmental Scores, Cortical Volume scores remained a significant predictor of Cognitive scores ($\beta = 1.07$, $SE(\beta) = 0.372$, $t(3281) = 2.879$, $p = 0.004$ (**c' path**). The indirect path, (typically referred to as the **a** and **b path** in Baron-Kenney regression mediation analyses), indicated that Cortical Volume scores were a significant predictor of Environment scores ($\beta = 0.585$, $SE(\beta) = 0.014$, $t(3282) = 41.348$, $p < 0.001$), and Environment scores were a significant predictor of Cognitive scores ($\beta = 1.07$, $SE(\beta) = 0.372$, $t(3281) = 2.879$, $p = 0.004$). Therefore, the mediation analysis for this latent variable suggests that Environmental scores *partially* mediate the relationship between Cortical Volume scores and Cognitive scores. These results are summarized in Table 3.5.

Using a bayesian modeling mediation procedure in the `mediation` package in R and bootstrapping, we decomposed the total effect of the model into the Average Causal Mediated Effect (ACME) and the Average Direct Effect (ADE). The average total effect (as seen in the bottom panel of Figure 3.11 and in Table 3.5b) is estimated to be 2.269 with a 95 percent confidence interval of [1.668, 2.884]. The ACME effect was estimated to be 1.199, with a 95 percent confidence interval of [0.775, 2.884], while the ADE was estimated to be 1.070, with a 95 percent confidence interval of [1.66, 2.884]. These results suggest that Cortical Volume scores are associated with an increase in Cognitive scores, but that some of this change is due to increasing Environment scores in this latent variable. Thus, these mediation results suggest for this latent variable, characterized by **Affluence and Advantage**, *both* Cortical Volume and Environment scores are important.

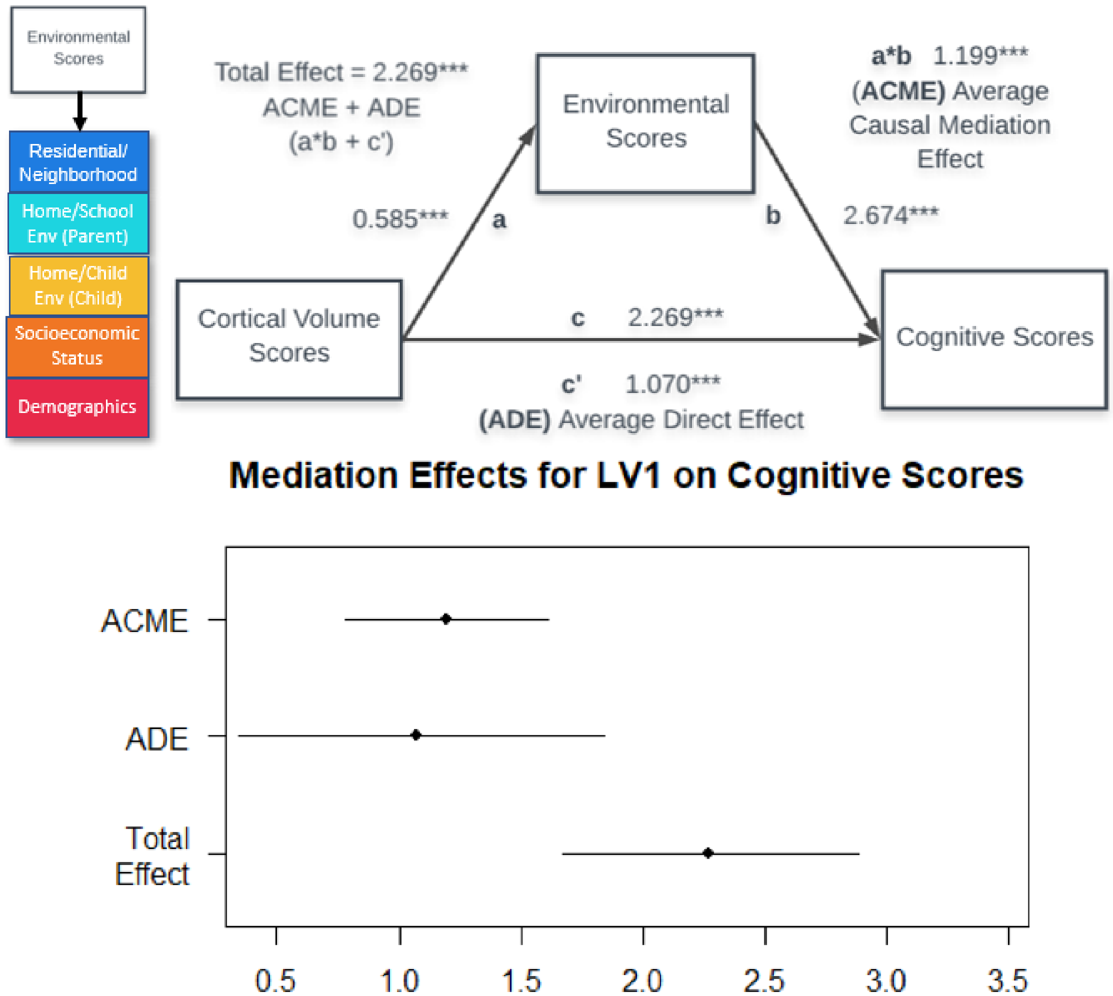


Figure 3.11: Mediation results on Cognitive scores using LV1. **(Upper Panel)** This diagram displays the mediation model, where the Average Direct Effect (ADE) is represented by the relationship between Cortical Volume Scores and total Cognitive score, while the Average Causal Mediation Effect (ACME) takes into account the indirect path including Environment Scores. **(Bottom Panel)** Mediation effects indicate that when accounting for the Environment Scores for this Latent Variable, the ADE and ACME are significantly positive, showing a significant partial mediation.

Table 3.5: Mediation analysis of Cognitive scores using Latent Variable 1

Table 3.5a: Mediation Regression Results

	Dependent variable:			
	Environment Scores	Cognitive Scores		
	(a)	(b)	(c)	(c')
Cortical Volume Scores	0.585***		2.269***	1.070***
	(0.014)		(0.303)	(0.372)
Environment Scores		2.674***		2.048***
		(0.302)		(0.372)
Constant	0.000	103.273***	103.273***	103.273***
	(0.014)	(0.302)	(0.303)	(0.301)
Observations	3,284	3,284	3,284	3,284
R^2	0.343	0.023	0.017	0.026
Adjusted R^2	0.342	0.023	0.017	0.025
Residual Std. Error	0.811	17.292	17.350	17.273
	(df = 3282)	(df = 3282)	(df = 3282)	(df = 3281)
F Statistic	1,709.667***	78.528***	56.145***	43.496***
	(df = 1; 3282)	(df = 1; 3282)	(df = 1; 3282)	(df = 2; 3281)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3.5b: Estimated Causal Mediation Effects

Quasi-Bayesian Confidence Intervals	Estimate	95% CI Lower	95% CI Upper	p-values
Avg Causal Mediated Effect (ACME)	1.199	0.781	1.606	0.000***
Avg Direct Effect (ADE)	1.070	0.344	1.842	0.003***
Total Effect	2.269	1.668	2.884	0.000***
Proportion Mediated	0.528	0.321	0.811	0.000***

Latent Variable 2–Disadvantage, Familialism, and Urbanism

This mediation model tested the hypothesis that Environment scores of latent variable 2, which are charactized by **high Disadvantage, Familialism, and Urbanism**, mediate the relationship between Cortical Volume scores and Cognitive scores (see Figure 3.12 for a structural representation of the model, and Figure 3.5 for the individual variable loadings of this latent variable). A mediation regression analysis (results shown in Table 3.6a)revealed that

Cortical Volume scores, while ignoring the mediator, were a significant predictor of Cognitive scores,(β = -1.322, $SE(\beta)$ = 0.305, $t(3282)$= -4.341, $p < 0.001$ (**c path**)). Once controlling for Environment scores, Cortical Volume scores were no longer a significant predictor of Cognitive scores ($\beta = 0.179$, $SE(\beta) = 0.32$, t(3281) = 0.561, $p = 0.575$). The indirect path, (typically referred to as the **a** and **b path** in Baron-Kenney regression mediation analyses), indicated that Cortical Volume scores were a significant predictor of Environment scores ($\beta = 0.37$, $SE(\beta) = 0.016$, t(3282) = 22.827, $p < 0.001$), and Environment scores were a significant predictor of Cognitive scores (β = -3.989, $SE(\beta) = 0.297$, $t(3282)$ = -13.42, $p <$ 0.001). Therefore, the mediation analysis for this latent variable suggests that Environment scores *fully* mediate the relationship between Cortical Volume scores and Cognitive scores. These results are summarized in Table 3.6.

Using a bayesian modeling mediation procedure in the *mediation* package in R and bootstrapping, we decomposed the total effect of the model into the Average Causal Mediated Effect (ACME) and the Average Direct Effect (ADE). The average total effect (as seen in the bottom panel of Figure 3.12 and in Table 3.6b) is estimated to be -1.322 with a 95 percent confidence interval of [-1.889, -0.719]. The ACME effect was estimated to be -1.501, with the 95 percent confidence interval of [-1.788, -1.239], while the ADE was estimated to be 0.179, with a 95 percent confidence interval of [-0.415, 0.825], failing to reach the significance criterion. Given the difference in sign between the ACME and the ADE, it seems that the Environment scores function as a suppressor in the relationship between Cortical Volume scores and Cognitive scores. These results suggest that the decrease in Cognitive Scores is due to increasing Environment scores in this latent variable, and less so with the association with Cortical Volume scores. Thus, these mediation results suggest for this latent variable, characterized by **Disadvantage and Familialism**, it is the Environment scores that are important.

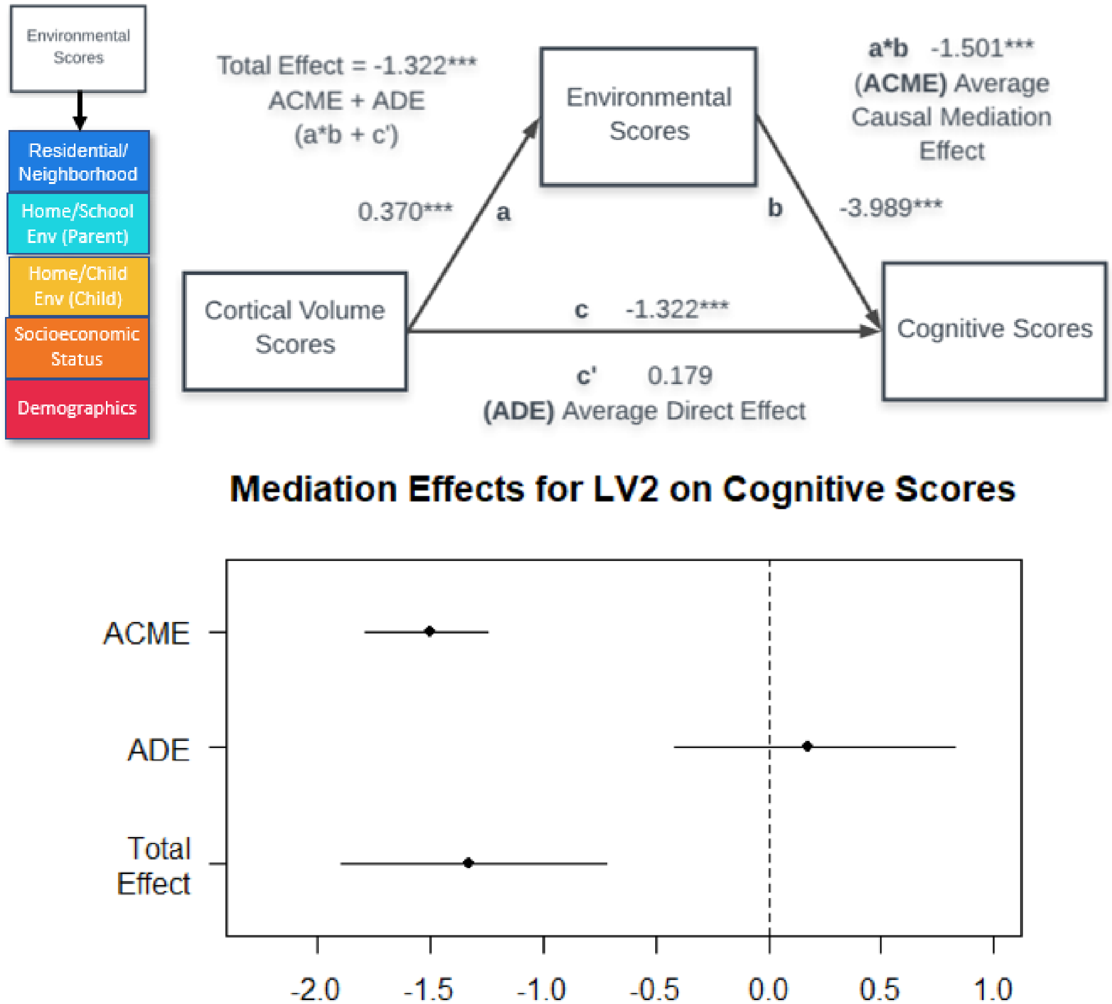


Figure 3.12: Mediation results on Cognitive scores using LV2. **(Upper Panel)** This diagram displays the mediation model, where the Average Direct Effect (ADE) is represented by the relationship between Cortical Volume Scores and Total Cognitive Score, while the Average Causal Mediation Effect (ACME) takes into account the indirect path including Environment scores. **(Bottom Panel)** Mediation effects indicate that when accounting for the Environment scores for this Latent Variable in the relationship between Cortical Volume and Cognitive scores, only the ACME is significantly negative, showing a complete mediation, such that only the indirect path through Environment scores reliably predicts Cognitive scores.

Table 3.6: Mediation analysis of Cognitive scores using Latent Variable 2

Table 3.6a: Mediation Regression Results

	Dependent variable:			
	Environment Scores	Cognitive Scores		
	(a)	(b)	(c)	(c')
Cortical Volume Scores	0.370***		−1.322***	0.179
	(0.016)		(0.305)	(0.320)
Environment Scores		−3.989***		−4.056***
		(0.297)		(0.320)
Constant	0.000	103.273***	103.273***	103.273***
	(0.016)	(0.297)	(0.304)	(0.297)
Observations	3,284	3,284	3,284	3,284
R^2	0.137	0.052	0.006	0.052
Adjusted R^2	0.137	0.052	0.005	0.052
Residual Std. Error	0.929	17.037	17.448	17.038
	(df = 3282)	(df = 3282)	(df = 3282)	(df = 3281)
F Statistic	521.094***	180.010***	18.842***	90.143***
	(df = 1; 3282)	(df = 1; 3282)	(df = 1; 3282)	(df = 2; 3281)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.6b: Estimated Causal Mediation Effects

Quasi-Bayesian Confidence Intervals	**Estimate**	**95% CI Lower**	**95% CI Upper**	**p-values**
Avg Causal Mediated Effect (ACME)	-1.501	-1.788	-1.239	0.000***
Avg Direct Effect (ADE)	0.179	-0.415	0.825	0.548
Total Effect	-1.322	-1.889	-0.719	0.000 ***
Proportion Mediated	1.136	0.774	2.080	0.000 ***

Latent Variable 3 – Low SES and Hispanic

This mediation model tested the hypothesis that Environment scores of latent variable 3, which are charactized by **being of low SES and identifying as Hispanic**, mediate the relationship between Cortical Volume scores and Cognitive scores (see Figure 3.13 for a structural representation of the model, and Figure 3.8 for the individual variable loadings of this latent variable). A mediation regression analysis (results shown in Table 3.7a) revealed that

Cortical Volume scores, while ignoring the mediator, were a significant predictor of Cognitive scores,(β = 1.408, $SE(\beta)$ = 0.304, $t(3282)$= 4.626, p < 0.001 (**c path**)). Once controlling for Environment scores, Cortical Volume scores were no longer a significant predictor of Cognitive scores (β = 0.504, $SE(\beta)$ = 0.313, $t(3281)$ = 1.612, p = 0.107). The indirect path, (typically referred to as the **a** and **b path** in Baron-Kenney regression mediation analyses), indicated that Cortical Volume scores were a significant predictor of Environment scores (β = 0.284, $SE(\beta)$ = 0.017, $t(3282)$ = 16.976, p < 0.001), and Environment scores were a significant predictor of Cognitive scores (β = 3.326, $SE(\beta)$ = 0.300, $t(3281)$ = 11.09, p < 0.001). Therefore, the mediation analysis for this latent variable suggests that Environment scores *fully* mediate the relationship between Cortical Volume scores and Cognitive scores. These results are summarized in Table 3.7.

Using a bayesian modeling mediation procedure in the `mediation` package in R and bootstrapping, we decomposed the total effect of the model into the Average Causal Mediated Effect (ACME) and the Average Direct Effect (ADE). The average total effect (as seen in the bottom panel of Figure 3.13 and in Table 3.7b) is estimated to be 1.408 with the 95 percent confidence interval of [0.840, 2.207]. The ACME effect was estimated to be 0.904, with the 95 percent confidence interval of [0.692, 1.123], while the ADE was estimated to be 0.504, with a 95 percent confidence interval of [-0.096, 1.136], failing to reach the significance criterion. These results suggest that the change in Cognitive scores is due to increasing Environment scores in this latent variable, and less so with the association with Cortical Volume scores. Thus, these mediation results suggest for this latent variable, characterized by **low SES and being Hispanic**, it is the Environment scores that are important.

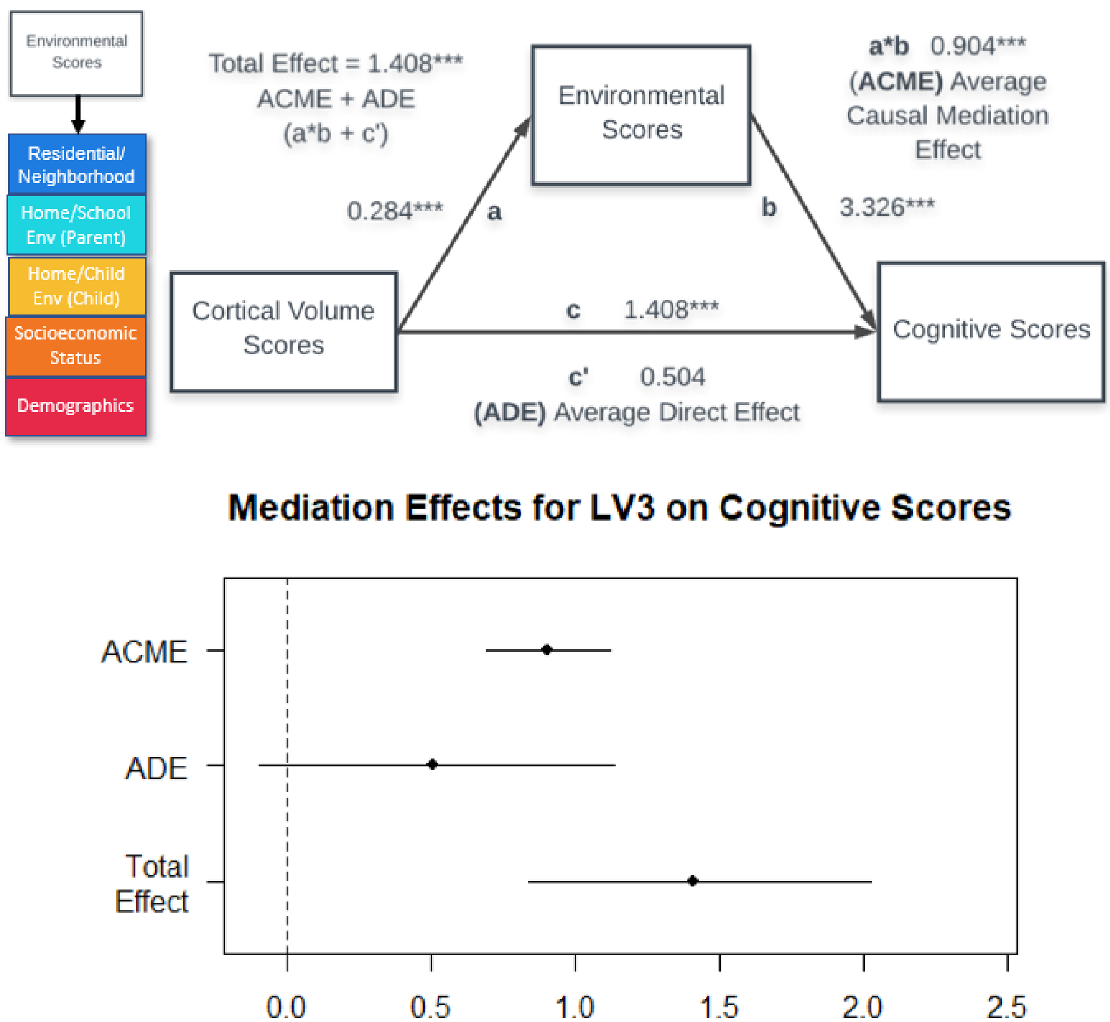


Figure 3.13: Mediation results on Cognitive scores using LV3. **(Upper Panel)** This diagram displays the mediation model, where the Average Direct Effect (ADE) is represented by the relationship between Cortical Volume Scores and Total Cognitive Score, while the Average Causal Mediation Effect (ACME) takes into account the indirect path including Environment Scores. **(Bottom Panel)** Mediation effects indicate that when accounting for the Environment Scores for this Latent Variable in the relationship between Cortical Volume and Cognitive scores, only the ACME is significantly and positive, showing a complete mediation, such that only the indirect path through Environment Scores reliably predicts Cognitive scores.

Table 3.7: Mediation analysis of Cognitive scores using Latent Variable 3

Table 3.7a: Mediation Regression Results

	Dependent variable:			
	Environment Scores	Cognitive Scores		
	(a)	(b)	(c)	(c')
Cortical Volume Scores	0.284*** (0.017)		1.408*** (0.304)	0.504 (0.313)
Environment Scores		3.326*** (0.300)		3.183*** (0.313)
Constant	0.000 (0.017)	103.273*** (0.300)	103.273*** (0.304)	103.273*** (0.300)
Observations	3,284	3,284	3,284	3,284
R^2	0.081	0.036	0.006	0.037
Adjusted R^2	0.080	0.036	0.006	0.036
Residual Std. Error	0.959 (df = 3282)	17.178 (df = 3282)	17.441 (df = 3282)	17.174 (df = 3281)
F Statistic	288.194*** (df = 1; 3282)	123.074*** (df = 1; 3282)	21.402*** (df = 1; 3282)	62.866*** (df = 2; 3281)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3.7b: Estimated Causal Mediation Effects

Quasi-Bayesian Confidence Intervals	**Estimate**	**95% CI Lower**	**95% CI Upper**	**p-values**
Avg Causal Mediated Effect (ACME)	0.904	0.692	1.123	0.000***
Average Direct Effect (ADE)	0.504	-0.096	1.136	0.092
Total Effect	1.408	0.840	2.027	0.000 ***
Proportion Mediated	0.642	0.415	1.099	0.000 ***

3.4 Discussion

The purpose of this study was to investigate the various ways in which social stratification may impact brain structure and cognitive performance in children. This study was inspired by a growing literature that illustrates the biological embedding of positive or negative environmental conditions. Specifically, this study set out to expand on literature highlighting the impact of Socioeconomic Status (SES) on cortical volume, by including variables that extended beyond traditional operationalizations of SES consisting of household income, family educational attainment, and occupational prestige. The reasoning for this was two-fold: First, to include additional variables that described the social dynamics of individual's neighborhood, elements of the built and natural environment, and elements of the their family, school, and home life, in addition to demographic factors that may impact their identity development and the amount of experiential stress they may encounter (such as belonging to a household of low SES status, or being a member of a historically marginalized racial/ethnic minority group). Second, to conduct a multivariate factor analysis, canonical correlations, that considered the overlapping relationships between all of these environmental variables and examine how jointly, these variables correlated to cortical morphometry, in this case cortical volume, and then were related to explaining variations in cognitive performance.

Our results resulted in the extraction of three significant latent variables that provided different accounts of the relationship between environmental scores and cortical volume, and subsequently, cognitive performance. The first latent variable, which we are interpreting as encapsulating Affluence and Advantage, was related to a global effect in cortical volume such that higher Affluence and Advantage was related to greater volume. A mediation model used explain the effects behind cognitive performance indicated a partial mediation, such that both environment scores and cortical volume scores were useful in describing the variation in cognitive scores. This result is consistent with previous research investigating the role of SES in explaining the connection between cortical volume and cognitive performance, such that greater environmental enrichment and lower deprivation contribute to greater cortical volume. It is important to note that in this first latent variable, the factor with the greatest loading was that of gender, which may contribute largely to the bimodal distribution in the density function in Figure 3.3. Although a large body of literature has documented this gender difference in cortical morphometry, a separate analysis conducted accounting for participant gender showed the same significant loadings in LV1, suggesting that this gender difference is not fully driving these results. An exception in this separate comparison is the significant loadings in the SRPF School Engagement variables, which are no longer significant when accounting for gender.

As opposed to the global cortical volume effect of the first latent variable, the second latent variable, which we interpreted to capture Structural Disadvantage, Famililism, and Urbanicity, was related to a heterogeneous effect across the cortex, where some brain regions were more positively associated with the Disadvantage, Famillism, and Urbanicity variables, and some were negatively associated (see Figure 3.5). Interestingly, the mediation analysis of these latent variable scores to explain variations in cognitive scores showed a full mediation, indicating that cortical morphometry, in this case, did not explain much of the variation in cognitive scores, and that this effect was driven by the environmental scores. The relationship between these environmental variables has been widely reported, such that being Black in the United States is highly associated with neighborhood deprivation, but this result, which does not show much a contribution of cortical volume to explain cognitive scores, suggests that investigations exploring the relationship of brain-SES-behavior, should consider additional variables such as race and ethnicity in conjunction with traditional SES indicators.

Also highlighted in Latent Variable 2 are the significant positive loadings of the Mexican-American Cultural Value (MACV) subscales, which tap into constructs such as Famillism, or *familismo*, which place the family as a strong and present element in a person's self-identity, and has been documented as being more present in Latinx and Black families. Findings from counseling psychology focusing on the impact of family on child socioemotional development across various racial/ethnic groups have noted that *familismo* may serve as a protective factor for social stressors associated with residential deprivation, as it fosters psychological resilience and higher-quality parenting (Gaylord-Harden, Burrow, & Cunningham, 2012; White, Liu, Nair, & Tien, 2015; White, Roosa, & Zeiders, 2012). Just as important, *familismo* has been shown to be closely related to how families communicate with a child's race, ethnicity, and social status, which not only impacts the development of their own racial/ethnic and status-based identity, but has strong implications for how they interpret the social dynamics of their local environments (Destin, Rheinschmidt-Same, & Richeson, 2017) and This highlights these factors as interesting areas of future study, and highlights their importance as contextual factors in research relating sociodemographic variables to brain, behavior and function.

The third latent variable from the canonical correlations analysis showed a negative relationship between low income, low educational attainment, and being Hispanic, and cortical volume in left temporal pole and left caudal medial frontal areas. Unfortunately, we are limited in our ability to make any inferences as to the possible mechanisms behind this finding given the lack of other significant contextual variables, beyond the low household income and low educational attainment variables. Given that each subsequent latent variable is derived from the residual scores of the previous latent variable, it is possible that this relationship may be augmented once the relationships in latent variables 1 and 2 have been calculated, and this may be a left over effect of the dynamics captured in LV 2, which showed a large distinction between Black and White racial identification. It is important to note that race/ethnicity categories were computed using epidemiological conventions which identified participants as belonging to only one racial/ethnic category, even though racial and ethnic identification questions are asked separately, prioritizing identifying as Hispanic before considering racial identification. It is possible that using a different coding scheme, such as considering membership in multiple racial/ethnic categories, may result in different loadings for the racial/ethnic identification variables.

While the findings of this chapter suggest that including measures beyond traditional measures of SES provide a more vivid illustration of the particular ways that social stratification may impact a child's environment, it does not come without a number of limitations or possible avenues for further inquiry. For this study, our chosen measure of cortical morphometry was cortical volume, and while our justification was to use this measure, which is derived as the multiplication of cortical thickness and cortical surface area, as a proof of concept of this multivariate approach, many recent studies have suggested to use surface area and cortical thickness instead, as using the composite measure obscures the particular contributions of these two properties. Future studies using this approach and frameworks should consider using cortical thickness and surface area instead of cortical volume.

The choice to focus on cortical structure instead of cortical function was inspired by a literature indicating that environmental exposures have cumulative effects across the life course, and as such, may have implications for structural elements. However, this does leave an opportunity open for individual-level deterministic interpretations of our results, which we strongly advise against. Future studies will focus on functional cortical dynamics instead, which we anticipate to be more relevant to cognitive behavior than our results here, which explain a very small percentage of variance, which is reported as typical in other "big-data" cognitive neuroscience studies. In addition, although this study is using a rather large sample, it should be noted that the dataset used for this chapter was collected across 21 sites, each with different target demographic recruitment goals, and a different research team. While great efforts were made to ensure consistent protocol implementation across the various sites, it means that the distribution of environmental variables varied by location, so interpreters of these results should be wary of making individual-level inferences and predictions based on these data.

In conclusion, this study is an exciting first step at synthesizing variables from multiple domains to characterize elements of the environment, extending beyond the traditional measures of SES, in order to elucidate how these factors relate to cortical development and cognitive performance.

CHAPTER 4
SOCIOECONOMIC STATUS, MINORITY STATUS, AND NEIGHBORHOOD SUPPORTIVENESS ON MENTAL HEALTH: A MULTIVARIATE ANALYSIS OF THE CCAHS DATASET

4.1 Introduction

The purpose of the present study is to evaluate the interaction of neighborhood greenspace, perceptions of ones residential community, and individual personality differences on health-related behaviors and mental health outcomes in a US urban setting. Initiatives, such as Healthy People 2020 from the US Department of Health and Human Services, have emphasized a holistic approach to health by explicitly acknowledging and focusing on social and physical determinants of health, such as exposure to natural and built environments, social and community context, and utilization and access to health care services. In support of this integrative perspective, previous research has suggested a relationship between exposure to greenspace and human health (Kardan et al., 2015; Sarkar et al., 2018). Problematically, research has shown that green spaces and associated ecosystem services are not equitably distributed across urban populations, highlighting great disparities to communities predominated by low-income and/or minority populations (see Wolch et al., 2014 for a review). In addition to lower access to parks and other green spaces, evidence suggests that socio-cultural qualities of the neighborhood, such as collective perceived safety, social cohesion, and collective perceived belongingness may also impact the degree to which individuals engage with public services/amenities (Byrne, 2012; Byrne & Wolch, 2009).

Although there is ample evidence supporting the positive relationship between subjective social status and health (Adler et al., 2000; Franzini & Fernandez-Esquer, 2006), a recent study by Roy et al. (2016) has found that this relationship may be moderated by neighborhood median income, such that a person high in subjective social status living in a low-income neighborhood would not show the positive relationship with self-reported health. The results of this study highlight the importance of neighborhood context when looking at health outcomes. Therefore, the goal of this study is to examine the interaction of physical and natural neighborhood factors, socio-cultural elements of an individuals local community, and individual-level variables in determining individual health-related behaviors and health outcomes.

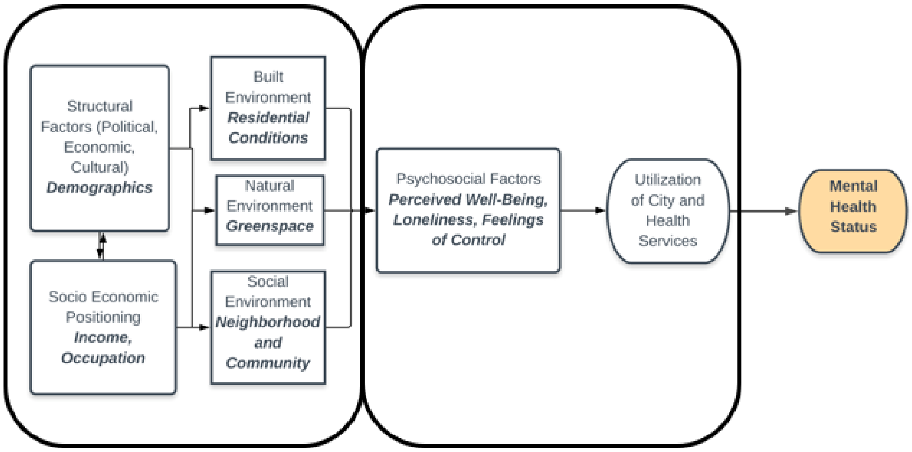
Therefore, the goal of this study is to examine the interaction of neighborhood greenspace and perceptions of an individuals local community on health-related behaviors and mental health outcomes, while also considering the contribution of individual differences, particularly those related to perceived social standing and feelings of life purpose, and differences across groups differing in race/ethnicity and/or socioeconomic status.

To accomplish this research goal, I used data from the Chicago Community Adult Health Survey (CCAHS), and tree canopy data from the National Land Cover Database to evaluate the impact of the local natural environment. The Chicago Community Adult Health Survey (CCAHS) was collected in 2001 as a multiracial and multiethnic survey sample of 3105 individuals across 343 neighborhood clusters around the city of Chicago, IL. Together with the tree canopy data, data in the following 6 categories was analyzed: 1) Individual Community Ratings, 2) Neighborhood Socioeconomic Conditions, 3) Satellite Measures (e.g., tree canopy, soil coverage, etc.), 4) Demographics, 5) Self-Reported Health Behaviors, and 6) Psychosocial Measures. Measures were then analyzed using a Canonical Correlations Analysis (CCA), a multivariate analysis approach that allows us to find linear combinations of two sets of variables that have maximum correlation with each other, termed Latent Variables (LVs). The CCA yielded one LV that showed a reliable relationship between percent neighborhood tree canopy, positive community ratings, healthy behaviors and being White and affluent. While the CCA yielded two additional reliable and significant LVs, these did not show a contribution from neighborhood tree canopy. The results of the present study complement existing literature on the connection of greenspace and health, but highlight the importance of considering local neighborhood dynamics and the context in which neighborhood greenspace exists.

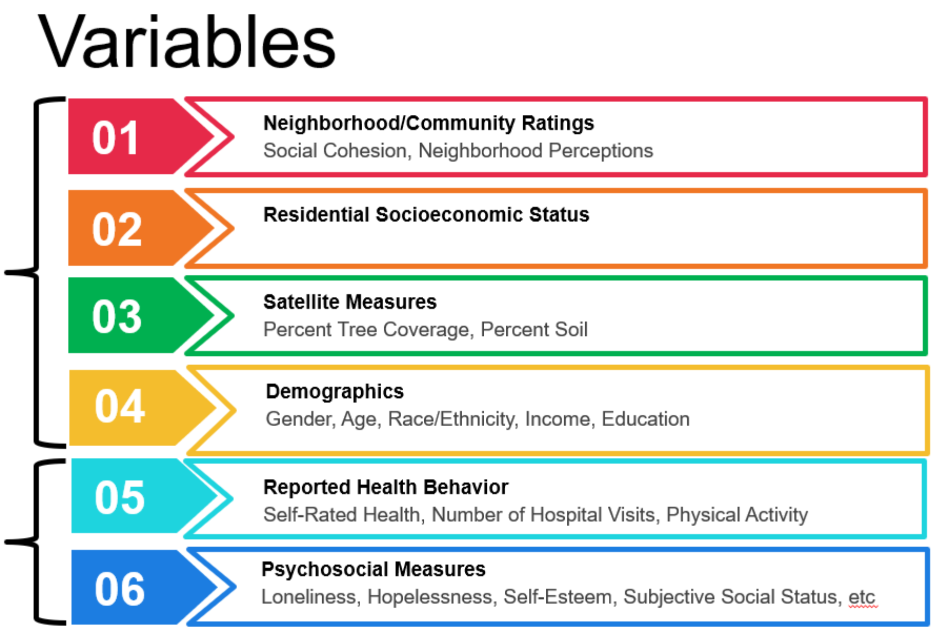
4.2 Materials and Methods

4.2.1 Dataset

To assess the association of individual psychological variables with neighborhood characteristics and health, we use a multilevel probability sample of 3,105 adults age 18 and older. The Chicago Community Adult Health Study (CCAHS) consists of face-to-face interviews (71.8% response rate), systemic social observation, a community survey, and linkage with archival data. The survey elicits individual level data about socioeconomic, psychosocial, behavioral factors, health, and perceived social and physical characteristics of neighborhoods. Neighborhoods in the CCAHS are operationalized as one of 343 clusters (Neighborhood Clusters, or NCs) of contiguous census tracts, based on the clustered sampling framework of the Project on Human Development in Chicago Neighborhoods and reflecting physical barriers, local cultural knowledge, and cluster analyses of census data so that the NCs are relatively homogeneous and cover the entire city. On average 9 respondents live in each of the 343 NCs. The sociodemographic composition is reported in Table 4.1. It is important to note that this sample contains a substantial number of minorities and a broad range of adult ages and socioeconomic statuses. Data collection for the CCAHS was approved under the University of Michigan Health Sciences and Behavioral Sciences Institutional Review Boards. Respondents gave written informed consent, and data were deidentified prior to public release. A summary of included measures in the analysis can be found in Table 4.2.



(a) Schematic model for this study



(b) Description of variable categories in this study

Figure 4.1: Structural Model for this Study and Variable Categories. **(a)** The schematic modele of the theorized relationships between variables in this study are shown here. The black ovals indicate how these variables will be entered into the Canonical Correlations and Mediation analyses. Variables indicating structural factors and elements of the participants' neighborhood are shown on the right, while individual-level factors are included on the right oval. Also shown on this figure are the mental health outcomes (Depression and Anxiety) that will be modeled as being the result of the previous two factors. **(b)** Shown in this figure are the five categories of variables that will be used for analysis in this chapter. The colors used in this figure will be used as a visual aid in the results for the Canonical Correlations and Mediation analyses. The brackets on the left indicate the grouping of variables as described in **a**.

Table 4.1: Participant Demographics for CCAHS

N		3037
Age		
18−29	794	26.1%
30−39	730	24.0%
40−49	593	19.5%
50−59	392	12.9%
60−69	281	9.2%
70+	281	9.2%
Gender		
Female	1822	60.0%
Male	1215	40.0%
Race/Ethnicity		
Hispanic	783	25.8%
Non-Hispanic White	966	31.8%
Non-Hispanic Black	1211	39.9%
Other	77	2.5%
Household Income		
Less than $10K	410	13.5%
Between $10−30K	1074	35.4%
Between $30−50K	714	23.5%
$50K or more	839	27.6%
Educational Attainment		
Less than High School	709	23.4%
High School Diploma/GED/Some College	1614	53.1%
Bachelor's Degree or more	714	23.5%
Immigration Generation		
First Generation	752	24.8%
Second Generation	371	12.2%
Third Generation or More	1914	63.0%
Have Insurance	2406	79.2%

4.2.2 Community Health Survey and Subject-Reported Variables

Demographic Variables

Previous research has shown that individual sociodemographic factors may predict both the experience of negative experiences and the neighborhoods in which people may live. Since

Table 4.2: Measures from the Chicago Community Adult Health Survey

Neighborhood/Community Ratings	Health and Health-Related Behaviors
Social Cohesion	Physical Impairment Index
Social Contact	Functional Health Index
Intergenerational Closure	Physical Activity Index
Reciprocal Exchange	Self−Rated Health
Friend/Kin Networks	Preventative Health Care Index
Perceived Discord	Quality of Services Index
Perceived Violence	Number of Hospital Visits (12mo.)
Tolerance of Deviance	**Psychosocial Measures**
Organizational Participation	Anger-In Scale
Total Victimization	Anger-Out Scale
Residential Socioeconomic Status	Cynic Hostility Scale
Disadvantage	Hopelessness Measure
Affluence	Loneliness Index
Hispanic/Foreign-Born	LOT-Pessimism Subscale
Older	LOT-Optimism Subscale
Satellite Measures	Rosenberg Self-Esteem Scale
Percent Tree Canopy	Pearlin Mastery/Self-Control
Percent Bare Soil	Anomie
Demographics	John Henryism Scale
Age, Gender, Race/Ethnicity	Subjective Social Status
Educational Attainment, Household Income	*Community-Level*
Immigrant Status	*Society- Level*

we are interested in how these sociodemographic factors may be related to neighborhood and individual level factors to predict health, we included measures of age, gender, race/ethnicity (non-Hispanic Black, Hispanic, non-Hispanic other, and non-Hispanic White), and household income, individual educational attainment, and whether an individual is first generation immigrant. For a participant's race/ethnicity, the CCAHS followed conventions used by the US Decennial Census, in which participants are first asked if identify as Latino/Hispanic, before asking if they identify with any of the following "racial" groups: White, Black/African-American, American Indian, Asian, Pacific Islander, or another race that was not listed. For this analysis, we imposed a mutually exclusive categorization of race/ethnicity on this multiracial/multiethnic data structure which consisted of the following categories: Hispanic, which includes all people who reported being of Latino/Hispanic origin, regardless of their identification with any other racial groups, non-Hispanic Black, non-Hispanic White, and non-Hispanic Other, which included those that may have identified as Asian, Pacific Islander, American Indian, or another race. Gender was coded as a binary variable (using 'Male' as a reference), educational attainment was coded as number of years in school, while household income was log transformed to account for the right skew in the distribution.

Community/Neighborhood Ratings

The Community/Neighborhood perceived measures are from the Community Survey section of the CCAHS. Scales are based on the Project on Human Development in Chicago Neighborhoods (PHDCN) and use approximately five questions per scale, and aim to measure many elements of the dynamic structure of an individual's local community. The *Collective Efficacy* scale includes 10 items from two subscales and assesses a shared willingness *(Social Cohesion)* to take action to enforce collective norms *(Social Control)*. The *Total Victimization Scale* captures experiences of being a victim of crime (such as assault, property theft, robbery) in the neighborhood. *Reciprocal Exchange* focuses on the exchange of favors, advice, material goods, and information which make up a social support network within the community. *Social Contact* considers the degree of social contact between members of the neighborhood, while the *Friend/Kin Networks* measure identifies the number of friends or family within their network. The *Intergenerational Closure Scale* measures the extent to which strong relationships between children and their friends' parents and among parents. Additional measures included *Organizational Participation*, which indexed how much an individual participated in neighborhood programs, *Tolerance of Deviance* within the community, *Perceived Violence*, and *Perceived Disorder* within the community.

Residential Socioeconomic Status

Based on recent research reporting distinct relations between multiple dimensions of contextual socioeconomic conditions and outcomes, neighborhood disadvantage and affluence are assessed separately. Principal components factor analysis of 2000 Census NC-level measures yielded four factors included in this analysis. The *Neighborhood Disadvantage* factor loads negatively on high family incomes, and positively on low family incomes, high levels of poverty, public assistance, unemployment, and vacant housing. The *Affluence* factor loads positively on measures of the proportion of employed civilians ages 16 and over in professional or managerial occupations, the proportion of individuals ages 25 and over who have completed 16 or more years of education, and median home values. Disadvantage and affluence capture distinct but correlated aspects of neighborhood socioeconomic status, much as income and education represent distinct aspects of individual socioeconomic status. Many neighborhoods low in disadvantage are also low in affluence. The third factor *Hispanic/Foreign-born* loads positively for neighborhoods with a high percentage of Hispanic individuals, high percentage of foreign-born individuals and negatively on non-Hispanic Black percentage. The fourth factor loads positively on percentage of individuals over the age of 65, and moderately negatively on individuals that are unmarried and ages 18-29.

Land-Cover/Satellite Measures

To determine greenspace in participant communities, we used the tree canopy layer from the 2001 National Land Cover Database (NCLD) from the US Geological Survey, which measures the percentage of tree canopy at a resolution of 30 square meters across the United States. To compute tree canopy coverage, we will compute the percentage of tree canopy density at each of the neighborhood clusters within the city of Chicago, and link that to each individual in the CCAHS.

Health and Health-Related Variables

Included in this analysis were several variables related to healthcare utilization and health status of participants. The *Physical Impairment Index* assessed difficulty or discomfort in performing tasks across a number of domains. The *Functional Health Index* indicated impaired mobility and ability to perform everyday tasks. The *Physical Activity Index* indicates the level of exercise or activity that an individual may have during the week. The *Self-Rated Health Index* indicates how well the individual perceives their health to be at the time of the interview. The *Preventative Health Care Index* is a composite measure that indicates whether individuals had a dental cleaning, physical exam, blood pressure and cholesterol level checks within the past two years. The *Quality of Services Index* is a composite measure that evaluates satisfaction with public services, such as garbage collection, and satisfaction with access to neighborhood parks. Finally, we included the *Number of Hospital Visits* reported by individuals in the past 12 months.

Psychosocial Variables

Previous research has shown that a number of psychological variables may play an important pathway in the relationship between neighborhood conditions, identity, and health. As such, we included a number of measurements available in the CCAHS in our analysis here. From the State-Trait Anger Expression Inventory (STAXI), we used two subscales with 4 items each that measured anger expression profiles: the *Anger-In Index*, anger which is expressed but suppressed, and the *Anger-Out Index*, which is anger expressed towards other persons or environmental objects. We also a *Hopelessness Scale* previously used in predicting hypertension, in addition to the *Cynic Hostility Subscale* from the Cook-Medley Hostility Scale. We also included a revised version of the UCLA *Loneliness Scale* , in addition to the *Optimism and Pessimism Scales* from the Life Orientation Test, as these have also been shown to be related to experiential stress health outcomes. A 4-item measure of Self-Esteem adapted from the Rosenberg Self-Esteem Scale was included, as was the *Pearlin Mastery Scale*, which is a measure of self-control and coping. The included *Anomie* measure assesses the extent to which residents report a disconnection from basic societal rules. Given the large number of minorities in the sample and our interest in coping mechanisms, we also included a scale of *John Henryism*, a strategy for coping with prolonged exposure to stresses such as social discrimination by expending high levels of effort which results in accumulating physiological costs. Finally, we also included two measures of *Subjective Social Status*, in which individuals must indicate where they think they lie on a ladder representing either their community (*Community-Level*), or the United States (*Society-Level*), as this has shown to have a relationship in a number of epidemiological studies.

4.2.3 Statistical Analysis

Canonical Correlations Analysis

In a canonical correlation analysis, first, the weights that maximize the correlation of the two weighted sums (linear composites) of each set of variables (called canonical roots) are calculated. Then the first root is extracted and the weights that produce the second largest correlation between sum scores is calculated, subject to the constraint that the next set of sum scores is orthogonal to the previous one. Each successive root will explain a unique additional proportion of variability in the two sets of variables. There can be as many canonical roots as the minimum number of variables in the two sets, which is thirty-eight in this analysis. Therefore, we obtain thirty-eight sets of canonical weights for each set of variables, and each of these thirty-eight canonical roots have a canonical correlation coefficient which is the square root of the explained variability between the two weighted sums (canonical roots).

To obtain unbiased canonical weights for variables and canonical correlation coefficients, we averaged data values over the 30 imputations and performed canonical correlation analysis on the z-scores of the averaged data using MATLAB (MATLAB and Statistics Toolbox Release 2019a, The MathWorks, Inc., Natick, Massachusetts, United States). For a more straight-forward interpretation and better characterization of the underlying latent variable, instead of using the canonical weights, we calculated the Pearson correlation coefficient (canonical loading) of each observed variable in the set with the weighted sum scores for each of the four linear composites. This way, each canonical root (linear composite) could be interpreted as an underlying latent variable whose degree of relationship with each of the observed variables in the set (how much the observed variable contributes to the canonical variate) is represented by the loading of the observed variable and its errorbar (see canonical correlation results).

To estimate the standard errors of the canonical loadings, we bootstrapped z-scores from the data (2000 simulations for each) and performed canonical correlation analysis 2000 times using MATLAB. Then, we calculated the variances of the set of loadings, which were calculated as explained above.

Mediation Analysis

The mediations were implemented using R package 'mediation' (Tingley et al., 2014) with quasi-Bayesian confidence intervals. This method offers a more robust test of the model, as it uses a bootstrapping procedure (10,000 iterations) and is not as conservatively biased as the Sobel test for medation. Running moderation analyses using this package allows us to evaluate the the Average Direct Effects (ADE) of the model, traditionally called the **c'** path in Baron-Kenney mediation models, in addition to the Average Causal Mediation Effect, (ACME), traditionally called the **a*b** or indirect effect in Baron-Kenney mediation models.

4.3 Results

4.3.1 Canonical Correlations Analysis

Although the canonical correlations analysis yielded 20 latent variables, we will only interpret and focus on those latent variables that included at least one reliable variable based on the canonical correlation bootstrap analysis. That is, that the standard error calculated for the variable loading did not include zero. For this analysis, this yielded four latent variables which we will characterize and interpret below. The loadings for each of the variables within the CCA Latent Variables is listed in Table 4.4, where values in bold indicate that values as reliable based on a bootstrap analysis.

For ease of interpretation, we will refer to the four latent variables not only by their latent variable number, but with a descriptor summarizing the relationship captured by that latent variable. These are summarized in Table 4.3. The terms *Structural Advantage* and *Structural Disadvantage* will be used to indicate effects that either correspond to participants that identify as part of a majority racial/ethnic group (identifying as White), or identify as a minority racial/ethnic group (Black and/or Hispanic), given the extensive evidence supporting greater institutional racism and/or interpersonal prejudice by members of minority groups. In addition, the labels of *Supportive/Non-Supportive Communities* will be used to describe effects with favorable or unfavorable Neighborhood/Community Ratings. We opted to use this instead of other labels in the literature, such as "Area Deprivation" and "Social Cohesion" to highlight the positive elements of these dynamic and complex constructs, and to counteract interpretations that may have existing associations with marginalized groups, such as the term "deprivation" with Black/Hispanic groups and those of lower socioeconomic status.

Table 4.3: Canonical Correlation Analysis Latent Variable Descriptions

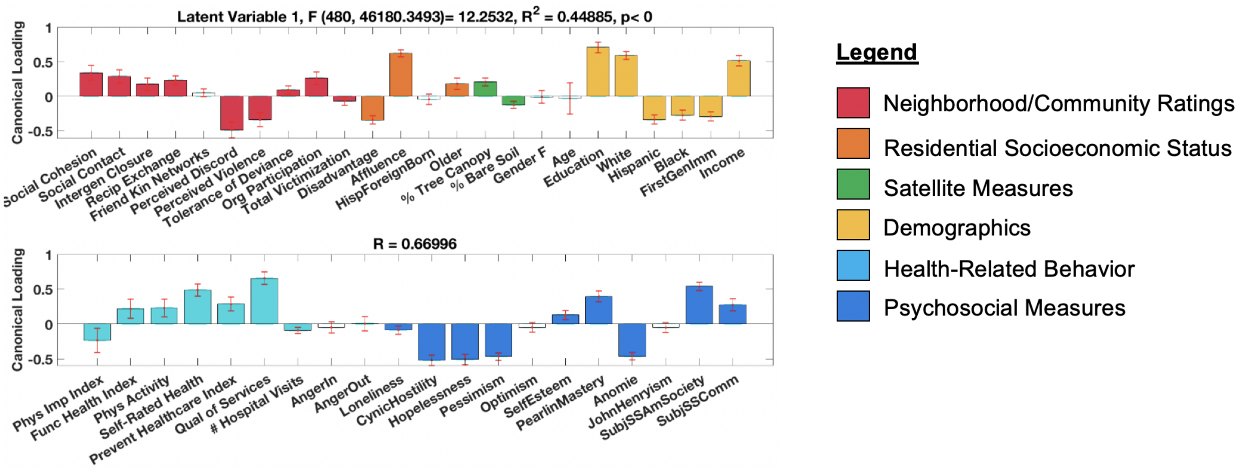
Latent Variable Number	**Description**
Latent Variable 1	Affluence, Structural Advantage, Healthy, Supportive Community
Latent Variable 2	Older, Unhealthy, Supportive Community
Latent Variable 3	Structural Disadvantage
Latent Variable 4	Structural Advantage, Unhealthy, Non-Supportive Community

Latent Variable 1–Affluence, Structural Advantage, Healthy, Supportive Community

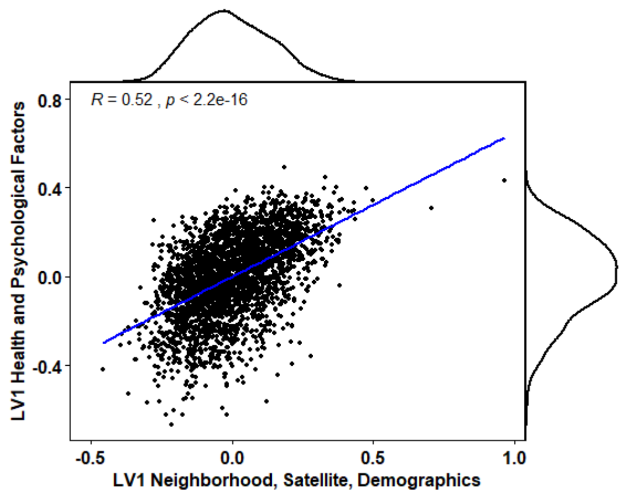
In the canonical correlations analysis, the linear composites that make up the first canonical root, which we will hereto refer to as the first Latent Variable, account for 37% of the variance of the two samples. The weighted canonical scores, or loadings, which indicate the correlation between the original variables and the latent variable scores, are shown in Figure 4.2a. The correlation of the environment scores and the individual-level scores to each other (r = 0.52, $p < 0.001$) is shown in Figure 4.2b. The scores associated with an individual's environment, *Neighborhood/Community Ratings, Residential Socioeconomic Status, Satellite Measures, and Demographics*, show a pattern consistent with elements of a "Supportive" Community, with significant positive loadings for measures of social cohesion, social contact, intergenerational closure, reciprocal exchange, organizational participation, and negative loadings for perceived violence, tolerance of deviance, and total victimization. In addition, this latent variable shows positive loading values for neighborhood affluence, educational attainment, percent tree canopy, being white, and household income, and negative loading values for neighborhood disadvantage, percent bare soil, and being Hispanic, Black, and being a first generation immigrant (all loading scores can be found on Table 4.4).

For the individual-level variables, *Psychosocial Measures and Health-Related Behaviors*, this latent variable shows elements related to positive health, with high loading values for functional health, physical activity, self-rated health, use of preventative health care resources, rated quality of services, and negative values for physical impairment and number of hospital visits. Psychosocial factors showing a positive loading include Pearlin Mastery/Self-Control, Self-Esteem, and Subjective Social Status both when using local community and the United States as a referent. Psychosocial factors showing a negative loading include loneliness, cynic hostility, hopelessness, pessimism, and anomie. Together, we characterize this latent variable as indexing **Affluence, Structural Advantage, Health, and Supportive Community.**

In addition, to see whether there were any spatial relation between the distribution of this latent variable's scores across the city of Chicago, we aggregated the scores for each side of the latent variable at the neighborhood cluster level, and plotted them on Figure 4.3. Using Moran's I statistic, and index of spatial clustering of a given set of values, we found significant clustering for both environmental variables, and for the individual-level variables.

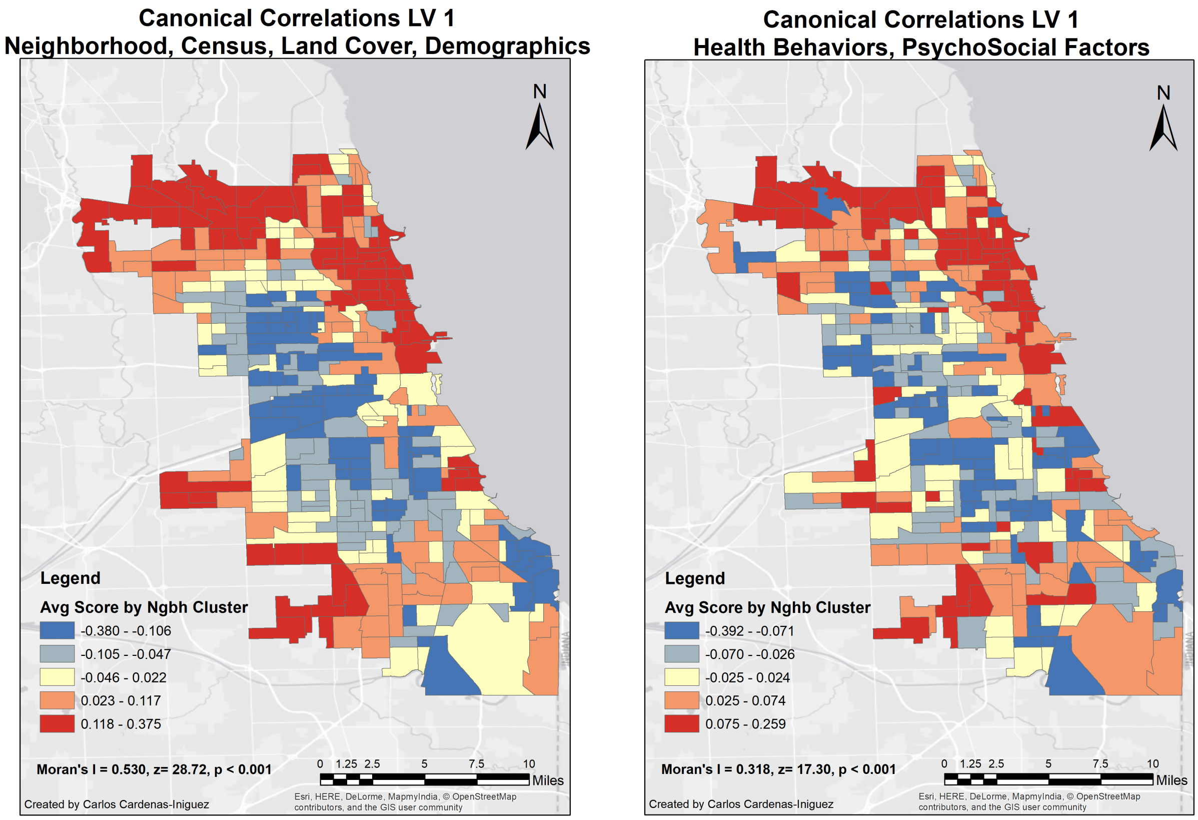


(a) Canonical correlation loadings for Latent Variable 1



(b) Correlation of canonical correlation scores

Figure 4.2: Canonical correlation results for Latent Variable 1. **(a)** Bars show correlation of each variable with the first set of weighted canonical scores (loadings). Error bars show ±2 standard errors. The bars on the top represent loadings of scores for the *Neighborhood/Community Ratings, Residential Socioeconomic Status, Satellite Measures, and Demographics*, while the bars on the bottom represent loadings of scores for *Health-Related Behaviors and Psychosocial Measures*. This pair of linear composites represents a pattern of ”Supportive” Communities being associated with affluent neighborhood Socioeconomic Status, White participants with high educational attainment and household income, and positive health-related behaviors and positive psychosocial ratings. For ease of interpretation, this Latent Variable will be described as indexing **Affluence, Structural Advantage, and Positive Health**. **(b)** The distribution and correlation between the *Neighborhood, Satellite, and Demographics* scores and *Health and Psychosocial Factor* scores for Latent Variable 1 are shown here. At the top is the density function for the *Neighborhood, Satellite, and Demographics* scores, and at the right is the density function for the *Health and Psychosocial Factor* scores.



(a) Average Neighborhood Cluster scores for Neighborhood, Satellite and Demographics

(b) Average Neighborhood Cluster scores for Health and Psychosocial Factors

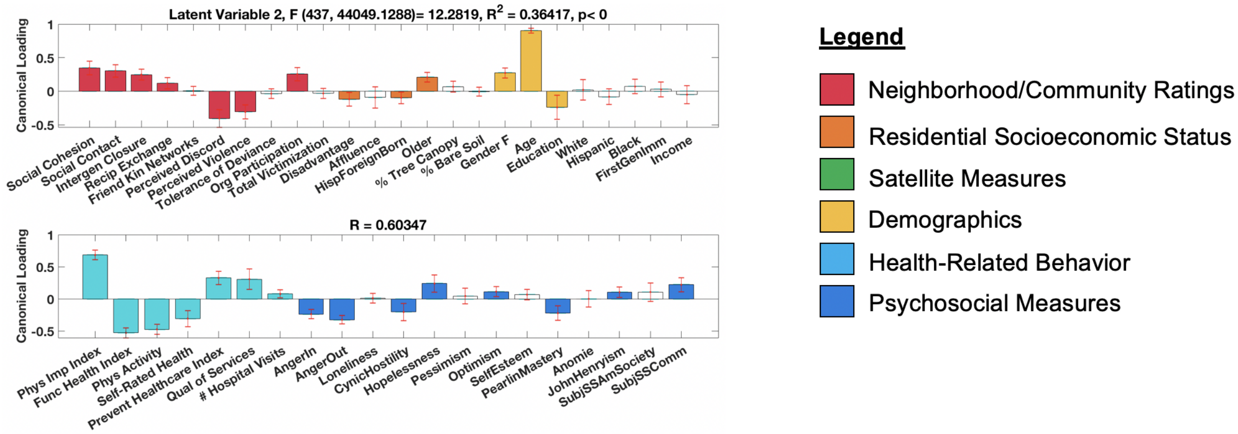
Figure 4.3: Spatial maps of canonical correlation results for Latent Variable 1. This Latent Variable indexes **Affluence, Structural Advantage, Positive Health**. Higher scores indicate having closer characteristics to the variables shown in Figure 4.2a. For display purposes, scores are binned into quintiles, although continuous scores were used for analysis. **(a)** Spatial maps of canonical correlation scores for *Neighborhood, Satellite, and Demographics* (top panel of Figure 4.2a) aggregated at the Neighborhood Cluster level for the city of Chicago, IL. This map has a Moran's I statistic of 0.53 ($z = 28.72$, $p < 0.001$), indicating strong spatial autocorrelation (spatial clustering) of these scores. **(b)** Spatial maps of canonical correlation scores for *Health and Psychosocial Factors* (bottom panel of Figure 4.2a) at the Neighborhood Cluster level for the city of Chicago, IL. This map has a Moran's I statistic of 0.32 ($z = 17.30$, $p < 0.001$), indicating a strong spatial autocorrelation (spatial clustering) of these scores.

Latent Variable 2–Older, Unhealthy, Supportive Community

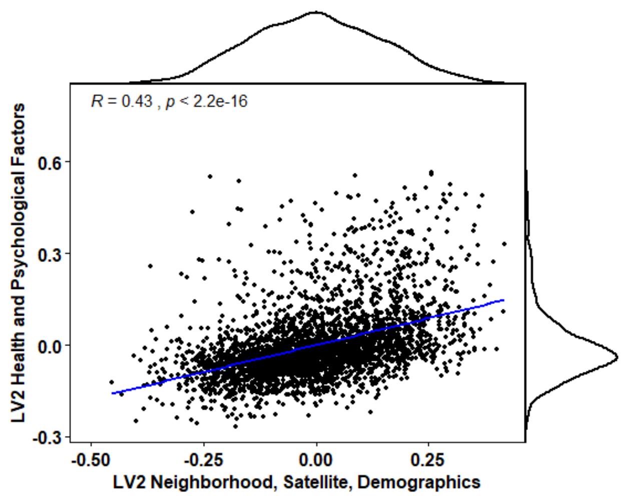
The results for the second latent variable, indicate a pattern reflecting **being Older, being Unhealthy, and being part of a Supportive Community.** The weighted canonical scores, or loadings, which indicate the correlation between the original variables and the latent variable scores, are shown in Figure 4.4a. The correlation of the environmental scores and the individual-level scores to each other (r = 0.43, $p < 0.001$) is shown in Figure 4.4b. The scores associated with an individual's environment, *Neighborhood/Community Ratings, Residential Socioeconomic Status, Satellite Measures, and Demographics*, show a pattern consistent with elements of a "Supportive" Community, with significant positive loadings for measures of social cohesion, social contact, intergenerational closure, reciprocal exchange, organizational participation, and negative loadings for perceived discord, and perceived violence. In addition, this latent variable shows positive loading values for higher neighborhood age, being female, and negative loading values for neighborhood disadvantage, neighborhood having a high percentage of Hispanic and Foreign-Born individuals (all loading scores can be found on Table 4.4). It is important to note that as opposed to Latent Variable 1, none of the participant-reported categories related to race/ethnicity or income were significant.

For the individual-level variables, *Psychosocial Measures and Health-Related Behaviors*, this latent variable shows elements related to negative health, with high negative loading values for functional health, physical activity, self-rated health, and positive values for ratings of physical impairment, number of hospital visits, and use of both general services and preventative healthcare facilities. Psychosocial factors showing a positive loading include hopelessness, optimism, John Henrysm, and Subjective Social Status when using local community as a referent. Psychosocial factors showing a negative loading include both subscales of anger, cynic hostility, loneliness, cynic hostility, and Pearlin Mastery/locus of control. Together, we characterize this latent variable as indexing **being Older, Unhealthy, while being in a Supportive Community.**

In addition, to see whether there were any spatial relations between the distribution of this latent variable's scores across the city of Chicago, we aggregated the scores for each side of the Latent Variable at the neighborhood cluster level, and plotted them on Figure 4.5. Using Moran's I statistic, and index of spatial clustering of a given set of values, we found significant clustering for both environmental variables, and for the individual-level variables.

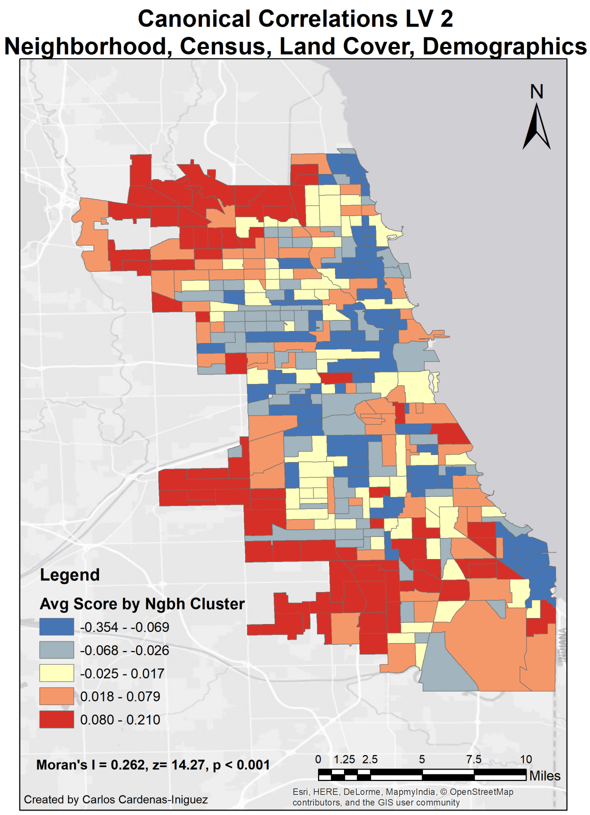


(a) Canonical correlation loadings for Latent Variable 2

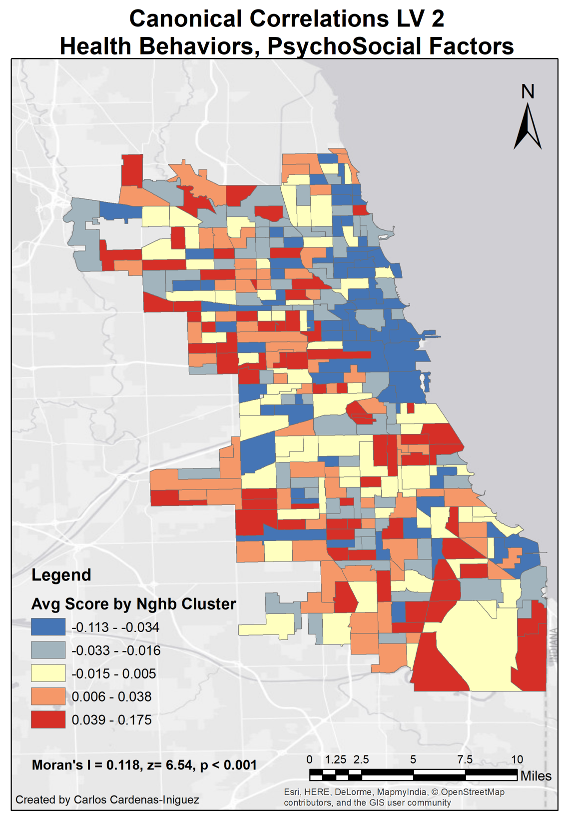


(b) Correlation of canonical correlation scores

Figure 4.4: Canonical correlation results for Latent Variable 2. **(a)** Bars show correlation of each variable with the second set of weighted canonical scores (loadings). Error bars show ±2 standard errors. The bars on the top represent loadings of scores for the *Neighborhood/Community Ratings, Residential Socioeconomic Status, Satellite Measures, and Demographics*, while the bars on the bottom represent loadings of scores for *Health-Related Behaviors and Psychosocial Measures*. This pair of linear composites represents a pattern of ”Supportive” Communities being associated with participants that are older in age, and associated with more health impairments and greater use of medical amentities. For ease of interpretation, this Latent Variable will be described as indexing **Being Older, Being Unhealthy, with a Supportive Community**. **(b)** The distribution and correlation between the *Neighborhood, Satellite, and Demographics* scores and *Health and Psychosocial Factor* scores for Latent Variable 2 are shown here. At the top is the density function for the *Neighborhood, Satellite, and Demographics* scores, and at the right is the density function for the *Health and Psychosocial Factor* scores.



(a) Average Neighborhood Cluster Scores for Neighborhood, Satellite and Demographics



(b) Average Neighborhood Cluster Scores for Health and Psychosocial Factors

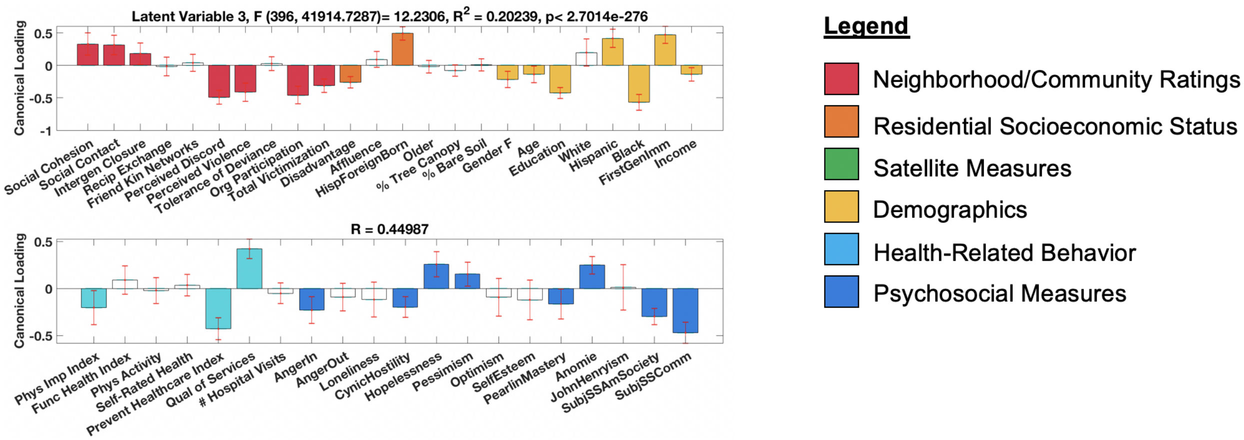
Figure 4.5: Spatial maps of canonical correlation results for Latent Variable 2. This Latent Variable indexes **Being Older, Being Unhealthy, with a Supportive Community**. Higher scores indicate having closer characteristics to the variables shown in Figure 4.4a. For display purposes, scores are binned into quintiles, although continuous scores were used for analysis. **(a)** Spatial maps of canonical correlation scores for *Neighborhood, Satellite, and Demographics* (top panel of Figure 4.4a) aggregated at the Neighborhood Cluster level for the City of Chicago, IL. This map has a Moran's I statistic of 0.26 ($z = 14.27$, $p < 0.001$), indicating strong spatial autocorrelation (spatial clustering) of these scores. **(b)** Spatial maps of canonical correlation scores for *Health and Psychosocial Factors* (bottom panel of Figure 4.4a) at the Neighborhood Cluster level for the City of Chicago, IL. This map has a Moran's I statistic of 0.12 ($z = 6.54$, $p < 0.001$), indicating a strong spatial autocorrelation (spatial clustering) of these scores.

Latent Variable 3– Structural Disadvantage

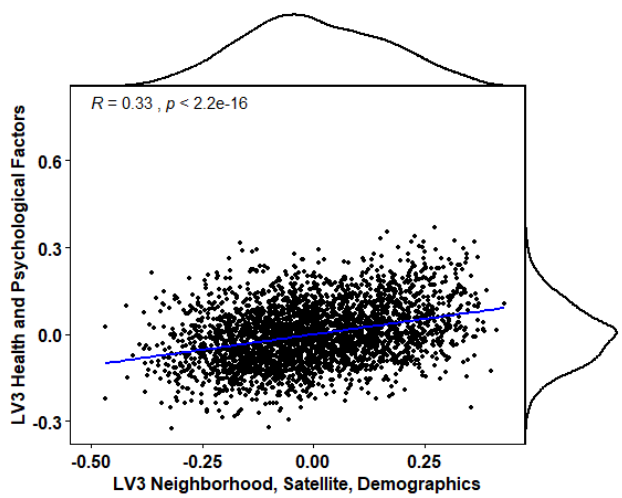
The results for the third Latent Variable indicate a pattern reflecting **Structural Disadvantage.** The weighted canonical scores, or loadings, which indicate the correlation between the original variables and the latent variable scores, are shown in Figure 4.6. The correlation of the environment scores and the individual-level scores to each other (r = 0.33, $p < 0.001$) is shown in Figure 4.6. The scores associated with an individual's environment, *Neighborhood/Community Ratings, Residential Socioeconomic Status, Satellite Measures, and Demographics*, show a pattern consistent with elements of a "Supportive" Community, with significant positive loadings for measures of social cohesion, social contact, and intergenerational closure, and negative loadings for perceived discord, and perceived violence, organizational participation, and total victimization. In addition, this latent variable shows positive loading values for higher neighborhood having a high percentage of Hispanic and Foreign-Born individual, being Hispanic, and being a first-generation immigrant. Significant negative loading variables included being female, age, educational attainment, being Black, and income (all loading scores can be found on Table 4.4). Interestingly, being white was not significant, suggesting that this latent variable highlights a contrast between being Hispanic and being Black

For the individual-level variables, *Psychosocial Measures and Health-Related Behaviors*, this latent variable shows more variability than the previous two latent variables, with positive loadings for rated quality of services, and negative loadings for physical impairments and use of preventative healthcare services. Psychosocial factors showing a positive loading include hopelessness, pessimism, and anomie, while negative loadings included Anger-In, cynic hostility, Pearlin Mastery/locus of control, and Subjective Social status when using local community and the United States as a referent. Together, we characterize this latent variable as indexing **Structural Disadvantage.**

In addition, to see whether there were any spatial relations between the distribution of this latent variable scores across the city of Chicago, we aggregated the scores for each side of the latent variable at the neighborhood cluster level, and plotted them on Figure 4.7. Using Moran's I statistic, and index of spatial clustering of a given set of values, we found significant clustering for both environmental variables, and for the individual-level variables.

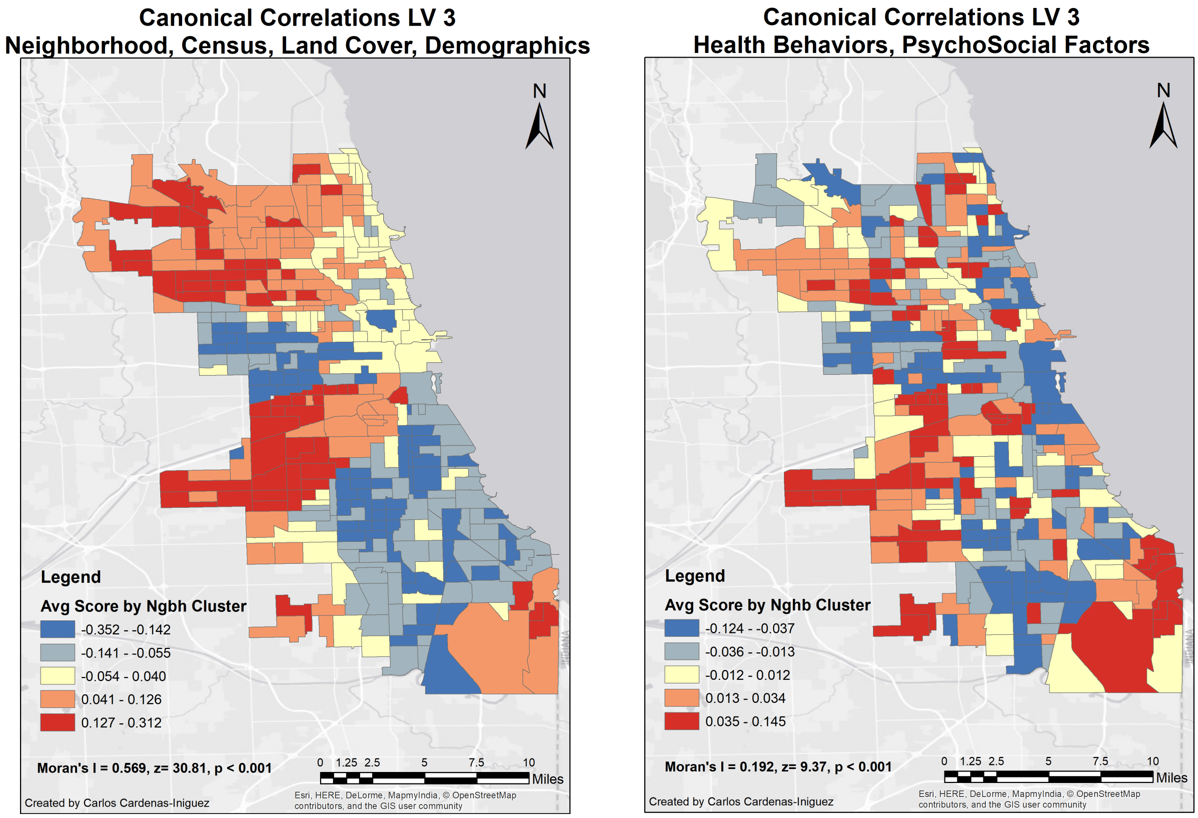


(a) Canonical correlation loadings for Latent Variable 3



(b) Correlation of canonical correlation scores

Figure 4.6: Canonical correlation results for Latent Variable 3. **(a)** Bars show correlation of each variable with the second set of weighted canonical scores (loadings). Error bars show ±2 standard errors. The bars on the top represent loadings of scores for the *Neighborhood/Community Ratings, Residential Socioeconomic Status, Satellite Measures, and Demographics*, while the bars on the bottom represent loadings of scores for *Health-Related Behaviors and Psychosocial Measures*. This pair of linear composites represents a pattern of **Structural Disadvantage**, where values further away from zero represent either an association with being Black, or bring Hispanic. As opposed to LV 1, this LV captures the relationship of non-White participants. For ease of interpretation, we will refer to this Latent Variable as indexing **Structural Disadvantage**. **(b)** The distribution and correlation between the *Neighborhood, Satellite, and Demographics* scores and *Health and Psychosocial Factor* scores for Latent Variable 3 are shown here. At the top is the density function for the *Neighborhood, Satellite, and Demographics* scores, and at the right is the density function for the *Health and Psychosocial Factor* scores.



(a) Average Neighborhood Cluster scores for Neighborhood, Satellite and Demographics

(b) Average Neighborhood Cluster scores for Health and Psychosocial Factors

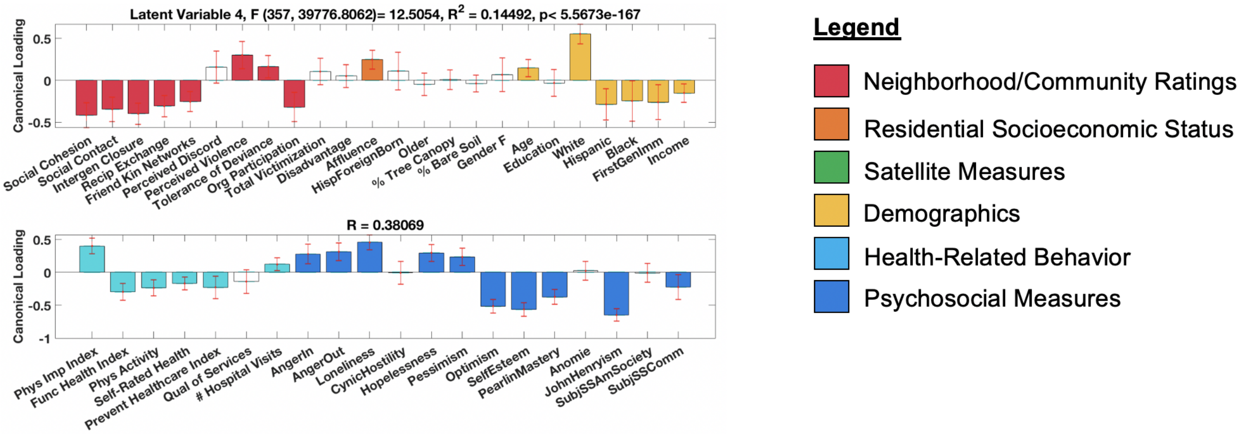
Figure 4.7: Spatial maps of canonical correlation results for Latent Variable 3. This Latent Variable indexes **Structural Disadvantage**. Higher scores indicate having closer characteristics to the variables shown in Figure 4.6a. For display purposes, scores are binned into quintiles, although continuous scores were used for analysis. **(a)** Spatial maps of canonical correlation scores for *Neighborhood, Satellite, and Demographics* (top panel of Figure 4.6a) aggregated at the Neighborhood Cluster level for the city of Chicago, IL. This map has a Moran's I statistic of 0.57 ($z = 30.81$, $p < 0.001$), indicating strong spatial autocorrelation (spatial clustering) of these scores. **(b)** Spatial maps of canonical correlation Scores for *Health and Psychosocial Factors* (bottom panel of Figure 4.6a) at the Neighborhood Cluster level for the city of Chicago, IL. This map has a Moran's I statistic of 0.19 ($z = 9.37$, $p < 0.001$), indicating a strong spatial autocorrelation (spatial clustering) of these scores.

Latent Variable 4– Structural Advantage, Unhealthy, "Non-Supportive" Community

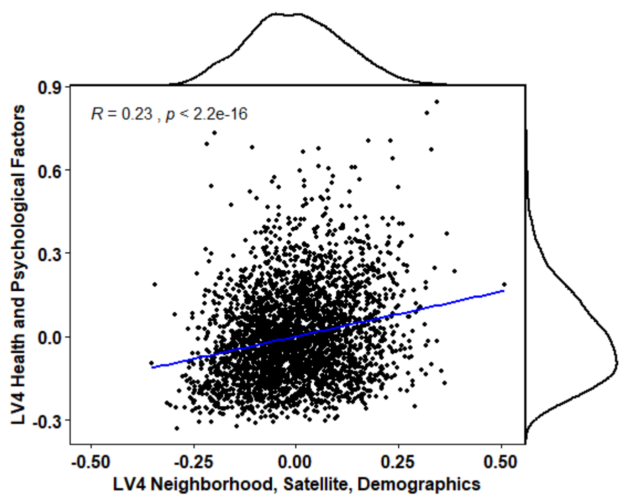
The results for the fourth Latent Variable indicate a pattern reflecting **Structural Advantage, being unhealthy and being in a "Non-Supportive" Community.** The weighted canonical scores, or loadings, which indicate the correlation between the original variables and the Latent Variable scores, are shown in Figure 4.8. The correlation of the environmental scores and the individual-level scores to each other (r = 0.23, $p < 0.001$) is shown in Figure 4.8. The scores associated with an individual's environment, *Neighborhood/Community Ratings, Residential Socioeconomic Status, Satellite Measures, and Demographics*, show a pattern consistent with elements of a "Non-Supportive" Community, with significant negative loadings for measures of social cohesion, social contact, intergenerational closure, reciprocal exchange, friend/kin networks, and organizational participation, and positive loadings for perceived violence, and tolerance of deviance. In addition, this Latent Variable shows positive loading values for neighborhood affluence, age, and being white, and negative values for being Hispanic, being Black, being a first-generation immigrant, and income (all loading scores can be found on Table 4.4).

For the individual-level variables, *Psychosocial Measures and Health-Related Behaviors*, this Latent Variable shows pattern associated with negative health with negative loadings for functional health, physical activity, self-rated health, use of preventative healthcare facilities, and positive loadings for physical impairments and number of hospital visits. Psychosocial factors showing a positive loading include both anger subscales, loneliness, hopelessness, pessimism, and negative loadings for optimist, self-esteem, John Henryism, and Subjective Social Status when using local community as a referent. Together, we characterize this Latent Variable as indexing **Structural Advantage, being Unhealthy, and being in a "Non-Supportive" Community.**

In addition, to see whether there were any spatial relations between the distribution of this Latent Variable scores across the city of Chicago, we aggregated the scores for each side of the Latent Variable at the neighborhood cluster level, and plotted them on Figure 4.9. Using Moran's I statistic, and index of spatial clustering of a given set of values, we found significant clustering for both environmental variables, and for the individual-level variables.

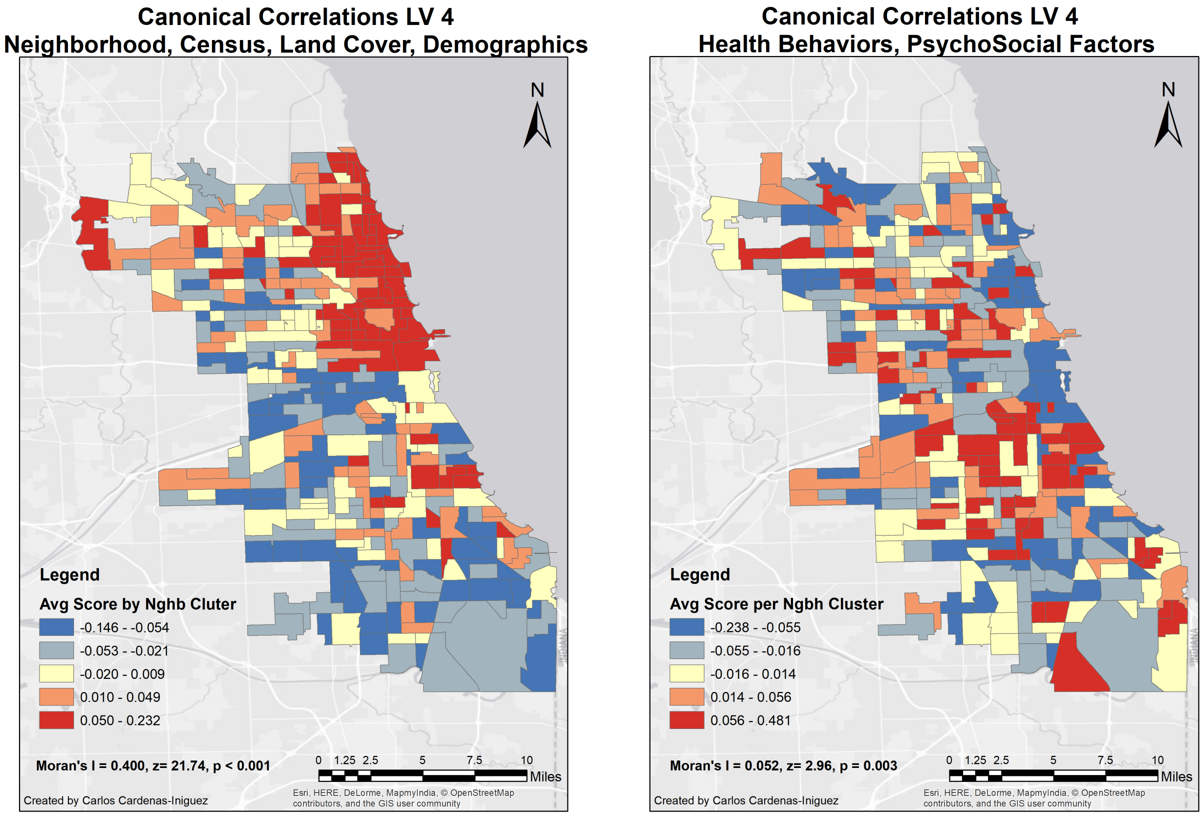


(a) Canonical correlation loadings for Latent Variable 4



(b) Correlation of canonical correlation scores

Figure 4.8: Canonical correlation results for Latent Variable 4. **(a)** Bars show correlation of each variable with the second set of weighted canonical scores (loadings). Error bars show ±2 standard errors. The bars on the top represent loadings of scores for the *Neighborhood/Community Ratings, Residential Socioeconomic Status, Satellite Measures, and Demographics*, while the bars on the bottom represent loadings of scores for *Health-Related Behaviors and Psychosocial Measures*. This pair of linear composites represents a pattern of "Non-Supportive" Communities being associated with being White, and greater health impairments and usage of medical facilities, and greater negative psychological ratings. For ease of interpretation, we will refer to this Latent Variable as indexing **Structural Advantage, and being in a "Non-Supportive" Community**. **(b)** The distribution and correlation between the *Neighborhood, Satellite, and Demographics* scores and *Health and Psychosocial Factor* scores for Latent Variable 4 are shown here. At the top is the density function for the *Neighborhood, Satellite, and Demographics* scores, and at the right is the density function for the *Health and Psychosocial Factor* scores.



(a) Average Neighborhood Cluster scores for Neighborhood, Satellite and Demographics

(b) Average Neighborhood Cluster scores for Health and Psychosocial Factors

Figure 4.9: Spatial maps of canonical correlation results for Latent Variable 4. This Latent Variable indexes **Structural Advantage, and being in a "Non-Supportive" Community**. Higher scores indicate having closer characteristics to the variables shown in Figure 4.8a. For display purposes, scores are binned into quintiles, although continuous scores were used for analysis. **(a)** Spatial maps of canonical correlation scores for *Neighborhood, Satellite, and Demographics* (top panel of Figure 4.8a) aggregated at the Neighborhood Cluster level for the city of Chicago, IL. This map has a Moran's I statistic of 0.400 ($z = 21.74$, $p < 0.001$), indicating strong spatial autocorrelation (spatial clustering) of these scores. **(b)** Spatial maps of canonical correlation scores for *Health and Psychosocial Factors* (bottom panel of Figure 4.8a) at the Neighborhood Cluster level for the city of Chicago, IL. This map has a Moran's I statistic of 0.05 ($z = 2.96$, $p = 0.003$), indicating a strong spatial autocorrelation (spatial clustering) of these scores.

Table 4.4: Canonical correlation Latent Variable loadings

Category	**Variable**	**LV1**	**LV2**	**LV3**	**LV4**
Neighborhood/ Community Ratings	Social Cohesion	**0.340**	**0.347**	**0.329**	**-0.416**
	Social Contact	**0.289**	**0.303**	**0.315**	**-0.346**
	Intergenerational Closure	**0.176**	**0.248**	**0.181**	**-0.401**
	Reciprocal Exchange	**0.235**	**0.119**	-0.015	**-0.308**
	Friend/Kin Networks	0.053	0.005	0.037	**-0.254**
	Perceived Discord	**-0.492**	**-0.404**	**-0.492**	0.160
	Perceived Violence	**-0.342**	**-0.308**	**-0.413**	**0.300**
	Tolerance of Deviance	**0.093**	-0.038	0.029	**0.162**
	Organizational Participation	**0.262**	**0.255**	**-0.458**	**-0.319**
	Total Victimization	**-0.069**	-0.031	**-0.314**	0.106
Residential Socioeconomic Status (Census)	Disadvantage	**-0.344**	**-0.119**	**-0.262**	0.049
	Affluence	**0.620**	-0.094	0.089	**0.246**
	Hispanic/Foreign-Born	-0.043	**-0.097**	**0.491**	0.111
	Older	**0.183**	**0.206**	-0.017	-0.048
Satellite Measures	Percent Tree Canopy	**0.208**	0.067	-0.079	0.008
	Percent Bare Soil	**-0.128**	-0.007	0.007	-0.038
Demographics	Female	-0.009	**0.271**	**-0.218**	0.067
	Age	-0.025	**0.902**	**-0.139**	**0.145**
	Education	**0.706**	**-0.242**	**-0.425**	-0.030
	White	**0.591**	0.018	0.194	**0.555**
	Hispanic	**-0.336**	-0.081	**0.416**	**-0.287**
	Black	**-0.275**	0.070	**-0.566**	**-0.246**
	Immigrant Status (First-Generation)	**-0.292**	0.026	**0.472**	**-0.261**
	Household Income	**0.513**	-0.050	**-0.136**	**-0.151**
Health and Health-Related Behaviors	Physical Impairment Index	**-0.231**	**0.683**	**-0.205**	**0.399**
	Functional Health Index	**0.217**	**-0.528**	0.089	**-0.295**
	Physical Activity Index	**0.229**	**-0.474**	-0.021	**-0.238**
	Self-Rated Health	**0.487**	**-0.307**	0.035	**-0.167**
	Preventative Health Care Index	**0.288**	**0.326**	**-0.428**	**-0.229**
	Quality of Services Index	**0.659**	**0.307**	**0.423**	-0.141
	Number of Hospital Visits (12 mo.)	**-0.090**	**0.080**	-0.053	**0.121**
Psychosocial Measures	Anger-In Scale	-0.049	**-0.237**	**-0.230**	**0.279**
	Anger-Out Scale	0.005	**-0.325**	-0.094	**0.314**
	Loneliness Index	**-0.088**	0.012	-0.119	**0.456**
	Cynic Hostility Scale	**-0.520**	**-0.202**	**-0.196**	-0.007
	Hopelessness Measure	**-0.506**	**0.242**	**0.257**	**0.296**
	Pessimism Subscale	**-0.465**	0.046	**0.153**	**0.233**
	Optimism Subscale	-0.046	**0.114**	-0.094	**-0.516**
	Self-Esteem Scale	**0.133**	0.066	-0.120	**-0.563**
	Pearlin Mastery/Self-Control	**0.397**	**-0.222**	**-0.164**	**-0.372**
	Anomie	**-0.461**	0.000	**0.249**	0.023
	John Henryism Scale	-0.048	**0.105**	0.013	**-0.651**
	Subjective Social Status, Society-Level	**0.542**	0.105	**-0.298**	-0.009
	Subjective Social Status, Community-Level	**0.277**	**0.220**	**-0.471**	**-0.224**

Note: Numbers in bold indicate reliable loadings based on bootstrap analysis

4.3.2 Mediation Analyses on CESD (Depression)

Latent Variable 1-Affluence, Structural Advantage, Health, Supportive Community, White

This mediation model tested the hypothesis that *Health and Psychosocial Factors* of Latent Variable 1, characterized as indexing **Affluence, Structural Advantage, Positive Health, Being White**, mediate the relationship between *Neighborhood, Satellite, and Demographics scores* and Depression (CESD) scores (see Figure 4.10 for a structural representation of the model, and Figure 4.2 for the individual variable loadings of this Latent Variable). A mediation regression analysis (results shown in Table 4.5a) revealed that *Neighborhood, Satellite, and Demographics* scores, while ignoring the mediator, were a significant predictor of Depression scores,(β = -0.809, $SE(\beta)$ = 0.071, t(3035)= -11.39, p < 0.001 (**c path**)). Once controlling for *Health and Psychosocial Factor* scores, *Neighborhood, Satellite, and Demographic* scores were still a significant predictor of Depression scores ($\beta = 0.282$, $SE(\beta) =$ 0.074, t(3281) = 3.823, $p < 0.001$). The indirect path, (typically referred to as the **a** and **b path** in Baron-Kenney regression mediation analyses), indicated that *Neighborhood. Satellite, and Demographic* scores were a significant predictor of *Health and Psychosocial* scores ($\beta = 0.649$, $SE(\ \beta) = 0.02$, t(3035) = 33.299, $p < 0.001$), and *Health and Psychosocial* scores were a significant predictor of Depression scores ($\beta = 0.282$, $SE(\ \beta) = 0.074$, $t(3034) = 3.823$, $p < 0.001$). Therefore, the mediation analysis for this Latent Variable suggests that *Health and Psychosocial* scores *partially* mediate the relationship between *Neighborhood, Satellite and Demographic* scores and Depression scores. These results are summarized in Table 4.5a.

Using a bayesian modeling mediation procedure in the `mediation` package in R and bootstrapping, we decomposed the total effect of the model into the Average Causal Mediated Effect (ACME) and the Average Direct Effect (ADE). The average total effect (as seen in the bottom panel of Figure 4.10 and in Table 4.5b) is estimated to be -0.809 with the 95 percent confidence interval of [-0.942, -0.668]. The ACME effect was estimated to be -1.09, with the 95 percent confidence interval of [-1.191, -0.990], while the ADE was estimated to be 0.282, with a 95 percent confidence interval of [0.137, 0.432]. Given the difference in sign between the ACME and the ADE, it seems that the *Health and Psychosocial* scores function as a suppressor in the relationship between *Neighborhood, Satellite and Demographics* scores and Depression scores. These results suggest that the decrease in Depression is dominated by the increasing in *Health and Psychosocial* scores in this Latent Variable, although there the direct relationship between *Neighborhood, Satellite, and Demographics* and Depression is still significant and positive. Thus, these mediation results suggest that for this Latent Variable, characterized by **Affluence, Structural Advantage, Health, and Supportive Community**, both *Neighborhood, Satellite, and Demographics* scores and *Health and Psychosocial* Factor scores are important, but this relationship is dominated by individual *Health and Psychosocial Factors*.

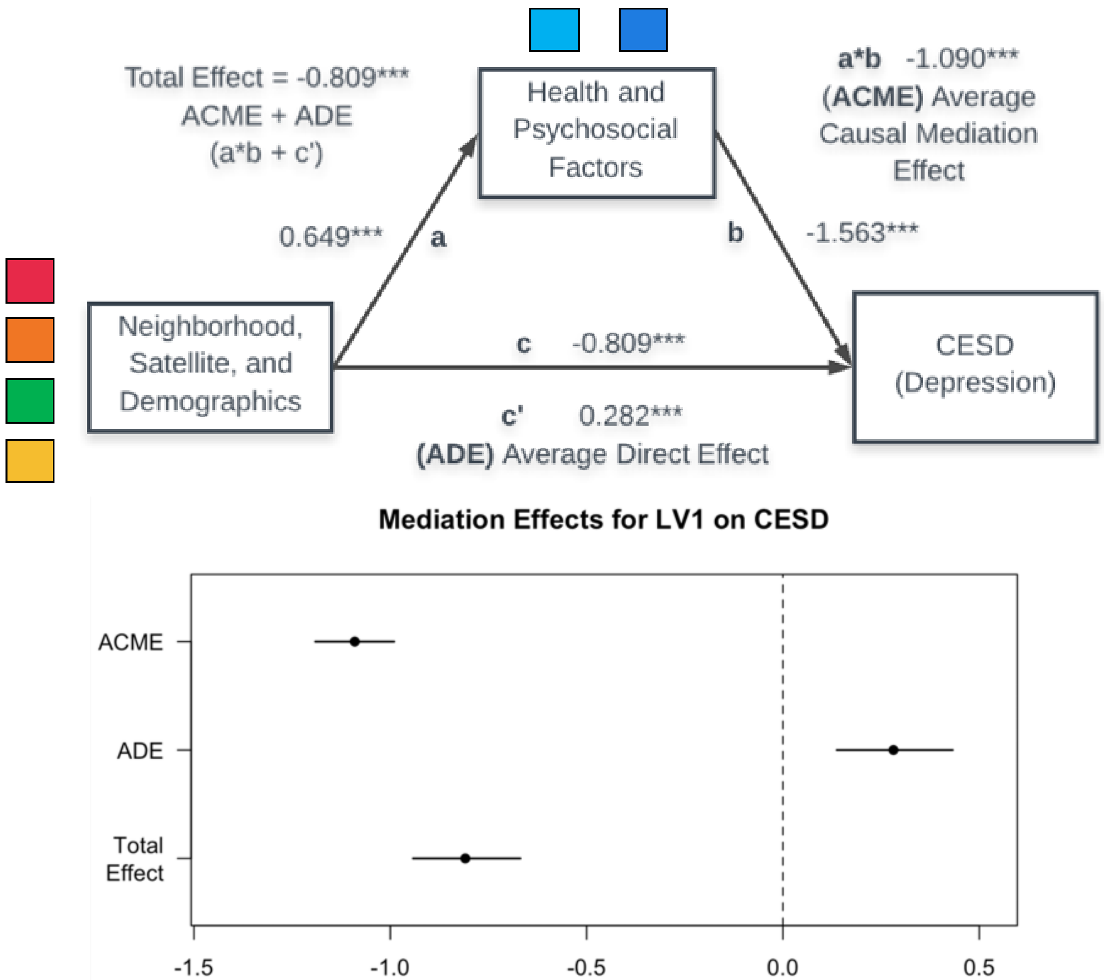


Figure 4.10: Mediation results on Depression using Latent Variable 1. **(Upper Panel)** This diagram displays the mediation model, where the Average Direct Effect (ADE) is represented by the relationship between *Neighborhood, Satellite, and Demographics* and Depression Scores, while the Average Causal Mediation Effect (ACME) takes into account the indirect path including Individual *Health and Psychosocial* scores. **(Bottom Panel)** Mediation effects indicate a partial mediation such that the direct relationship between *Neighborhood, Satellite, and Demographics* and Depression Scores is significant and positive, the indirect effect through individual behavior scores is also significant and dominates the Total Effect.

Table 4.5: Mediation analysis of CESD (Depression) using Latent Variable 1

Table 4.5a: Mediation Regression Results

	Dependent variable:			
	Health and Psychosocial	CESD (Depression)		
	(a)	(b)	(c)	(c')
Neighborhood, Satellite, and Demographics	0.649*** (0.020)		−0.809*** (0.071)	0.282*** (0.074)
Health and Psychosocial Factors		−1.563*** (0.050)		−1.679*** (0.059)
Constant	0.000 (0.003)	1.864*** (0.009)	1.864*** (0.010)	1.864*** (0.009)
Observations	3,037	3,037	3,037	3,037
R^2	0.268	0.241	0.041	0.245
Adjusted R^2	0.267	0.241	0.041	0.244
Residual Std. Error	0.155 (df = 3035)	0.501 (df = 3035)	0.564 (df = 3035)	0.500 (df = 3034)
F Statistic	1,108.795*** (df = 1; 3035)	965.199*** (df = 1; 3035)	129.743*** (df = 1; 3035)	492.073*** (df = 2; 3034)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4.5b: Estimated Causal Mediation Effects

Quasi-Bayesian Confidence Intervals	**Estimate**	**95% CI Lower**	**95 % CI Upper**	**p-value**
Avg Causal Mediation Effect (ACME)	-1.090	-1.191	-0.990	0.000
Avg Direct Effect (ADE)	0.282	0.137	0.432	0.000
Total Effect	-0.809	-0.942	-0.668	0.000
Proportion Mediated	1.348	1.152	1.620	0.000

Latent Variable 2–Older, Unhealthy, Supportive Community

This mediation model tested the hypothesis that *Health and Psychosocial Factors* of Latent Variable 2, characterized as indexing **being Older, Unhealthy, and part of Supportive Community**, mediate the relationship between *Neighborhood, Satellite, and Demo-*

graphic scores and Depression (CESD) scores (see Figure 4.11 for a structural representation of the model, and Figure 4.4 for the individual variable loadings of this Latent Variable). A mediation regression analysis (results shown in Table 4.6a) revealed that *Neighborhood, Satellite, and Demographics* scores, while ignoring the mediator, were a significant predictor of Depression scores,(β = -0.602, $SE(\ \beta)$ = 0.07, $t(3035)$= -8.561, $p < 0.001$ (**c path**)). Once controlling for *Health and Psychosocial Factor* scores, *Neighborhood, Satellite, and Demographic* scores were still a significant predictor of Depression scores (β = -1.007, $SE(\ \beta)$ = 0.076, $t(3034)$ =-13.265, $p < 0.001$). The indirect path, (typically referred to as the **a** and **b path** in Baron-Kenney regression mediation analyses), indicated that *Neighborhood, Satellite, and Demographic* scores were a significant predictor of *Health and Psychosocial* scores (β = 0.353, $SE(\ \beta)$ = 0.014, $t(3035)$ =26.033, $p < 0.001$), and *Health and Psychosocial* scores were a significant predictor of Depression scores (β = -1.007, $SE(\ \beta)$ = 0.076, $t(3034)$ = -13.265, $p < 0.001$). Therefore, the mediation analysis for this Latent Variable suggests that *Health and Psychosocial* scores *partially* mediate the relationship between *Neighborhood, Satellite, and Demographic* scores and Depression scores. These results are summarized in Table 4.6a.

Using a bayesian modeling mediation procedure in the `mediation` package in R and bootstrapping, we decomposed the total effect of the model into the Average Causal Mediated Effect (ACME) and the Average Direct Effect (ADE). The average total effect (as seen in the bottom panel of Figure 4.11 and in Table 4.6b) is estimated to be -0.602 with the 95 percent confidence interval of [-0.741, -0.466]. The ACME effect was estimated to be 0.405, with the 95 percent confidence interval of [0.330, 0.481], while the ADE was estimated to be -1.007, with a 95 percent confidence interval of [-1.151, -0.861]. Thus, these mediation results suggest that for this Latent Variable, characterized by **being Older, Unhealthy, and part of Supportive communities**, both *Neighborhood, Satellite, and Demographics* scores and *Health and Psychosocial Factor* scores are important, but this relationship is dominated by the direct relationship between *Neighborhood, Satellite, and Demographics* and Depression.

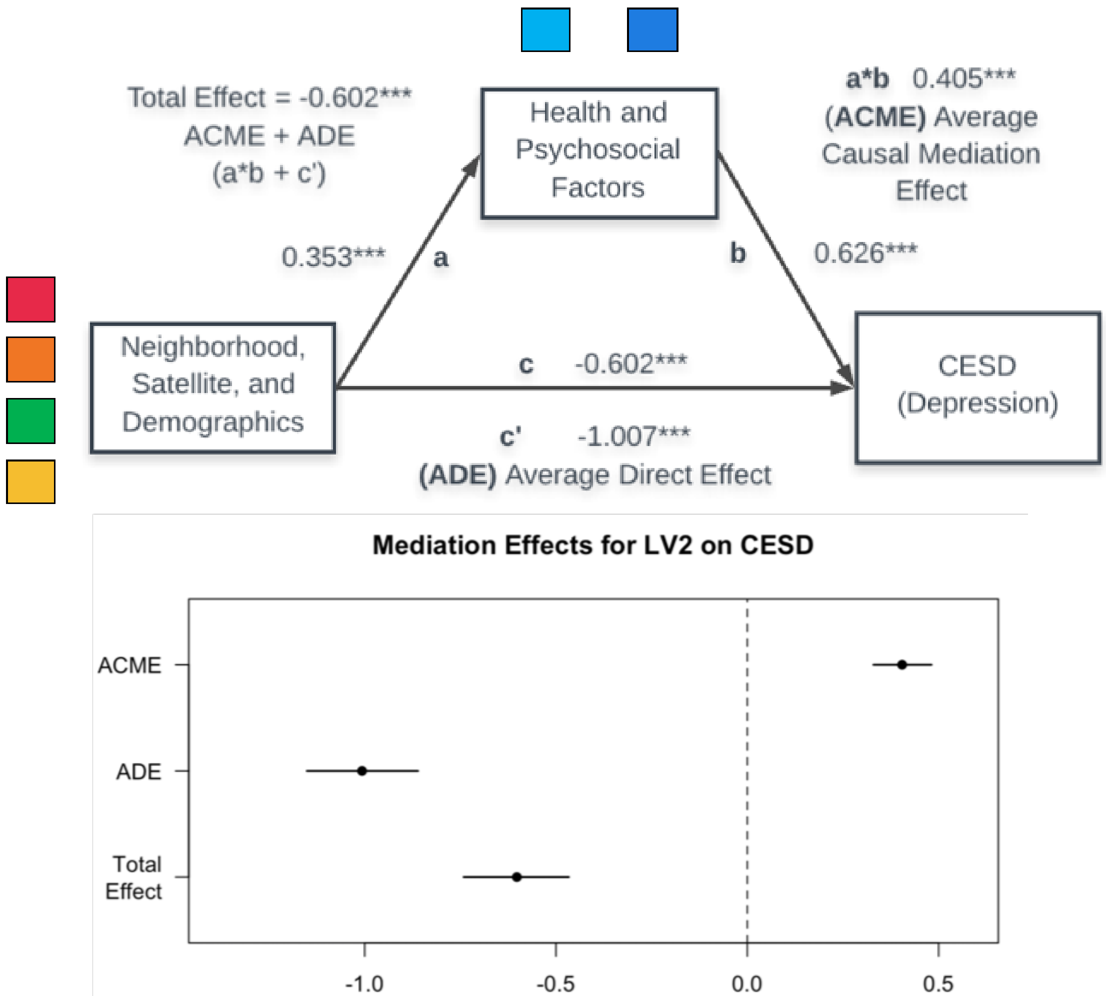


Figure 4.11: Mediation results on Depression using LV2. **(Upper Panel)** This diagram displays the mediation model, where the Average Direct Effect (ADE) is represented by the relationship between *Neighborhood, Satellite, and Demographics* and Depression Scores, while the Average Causal Mediation Effect (ACME) takes into account the indirect path including individual *Health and Psychosocial* scores. **(Bottom Panel)** Mediation effects indicate a partial mediation such that the direct relationship between *Neighborhood, Satellite, and Demographics* and Depression scores is significant and positive, the indirect effect through individual behavior Scores is also significant and dominates the Total Effect.

Table 4.6: Mediation analysis of CESD (Depression) using Latent Variable 2

Table 4.6a: Mediation Regression Results

	Dependent variable:			
	Health and Psychosocial	CESD (Depression)		
	(a)	**(b)**	**(c)**	**(c')**
Neighborhood, Satellite, and Demographics	0.353^{***}		-0.602^{***}	-1.007^{***}
	(0.014)		(0.070)	(0.076)
Health and Psychosocial Factors		0.626^{***}		1.148^{***}
		(0.086)		(0.092)
Constant	0.000	1.864^{***}	1.864^{***}	1.864^{***}
	(0.002)	(0.010)	(0.010)	(0.010)
Observations	3,037	3,037	3,037	3,037
R^2	0.183	0.017	0.024	0.071
Adjusted R^2	0.182	0.017	0.023	0.071
Residual Std. Error	0.109 (df = 3035)	0.571 (df = 3035)	0.569 (df = 3035)	0.555 (df = 3034)
F Statistic	677.734^{***} (df = 1; 3035)	53.612^{***} (df = 1; 3035)	73.286^{***} (df = 1; 3035)	116.332^{***} (df = 2; 3034)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.6b: Estimated Causal Mediation Effects

Quasi-Bayesian Confidence Intervals	**Estimate**	**95 % CI Lower**	**95 % CI Upper**	**p-values**
Avg Causal Mediation Effect (ACME)	0.405	0.330	0.481	0.000
Avg Direct Effect (ADE)	-1.007	-1.151	-0.861	0.000
Total Effect	-0.602	-0.741	-0.466	0.000
Proportion Mediated	-0.672	-0.941	-0.494	0.000

Latent Variable 3–Structural Disadvantage

This mediation model tested the hypothesis that *Health and Psychosocial Factors* of Latent Variable 3, characterized as indexing **Structural Disadvantage**, mediate the relationship between *Neighborhood, Satellite, and Demographic* scores and Depression (CESD) scores (see Figure 4.12 for a structural representation of the model, and Figure 4.6 for the individual variable loadings of this Latent Variable). A mediation regression analysis (results shown in Table 4.7a) revealed that *Neighborhood, Satellite, and Demographics* scores, while ignoring the mediator, were a significant predictor of Depression scores,(β = -0.702, $SE(\beta)$ = 0.064, $t(3035)$= -10.905, $p < 0.001$ (**c path**)). Once controlling for *Health and Psychosocial Factor* scores, *Neighborhood, Satellite, and Demographic* scores were still a significant predictor of Depression scores (β = -0.934, $SE(\beta)$ = 0.067, $t(3034)$ = -13.979, $p < 0.001$). The indirect path, (typically referred to as the **a** and **b path** in Baron-Kenney regression mediation analyses), indicated that *Neighborhood, Satellite, and Demographic* scores were a significant predictor of *Health and Psychosocial* scores (β = 0.213, $SE(\beta)$ = 0.011, t(3035) = 18.969, $p < 0.001$), and *Health and Psychosocial* scores were a significant predictor of Depression scores (β = -0.934, $SE(\beta)$ = 0.067, $t(3034)$ = -13.979, $p < 0.001$). Therefore, the mediation analysis for this Latent Variable suggests that *Health and Psychosocial* scores *partially* mediate the relationship between *Neighborhood, Satellite, and Demographic* scores and Depression scores. These results are summarized in Table 4.7a.

Using a bayesian modeling mediation procedure in the *mediation* package in R and bootstrapping, we decomposed the total effect of the model into the Average Causal Mediated Effect (ACME) and the Average Direct Effect (ADE). The average total effect (as seen in the bottom panel of Figure 4.12 and in Table 4.7b) is estimated to be -0.702 with the 95 percent confidence interval of [-0.833, -0.569]. The ACME effect was estimated to be 0.232, with the 95 percent confidence interval of [0.185, 0.285], while the ADE was estimated to be -0.934, with a 95 percent confidence interval of [-1.068, -0.795]. Thus, these mediation results suggest that for this Latent Variable, characterized by **Structural Disadvantage**, both *Neighborhood, Satellite, and Demographics* scores and *Health and Psychosocial Factor* scores are important, but this relationship is dominated by the direct relationship between *Neighborhood, Satellite, and Demographics* and Depression.

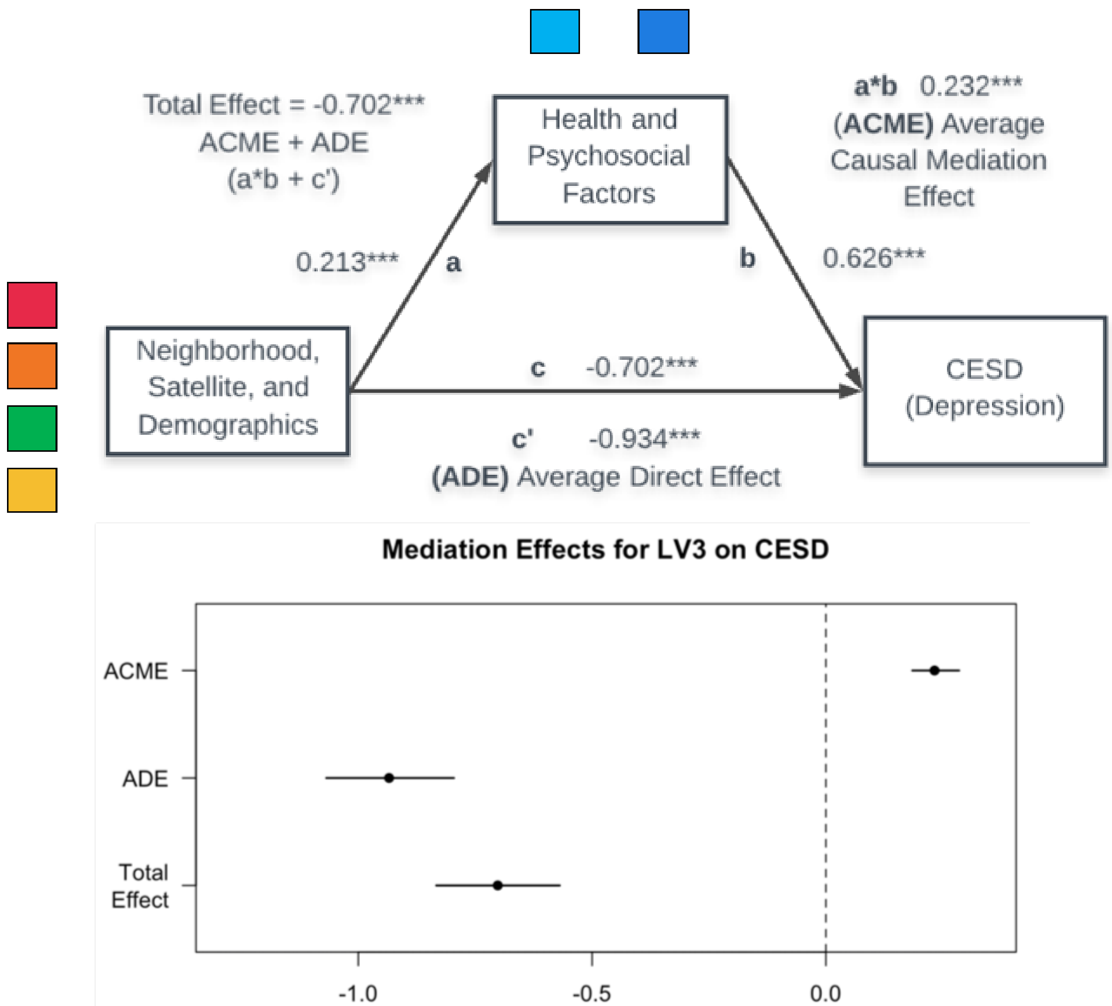


Figure 4.12: Mediation results on Depression using LV3. **(Upper Panel)** This diagram displays the mediation model, where the Average Direct Effect (ADE) is represented by the relationship between *Neighborhood, Satellite, and Demographics* and Depression Scores, while the Average Causal Mediation Effect (ACME) takes into account the indirect path including individual *Health and Psychosocial*. **(Bottom Panel)** Mediation effects indicate a partial mediation such that the direct relationship between *Neighborhood, Satellite, and Demographics* and Depression scores is significant and negative and dominates the total effect, while the indirect effect through individual behavior Scores is also significant, but positive.

Table 4.7: Mediation analysis of CESD (Depression) using Latent Variable 3

Table 4.7a: Mediation Regression Results

	Dependent variable:			
	Health and Psychosocial	CESD (Depression)		
	(a)	(b)	(c)	(c')
Neighborhood, Satellite, and Demographics	0.213***		−0.702***	−0.934***
	(0.011)		(0.064)	(0.067)
Health and Psychosocial Factors		0.626***		1.091***
		(0.100)		(0.102)
Constant	0.000	1.864***	1.864***	1.864***
	(0.002)	(0.010)	(0.010)	(0.010)
Observations	3,037	3,037	3,037	3,037
R^2	0.106	0.013	0.038	0.073
Adjusted R^2	0.106	0.013	0.037	0.072
Residual Std. Error	0.099 (df = 3035)	0.572 (df = 3035)	0.565 (df = 3035)	0.554 (df = 3034)
F Statistic	359.834*** (df = 1; 3035)	39.532*** (df = 1; 3035)	118.914*** (df = 1; 3035)	118.742*** (df = 2; 3034)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.7b: Estimated Causal Mediation Effects

Quasi-Bayesian Confidence Intervals	**Estimate**	**95 % CI Lower**	**95 % CI Upper**	**p-values**
Avg Causal Mediation Effect (ACME)	0.232	0.185	0.285	0.000
Avg Direct Effect (ADE)	-0.934	-1.068	-0.795	0.000
Total Effect	-0.702	-0.833	-0.569	0.000
Proportion Mediated	-0.331	-0.445	-0.246	0.000

Latent Variable 4– Structural Advantage, "Non-Supportive" Community

This mediation model tested the hypothesis that *Health and Psychosocial Factors* of Latent Variable 4, characterized as indexing **Structural Advantage, and being part of a "non-supportive" community**, mediate the relationship between *Neighborhood, Satellite,* *and Demographic* scores and Depression (CESD) scores (see Figure 4.13 for a structural representation of the model, and Figure 4.8 for the individual variable loadings of this Latent Variable). A mediation regression analysis (results shown in Table 4.8a) revealed that *Neighborhood, Satellite, and Demographics* scores, while ignoring the mediator, were a significant predictor of Depression scores (β = 0.727, $SE(\beta)$ = 0.088, t(3035)= 8.22, $p < 0.001$ (**c path**)). Once controlling for *Health and Psychosocial Factor* scores, *Neighborhood, Satellite, and Demographic* scores were no longer a significant predictor of Depression scores (β = 0.109, $SE(\beta)$ = 0.076, t(3034) = 1.433, p = 0.152). The indirect path, (typically referred to as the **a** and **b path** in Baron-Kenney regression mediation analyses), indicated that *Neighborhood, Satellite, and Demographic* scores were a significant predictor of *Health and Psychosocial* scores (β = 0.324, $SE(\beta)$ = 0.025, t(3035) = 12.854, $p < 0.001$), and *Health and Psychosocial* scores were a significant predictor of Depression scores (β = 1.927, $SE(\beta)$ = 0.052, t(3035) = -36.950, $p < 0.001$). Therefore, the mediation analysis for this Latent Variable suggests that *Health and Psychosocial* scores *fully* mediate the relationship between *Neighborhood, Satellite, and Demographic* scores and Depression scores. These results are summarized in Table 4.8a.

Using a bayesian modeling mediation procedure in the `mediation` package in R and bootstrapping, we decomposed the total effect of the model into the Average Causal Mediated Effect (ACME) and the Average Direct Effect (ADE). The average total effect (as seen in the bottom panel of Figure 4.13 and in Table 4.8b) is estimated to be 0.727 with the 95 percent confidence interval of [0.547, 0.900]. The ACME effect was estimated to be 0.618, with the 95 percent confidence interval of [0.511, 0.721], while the ADE was estimated to be 0.109, with a 95 percent confidence interval of [-0.036, 0.254], therefore not considered reliable since the confidence interval crosses zero. These mediation results suggest that for this Latent Variable, characterized by **Structural Advantage while in "Non-Supportive" Communities**, it is the *Health and Psychosocial* Factor scores that are more important.

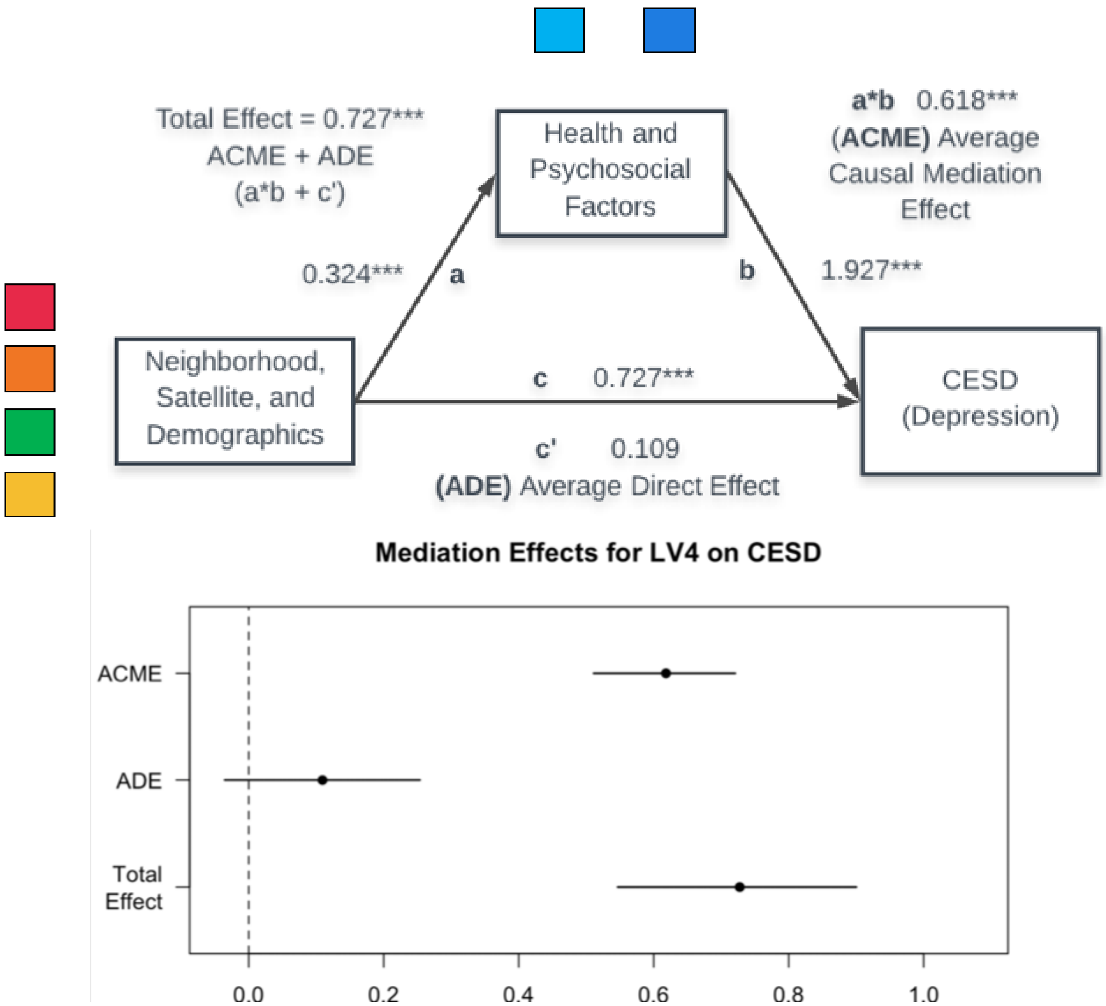


Figure 4.13: Mediation results on Depression using LV4. **(Upper Panel)** This diagram displays the mediation model, where the Average Direct Effect (ADE) is represented by the relationship between *Neighborhood, Satellite, and Demographics* and Depression Scores, while the Average Causal Mediation Effect (ACME) takes into account the indirect path including individual *Health and Psychosocial Factors*. **(Bottom Panel)** Mediation effects indicate a complete mediation, since only the positive indirect effect through individual behavior scores is significant.

Table 4.8: Mediation analysis of CESD (Depression) using Latent Variable 4

Table 4.8a: Mediation Regression Results

	Dependent variable:			
	Health and Psychosocial	CESD (Depression)		
	(a)	**(b)**	**(c)**	**(c')**
Neighborhood, Satellite, and Demographics	0.324***		0.727***	0.109
	(0.025)		(0.088)	(0.076)
Health and Psychosocial Factors		1.927***		1.909***
		(0.052)		(0.054)
Constant	0.000	1.864***	1.864***	1.864***
	(0.003)	(0.009)	(0.010)	(0.009)
Observations	3,037	3,037	3,037	3,037
R^2	0.052	0.310	0.022	0.311
Adjusted R^2	0.051	0.310	0.021	0.310
Residual Std. Error	0.162 (df = 3035)	0.478 (df = 3035)	0.569 (df = 3035)	0.478 (df = 3034)
F Statistic	165.224*** (df = 1; 3035)	1,364.931*** (df = 1; 3035)	67.576*** (df = 1; 3035)	683.728*** (df = 2; 3034)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4.8b: Estimated Causal Mediation Effects

Quasi-Bayesian Confidence Intervals	**Estimate**	**95 % CI Lower**	**95 % CI Upper**	**p-values**
Avg Causal Mediation Effect (ACME)	0.618	0.511	0.721	0.000
Avg Direct Effect (ADE)	0.109	-0.036	0.254	0.148
Total Effect	0.727	0.547	0.900	0.000
Proportion Mediated	0.850	0.703	1.062	0.000

4.3.3 Mediation Analyses on Anxiety

Latent Variable 1–Affluence, Structural Advantage, Healthy, Supportive Community

This mediation model tested the hypothesis that *Health and Psychosocial Factors* of Latent Variable 1, characterized as indexing **Affluence, Structural Advantage, Positive Health**, mediate the relationship between *Neighborhood, Satellite, and Demographic* scores and Anxiety scores (see Figure 4.14 for a structural representation of the model, and Figure 4.2 for the individual variable loadings of this Latent Variable). A mediation regression analysis (results shown in Table 4.9a) revealed that *Neighborhood, Satellite, and Demographics* scores, while ignoring the mediator, were a significant predictor of Depression scores,(β = -0.695, *SE*(β) = 0.075, t(3035)= -9.287, $p < 0.001$ (**c path**)). Once controlling for *Health and Psychosocial Factor* scores, *Neighborhood, Satellite, and Demographic* scores were still a significant predictor of Depression scores ($\beta = 0.299$, *SE*(β) = 0.08, $t(3034) = 3.731$, $p <$ 0.001). The indirect path, (typically referred to as the **a** and **b path** in Baron-Kenney regression mediation analyses), indicated that *Neighborhood, Satellite, and Demographic* scores were a significant predictor of *Health and Psychosocial* scores ($\beta = 0.649$, *SE*(β) = 0.02, t(3035) = 33.299, $p < 0.001$), and *Health and Psychosocial* scores were a significant predictor of Depression scores ($\beta = 0.299$, *SE*(β) = 0.08, $t(3034) = 3.731$, $p < 0.001$). Therefore, the mediation analysis for this Latent Variable suggests that *Health and Psychosocial* scores *partially* mediate the relationship between *Neighborhood, Satellite, and Demographic* scores and Depression scores. These results are summarized in Table 4.5a.

Using a bayesian modeling mediation procedure in the `mediation` package in R and bootstrapping, we decomposed the total effect of the model into the Average Causal Mediated Effect (ACME) and the Average Direct Effect (ADE). The average total effect (as seen in the bottom panel of Figure 4.14 and in Table 4.9b) is estimated to be -0.809 with the 95 percent confidence interval of [-0.942, -0.668]. The ACME effect was estimated to be -1.09, with the 95 percent confidence interval of [-1.191, -0.990], while the ADE was estimated to be 0.282, with a 95 percent confidence interval of [0.137, 0.432]. Given the difference in sign between the ACME and the ADE, it seems that the *Health and Psychosocial* scores function as a suppressor in the relationship between *Neighborhood, Satellite, and Demographics* scores and Anxiety scores. These results suggest that the decrease in Anxiety is dominated by the increasing *Health and Psychosocial* scores in this Latent Variable, although there the direct relationship between *Neighborhood, Satellite, and Demographics* and Anxiety is still significant and positive. Thus, these mediation results suggest that for this Latent Variable, characterized by **Affluence, Structural Advantage, Health, and Supportive Community**, both *Neighborhood, Satellite, and Demographics* scores and *Health and Psychosocial Factor* scores are important, but this relationship is dominated by individual *Health and Psychosocial* factors.

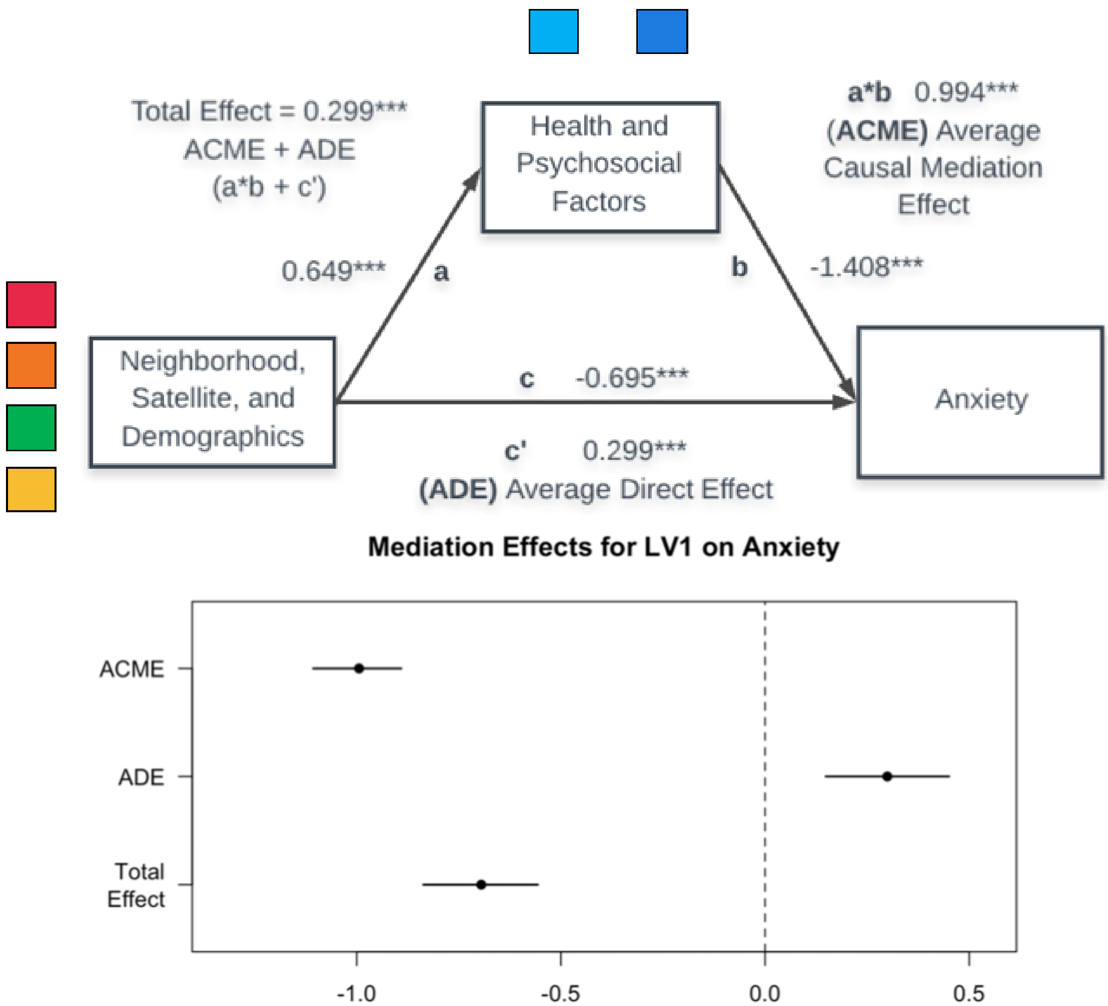


Figure 4.14: Mediation results on Anxiety using LV1. **(Upper Panel)** This diagram displays the mediation model, where the Average Direct Effect (ADE) is represented by the relationship between *Neighborhood, Satellite, and Demographics* and Anxiety scores, while the Average Causal Mediation Effect (ACME) takes into account the indirect path including individual *Health and Psychosocial* scores. **(Bottom Panel)** that the direct relationship between *Neighborhood, Satellite, and Demographics* and Anxiety scores is significant positive, the indirect effect through individual behavior scores is also negative and also significant, dominating the Total Effect.

Table 4.9: Mediation analysis of Anxiety using Latent Variable 1

Table 4.9a: Mediation Regression Results

	Dependent variable:			
	Health and Psychosocial	Anxiety		
	(a)	**(b)**	**(c)**	**(c')**
Neighborhood, Satellite, and Demographics	0.649*** (0.020)		−0.695*** (0.075)	0.299*** (0.080)
Health and Psychosocial Factors		−1.408*** (0.055)		−1.531*** (0.064)
Constant	0.000 (0.003)	1.581*** (0.010)	1.581*** (0.011)	1.581*** (0.010)
Observations	3,037	3,037	3,037	3,037
R^2	0.268	0.179	0.028	0.182
Adjusted R^2	0.267	0.178	0.027	0.182
Residual Std. Error	0.155 (df = 3035)	0.546 (df = 3035)	0.594 (df = 3035)	0.545 (df = 3034)
F Statistic	1,108.795*** (df = 1; 3035)	660.177*** (df = 1; 3035)	86.241*** (df = 1; 3035)	338.455*** (df = 2; 3034)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4.9b: Estimated Causal Mediation Effects

Quasi-Bayesian Confidence Intervals	**Estimate**	**95% CI Lower**	**95% CI Upper**	**p-values**
Avg Causal Mediation Effect (ACME)	-0.994	-1.107	-0.891	0.000
Avg Direct Effect (ADE)	0.299	0.148	0.451	0.000
Total Effect	-0.695	-0.837	-0.557	0.000
Proportion Mediated	1.431	1.183	1.780	0.000

Latent Variable 2– Older, Unhealthy, Supportive Community

This mediation model tested the hypothesis that *Health and Psychosocial Factors* of Latent Variable 2, characterized as indexing being **Older, Unhealthy and, and part of Supportive Community**, mediate the relationship between *Neighborhood, Satellite, and Demographic* scores and Anxiety scores (see Figure 4.15 for a structural representation of the model, and Figure 4.4 for the individual variable loadings of this Latent Variable). A mediation regression analysis (results shown in Table 4.10a)revealed that *Neighborhood, Satellite, and Demographics* scores, while ignoring the mediator, were a significant predictor of Anxiety scores,(β = -0.290, $SE(\beta)$ = 0.074, $t(3035)$= -3.899, $p < 0.001$ (**c path**)). Once controlling for *Health and Psychosocial Factor* scores, *Neighborhood, Satellite, and Demographic* scores were still a significant predictor of Anxiety scores (β = -0.677, $SE(\beta)$ = 0.081, $t(3034)$ = -8.403, $p < 0.001$). The indirect path, (typically referred to as the **a** and **b path** in Baron-Kenney regression mediation analyses), indicated that *Neighborhood, Satellite, and Demographic* scores were a significant predictor of *Health and Psychosocial* scores ($\beta = 0.353$, $SE(\beta)$ = 0.014, $t(3035)$ = 26.033, $p < 0.001$), and *Health and Psychosocial* scores were a significant predictor of Anxiety scores (β = -0.677, $SE(\beta)$ = 0.081, $t(3034)$ = -8.403, $p <$ 0.001). Therefore, the mediation analysis for this Latent Variable suggests that *Health and Psychosocial* scores *partially* mediate the relationship between *Neighborhood, Satellite, and Demographic* scores and Anxiety scores. These results are summarized in Table 4.10a.

Using a bayesian modeling mediation procedure in the `mediation` package in R and bootstrapping, we decomposed the total effect of the model into the Average Causal Mediated Effect (ACME) and the Average Direct Effect (ADE). The average total effect (as seen in the bottom panel of Figure 4.15 and in Table 4.10b) is estimated to be -0.290 with the 95 percent confidence interval of [-0.442, -0.139]. The ACME effect was estimated to be 0.387, with the 95 percent confidence interval of [0.302, 0.479], while the ADE was estimated to be -0.677, with a 95 percent confidence interval of [-0.841, -0.513]. Thus, these mediation results suggest that for this Latent Variable, characterized by **being Older, Unhealthy, and part of Supportive Communities**, both *Neighborhood, Satellite, and Demographics* scores and *Health and Psychosocial Factor* scores are important, but this relationship is dominated by the direct relationship between *Neighborhood, Satellite, and Demographics* and Anxiety.

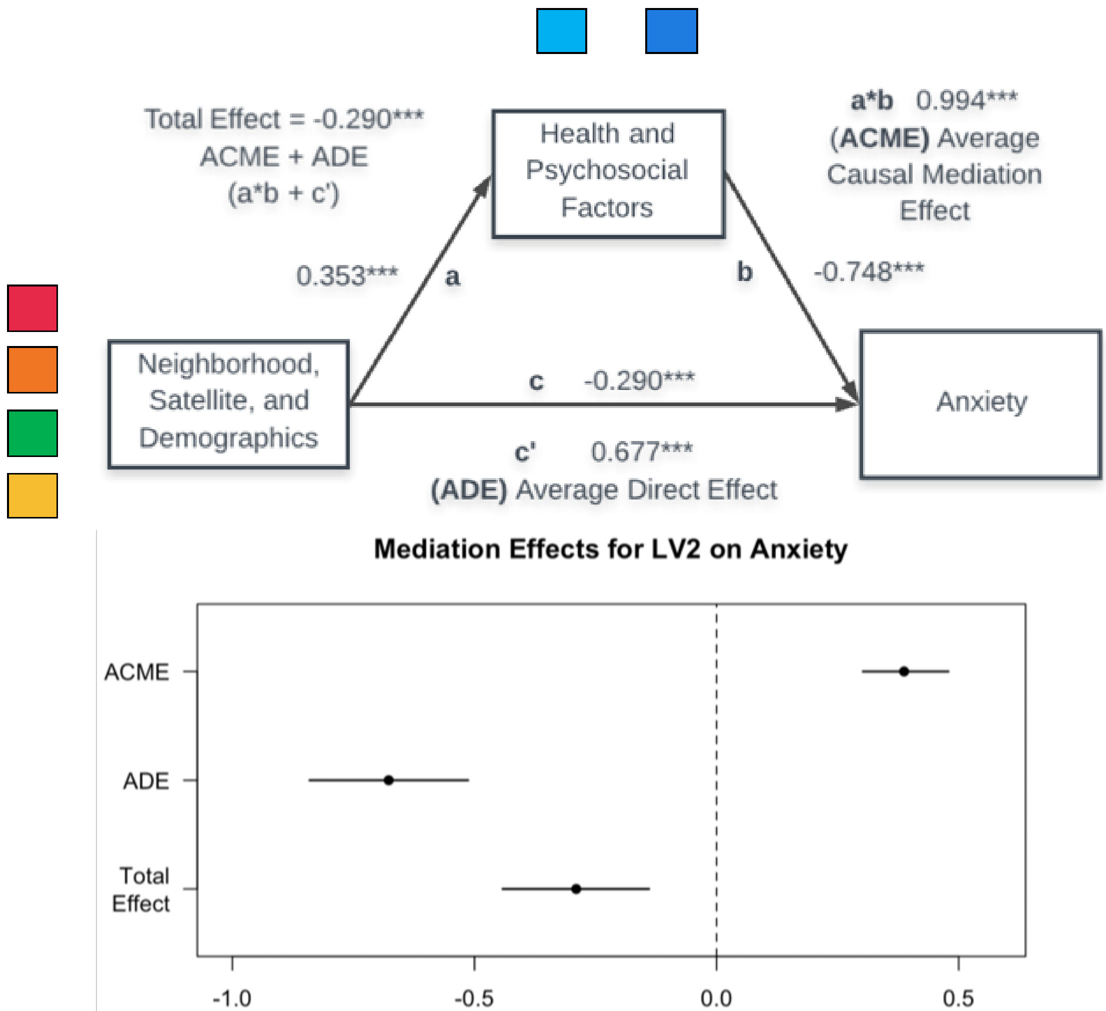


Figure 4.15: Mediation results on Anxiety using LV2. **(Upper Panel)** This diagram displays the mediation model, where the Average Direct Effect (ADE) is represented by the relationship between *Neighborhood, Satellite, and Demographics* and Anxiety Scores, while the Average Causal Mediation Effect (ACME) takes into account the indirect path including individual *Health and Psychosocial*. **(Bottom Panel)** Mediation effects indicate a partial mediation such that while the direct relationship between *Neighborhood, Satellite, and Demographics* and Anxiety Scores is significant and positive, the indirect effect through individual behavior Scores is also significant and dominates the Total Effect.

Table 4.10: Mediation analysis of Anxiety using Latent Variable 2

Table 4.10a: Mediation Regression Results

	Dependent variable:			
	Health and Psychosocial	Anxiety		
	(a)	(b)	(c)	(c')
Neighborhood, Satellite, and Demographics	0.353*** (0.014)		−0.290*** (0.074)	−0.677*** (0.081)
Health and Psychosocial Factors		0.748*** (0.089)		1.098*** (0.098)
Constant	0.000 (0.002)	1.581*** (0.011)	1.581*** (0.011)	1.581*** (0.011)
Observations	3,037	3,037	3,037	3,037
R^2	0.183	0.023	0.005	0.045
Adjusted R^2	0.182	0.022	0.005	0.044
Residual Std. Error	0.109 (df = 3035)	0.596 (df = 3035)	0.601 (df = 3035)	0.589 (df = 3034)
F Statistic	677.734*** (df = 1; 3035)	70.131*** (df = 1; 3035)	15.203*** (df = 1; 3035)	71.178*** (df = 2; 3034)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.10b: Estimated Causal Mediation Effects

Quasi-Bayesian Confidence Intervals	**Estimate**	**95% CI Lower**	**95% CI Upper**	**p-values**
Avg Causal Mediation Effect (ACME)	0.387	0.302	0.479	0.000
Avg Direct Effect (ADE)	-0.677	-0.841	-0.513	0.000
Total Effect	-0.290	-0.442	-0.139	0.000
Proportion Mediated	-1.336	-2.959	-0.800	0.000

Latent Variable 3–Structural Disadvantage

This mediation model tested the hypothesis that *Health and Psychosocial Factors* of Latent Variable 3, characterized as indexing **Structural Disadvantage**, mediate the relationship between *Neighborhood, Satellite, and Demographics* scores and Anxiety scores (see Figure 4.16 for a structural representation of the model, and Figure 4.6 for the individual variable loadings of this Latent Variable). A mediation regression analysis (results shown in Table 4.11a) revealed that *Neighborhood, Satellite, and Demographics* scores, while ignoring the mediator, were a significant predictor of Anxiety scores,(β = -0.599, $SE(\ \beta)$ = 0.068, $t(3035)$= -8.837, $p < 0.001$ (**c path**)). Once controlling for *Health and Psychosocial Factor* scores, *Neighborhood, Satellite, and Demographic* scores were still a significant predictor of Anxiety scores (β = -0.81, $SE(\ \beta)$ = 0.071, $t(3034)$ = -11.451, $p < 0.001$). The indirect path, (typically referred to as the **a** and **b path** in Baron-Kenney regression mediation analyses), indicated that *Neighborhood, Satellite, and Demographic* scores were a significant predictor of *Health and Psychosocial* scores (β = 0.213, $SE(\ \beta)$ = 0.011, t(3035) = 18.969, $p < 0.001$), and *Health and Psychosocial* scores were a significant predictor of Anxiety scores (β = -0.81, $SE(\ \beta)$ = 0.071, $t(3034)$ = -11.451, $p < 0.001$). Therefore, the mediation analysis for this Latent Variable suggests that *Health and Psychosocial* scores *partially* mediate the relationship between *Neighborhood, Satellite, and Demographic* scores and Anxiety scores. These results are summarized in Table 4.11a.

Using a bayesian modeling mediation procedure in the `mediation` package in R and bootstrapping, we decomposed the total effect of the model into the Average Causal Mediated Effect (ACME) and the Average Direct Effect (ADE). The average total effect (as seen in the bottom panel of Figure 4.16 and in Table 4.11b) is estimated to be -0.599 with the 95 percent confidence interval of [-0.740, -0.458]. The ACME effect was estimated to be 0.211, with the 95 percent confidence interval of [0.159, 0.265], while the ADE was estimated to be -0.810, with a 95 percent confidence interval of [-0.959, -0.663]. Thus, these mediation results suggest that for this Latent Variable, characterized by **Structural Disadvantage**, both *Neighborhood, Satellite, and Demographics* scores and *Health and Psychosocial Factor* scores are important, but this relationship is dominated by the direct relationship between *Neighborhood, Satellite, and Demographics* and Anxiety.

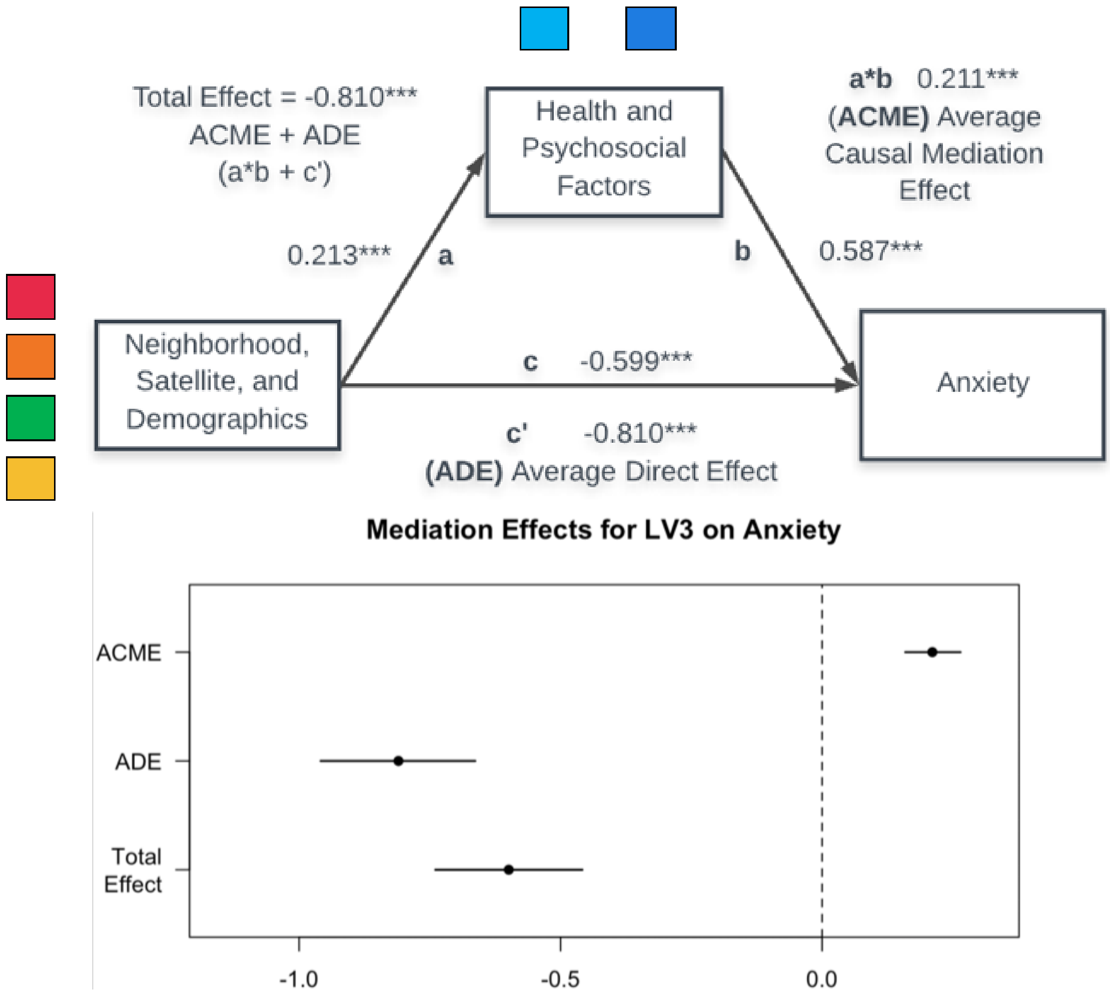


Figure 4.16: Mediation results on Anxiety using LV3. **(Upper Panel)** This diagram displays the mediation model, where the Average Direct Effect (ADE) is represented by the relationship between *Neighborhood, Satellite, and Demographics* and Anxiety Scores, while the Average Causal Mediation Effect (ACME) takes into account the indirect path including individual *Health and Psychosocial*. **(Bottom Panel)** Mediation effects indicate a partial mediation such that the direct relationship between *Neighborhood, Satellite, and Demographics* and Anxiety Scores is significant and negative and dominates the total effect, while the indirect effect through individual behavior Scores is also significant, but positive.

Table 4.11: Mediation analysis of Anxiety using Latent Variable 3

Table 4.11a: Mediation Regression Results

	Dependent variable:			
	Health and Psychosocial	Anxiety		
	(a)	**(b)**	**(c)**	**(c')**
Neighborhood, Satellite, and Demographics	0.213*** (0.011)		−0.599*** (0.068)	−0.810*** (0.071)
Health and Psychosocial Factors		0.587*** (0.104)		0.990*** (0.108)
Constant	0.000 (0.002)	1.581*** (0.011)	1.581*** (0.011)	1.581*** (0.011)
Observations	3,037	3,037	3,037	3,037
R^2	0.106	0.010	0.025	0.051
Adjusted R^2	0.106	0.010	0.025	0.051
Residual Std. Error	0.099 (df = 3035)	0.599 (df = 3035)	0.595 (df = 3035)	0.587 (df = 3034)
F Statistic	359.834*** (df = 1; 3035)	31.642*** (df = 1; 3035)	78.097*** (df = 1; 3035)	82.064*** (df = 2; 3034)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4.11b: Estimated Causal Mediation Effects

Quasi-Bayesian Confidence Intervals	**Estimate**	**95% CI Lower**	**95% CI Upper**	**p-values**
Avg Causal Mediation Effect (ACME)	0.211	0.159	0.265	0.000
Avg Direct Effect (ADE)	-0.810	-0.959	-0.663	0.000
Total Effect	-0.599	-0.740	-0.458	0.000
Proportion Mediated	-0.352	-0.508	-0.245	0.000

Latent Variable 4– Structural Advantage, Unhealthy, "Non-Supportive" Community

This mediation model tested the hypothesis that *Health and Psychosocial Factors* of Latent Variable 4, characterized as indexing **Structural Advantage, being Unhealthy and being part of a "non-supportive" community**, mediate the relationship between

Neighborhood, Satellite, and Demographics scores and Anxiety scores (see Figure 4.17 for a structural representation of the model, and Figure 4.8 for the individual variable loadings of this Latent Variable). A mediation regression analysis (results shown in Table 4.12a) revealed that *Neighborhood, Satellite, and Demographics* scores, while ignoring the mediator, were a significant predictor of Anxiety scores (β = 0.345, $SE(\ \beta)$ = 0.093, t(3035)= 3.695, $p < 0.001$ (**c path**)). Once controlling for *Health and Psychosocial Factor* scores, *Neighborhood, Satellite, and Demographic* scores were still a significant predictor of Anxiety scores, but to a lesser degree (β = -0.183, $SE(\ \beta)$ = 0.086, t(3034) = -2.123, p = 0.034). The indirect path, (typically referred to as the **a** and **b path** in Baron-Kenney regression mediation analyses), indicated that *Neighborhood, Satellite, and Demographic* scores were a significant predictor of *Health and Psychosocial* scores (β = 0.324, $SE(\ \beta)$ = 0.025, t(3035) = 12.854, $p < 0.001$), and *Health and Psychosocial* scores were a significant predictor of Anxiety scores (β = 0.587, $SE(\ \beta)$ = 0.104, t(3035) = 27.19, $p < 0.001$). Therefore, the mediation analysis for this Latent Variable suggests that *Health and Psychosocial* scores *partially* mediate the relationship between *Neighborhood, Satellite, and Demographic* scores and Anxiety scores. These results are summarized in Table 4.12a.

Using a bayesian modeling mediation procedure in the *mediation* package in R and bootstrapping, we decomposed the total effect of the model into the Average Causal Mediated Effect (ACME) and the Average Direct Effect (ADE). The average total effect (as seen in the bottom panel of Figure 4.17 and in Table 4.12b) is estimated to be -0.599 with the 95 percent confidence interval of [-0.740, -0.458]. The ACME effect was estimated to be 0.211, with the 95 percent confidence interval of [0.159, 0.265], while the ADE was estimated to be -0.810, with a 95 percent confidence interval of [-0.959, -0.663]. These mediation results suggest that for this Latent Variable, characterized by **Structural Advantage while in "Non-Supportive" Communities**, both the *Health and Psychosocial Factor* scores and *Neighborhood, Satellite, and Demographics* are important, but this relationship is dominated by the indirect effect.

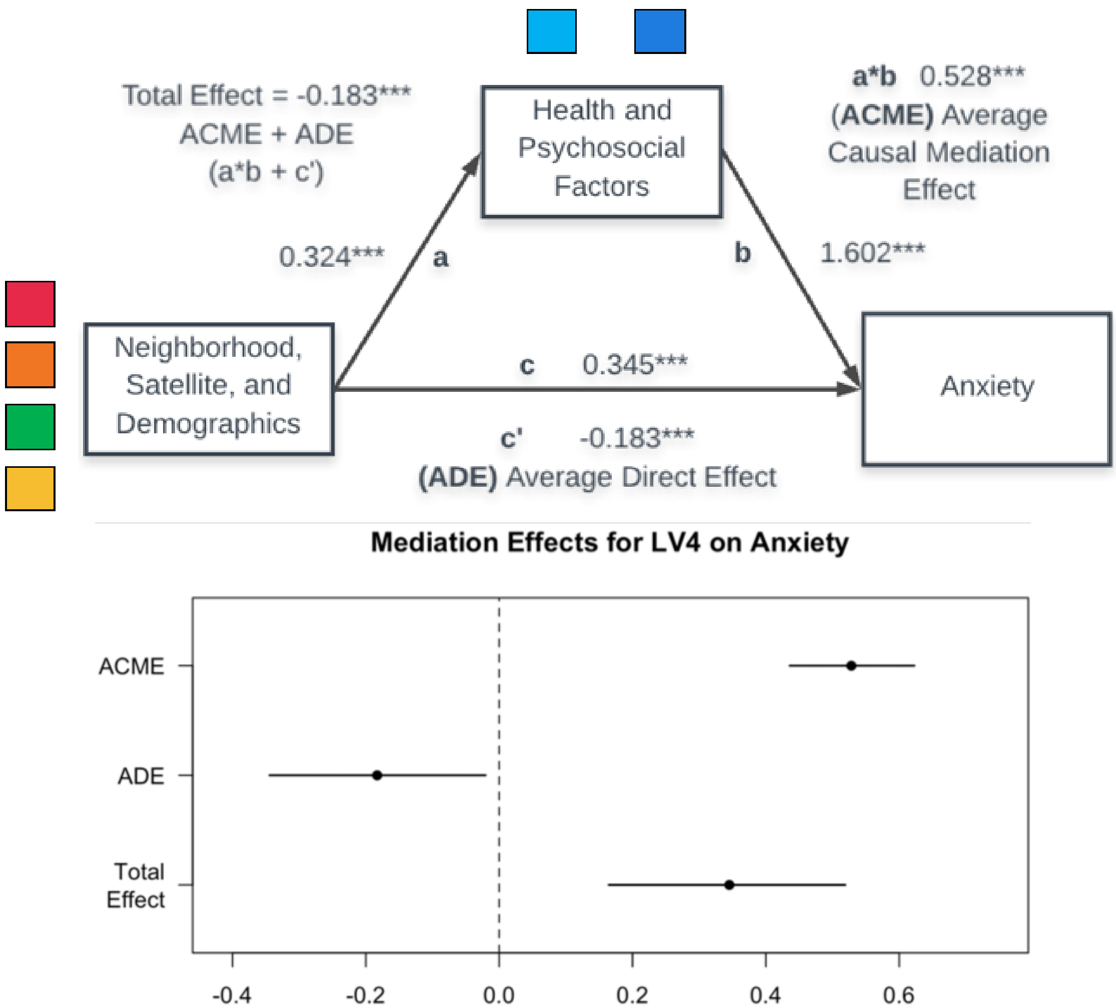


Figure 4.17: Mediation results on Anxiety using LV4. **(Upper Panel)** This diagram displays the mediation model, where the Average Direct Effect (ADE) is represented by the relationship between *Neighborhood, Satellite, and Demographics* and Anxiety Scores, while the Average Causal Mediation Effect (ACME) takes into account the indirect path including individual *Health and Psychosocial Factors*. **(Bottom Panel)** Mediation effects indicate a partial mediation, and while the direct effect between *Neighborhood, Satellite, and Demographics* and Anxiety scores is significant and negative, the positive indirect effect through individual behavior scores is significant and dominates the total effect.

Table 4.12: Mediation analysis of Anxiety Using Latent Variable 4

Table 4.12a: Mediation Regression Results

	Dependent variable:			
	Health and Psychosocial	Anxiety		
	(a)	(b)	(c)	(c')
Neighborhood, Satellite, and Demographics	0.324***		0.345***	−0.183**
	(0.025)		(0.093)	(0.086)
Health and Psychosocial		1.602***		1.632***
		(0.059)		(0.060)
Constant	0.000	1.581***	1.581***	1.581***
	(0.003)	(0.010)	(0.011)	(0.010)
Observations	3,037	3,037	3,037	3,037
R^2	0.052	0.196	0.004	0.197
Adjusted R^2	0.051	0.196	0.004	0.196
Residual Std. Error	0.162 (df = 3035)	0.540 (df = 3035)	0.601 (df = 3035)	0.540 (df = 3034)
F Statistic	165.224*** (df = 1; 3035)	739.101*** (df = 1; 3035)	13.654*** (df = 1; 3035)	372.230*** (df = 2; 3034)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4.12b: Estimated Causal Mediation Effects

Quasi-Bayesian Confidence Intervals	**Estimate**	**95% CI Lower**	**95% CI Upper**	**p-values**
Avg Causal Mediation Effect (ACME)	0.528	0.436	0.623	0.000
Avg Direct Effect (ADE)	-0.183	-0.344	-0.020	0.031
Total Effect	0.345	0.164	0.519	0.000
Proportion Mediated	1.530	1.041	2.990	0.000

4.4 Discussion

The purpose of this study was to investigate the various ways in which social stratification may impact the diagnosis of mental health disorders, such as depression and anxiety, by using various measures related to both an individual's built, local, and social environment, and individual-level health behaviors and psychosocial factors . This study was inspired by a growing literature that illustrates the biological embedding of positive or negative environmental conditions, while also setting to expand on traditional operationalizations of ES consisting of household income, family educational attainment, and occupational prestige. In addition, this study set out to include satellite measures that could determine the contribution of neighborhood greenspace to mental health, and how this relationship may be impact by the inclusion of social environment variables such as social cohesion and the degree to which a community is "supportive." Furthermore, this study used a multivariate factor analysis, canonical correlations, that considered the overlapping relationships between all of these environmental and individual-level variables to identify latent variables that could be used to explain variations in the incidence of mental health conditions.

Our results resulted in four significant latent variables that provided different accounts of the relationship between environmental scores and individual-level scores, and subsequently, mental health. The first latent variable, which we are interpreting as encapsulating Affluence, Structural Advantage, and Positive Health, replicated various effects previously seen in the literature, such as the association of greenspace with positive health. A mediation model used to explain the effects behind presence of depression and anxiety indicated a partial mediation, such that both environment scores and individual-level scores were useful in describing the variation in both depression and anxiety. However, the mediation analysis strongly suggested that the individual-level scores dominated the total effect, suggesting that variations in these scores helped to explain more of the mental health effect. A spatial analysis of the scores in this latent variable showed significant clustering, with several neighborhoods in the northern portion of the county showing positive scores, while a large number of central and western neighborhood clusters indicated low latent variable scores (indicating that they did not show a high correlation with the loadings shown in Figure 4.2). This results supports the idea that spatial distribution of features should be considered when considering community/neighborhood variables, as they may provide additional clues to what drives these effects, which in this case is the clustered nature of health, affluence, and supportive communities.

The second latent variable, which we interpreted as capturing Being Older, Being Unhealthy, with a Supportive Community, no longer showed a significant contribution from the greenspace satellite variable, and did show a significant clustering when looking at the spatial distribution of these scores, with high scores in this latent variable being a bit more scattered but higher on the western portions of the county, with lower scores along much of the downtown and northern area (see Figure 4.5). Interestingly, as opposed to latent variable 1, the mediation analysis for this variable showed that the direct relationship between environmental scores and both depression and anxiety dominated the total effect compared to the individual-level scores, suggesting that the neighborhood, and demographic loadings had a stronger contribution.

The third latent variable, indexing Structural Disadvantage, highlighted a slightly different relationship than the previous two latent variables. This latent variable showed a contrast between Hispanic and Black participants, as opposed to showing a difference across SES, and being Older, as in the latent variable 1 and 2 (respectively). As with the previous two latent variables, this latent variable showed significant clustering that shows many large clusters, with values near zero in the downtown and northern lake-adjacent communities, and alternating clusters of high and low values along the western part of Cook County, a pattern reflective of the clustered nature along racial/ethnic identification lines (see Figure 4.7). Consistent with these spatial maps, the mediation analysis showed that the relationship between the environment scores and depression and anxiety dominated the total effect, although the indirect effect through individual scores did still have a significant contribution. Contrasting latent variables 1 and 3 are an interesting comparison in that they show that when considering affluence and structural advantage, individual-level factors dominate the relationship with mental health, whereas when considering structural disadvantage, it is the environmental-level scores that dominate the relationship. The fourth and final latent variable, indexing Structural Advantage, but Non-Supportive Communities and Negative health, also show spatial clustering, in a similar map to that of latent variable 1 (see Figure 4.9). Interestingly, the mediation analyses show a full mediation for depression, and an effect that is very close to a full mediation for anxiety, where the indirect effect dominates the effect, as in latent variable 1. Again, this supports the distinction between the strength of individual-level scores for latent variables characterized by structural advantage, and the strength of the neighborhood-level variables for the latent variable characterized by Structural Disadvantage.

While the findings of this chapter suggest that including measures beyond traditional measures of SES to include elements of the local and social environment provide a more vivid illustration of the particular ways that social stratification may impact the incidence of mental health, it does not come without a number of limitations or possible avenues for further inquiry. This dataset used for this study was collected in 2001, and, if possible, should be done in the future with more recent data, given the number of changes that have occurred in various neighborhoods in Chicago. In addition, as mentioned in Chapter 3, the multivariate analysis strategy used here was chosen to identify and compare relationships between very broad categories of variables. Therefore, future studies should use methods that identify relationships more than 2 groupings of variables. A choice was made here to consider demographic variables as proxies for the social embedding of individuals within society, but some studies have argued that these variables may actually be more appropriate as an individual level factor that contextualizes health utilization and psychosocial factors.

Another limitation of this study is that it is correlational in nature, and only presents broad relationships within a large sample. We would advise against making any inferences at the individual level, or to interpret the spatial maps as determining the individual behaviors of the people within it. In conclusion, this study is an exciting first step at synthesizing variables from multiple domains to characterize elements of the environment, extending beyond the traditional measures of SES, in order to elucidate how these factors relate to individual behaviors, community and neighborhood dynamics, and mental health.

CHAPTER 5
GENERAL CONCLUSIONS

The purpose of this dissertation was to provide an example of a research approach which incorporated in the analysis of social stratification a wife range of elements of the social, cultural, built, and natural environment. In Chapter 2, I presented a number of frameworks that have inspired a multi-modal, yet critical perspective on how complex environmental phenomena related to social structures and the environment can have downstream effects on individual health and wellness. Then, in Chapter 3, I showed, using data from the first Annual Release of the Adolescent Brain Cognitive Development (ABCD) dataset, the degree to which environmental factors could mediate the relationship between cortical volume and cognitive scores, depending on whether individuals suffered negative impacts of social stratification. In chapter 4, I illustrated a very different implementation of the same framework in evaluating the impact of environmental determinants and social stratification by using data from the Chicago Community Adult Health Study (CCAHS) to examine the relationship of social, natural/built, and community factors to various health-behaviors and psychosocial attitudes and examine how they explained variations in depression and anxiety. These analysis similarly showed that for individuals that were negatively impacted by social stratification (as explained by supportiveness of their community, and residential socioeconomic conditions, and their demographics), neighborhood conditions were more predictive of mental health outcomes than individual psychosocial factors.

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