

**EXPLORING THE GEOGRAPHY OF NEIGHBORHOOD MENTAL
HEALTH VULNERABILITY IN THE CONTEXT OF RACIAL/ETHNIC
RESIDENTIAL SEGREGATION**

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**Donghee Koh
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DEDICATION

Soli Deo Gloria

ABSTRACT

Mental health matters because it affects all aspects of our lives. There is a growing body of literature about neighborhood effects on mental health. These studies argue that individuals living in socioeconomically disadvantaged neighborhoods are more likely to suffer from mental illnesses due to the higher prevalence of chronic stressors and their inability to cope with such problems. A neighborhood, however, is much more than just the sum of its socioeconomic characteristics, and I argue that there are many other important contextual factors that need to be considered to better understand the impact of neighborhood environment on mental health. Hence, the first chapter of this dissertation focuses on identifying other theoretically justifiable neighborhood contextual factors through a review of literature to more comprehensively assess neighborhood level mental health vulnerabilities. This chapter also investigates the relationships among different mental health vulnerability indicators in light of existing theories by employing a Self-Organizing Map (SOM) algorithm. In the second chapter, the spatial distribution patterns of neighborhood mental health vulnerabilities are examined in the context of racial/ethnic residential segregation. These relationships are also systematically examined through multinomial logistic regression analysis. The third chapter explores neighborhood textual review data to identify more of neighborhood contextual factors that are perceived as important by residents. For this purpose, an exploratory Latent Dirichlet Allocation (LDA) method is employed. The findings from this study revealed new patterns and relationships whose importance have been largely overlooked in previous mental health studies. This study also suggests that there exists a close relationship between neighborhood mental health vulnerabilities and racial/ethnic minority concentrations, but this relationship turns out to be much more complicated than our current theoretical understanding. The exploration of residents' perception data has identified 19 topics. When these are examined through the existing theoretical frameworks, 6 of them turn out to be new topics, which include: gentrification, diversity, natural disasters, green space, transportation, and walkability. The new knowledge obtained from this study offers valuable insights for the enhancement of our current theoretical understanding of the neighborhood effects on mental health and hence contributes to future research on similar topics.

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INTRODUCTION

Mental health is an integral part of our overall well-being. Mental health could influence all aspects of our lives such as marriage, child-rearing, work, and finances. There is also a clear link between mental health and chronic physical diseases such as cancer, heart disease, and diabetes (Bhattacharya et al. 2014; Clarke and Currie 2009). For this reason, severe mental health problems (e.g., bipolar disorder, schizophrenia, depression, alcohol abuse) could significantly reduce our life expectancy. For instance, Dr. Seena Fazel, a professor of forensic psychiatry at Oxford University, said in his interview: “We found that many mental health diagnoses are associated with a drop in life expectancy as great as that associated with smoking 20 or more cigarettes a day (Oxford. 2014, May 23).”

Traditionally, as for the causes of various mental illnesses, much emphasis has been given to individual level factors such as personal income level, educational achievement, epigenetic modification, or self-esteem (Hill and Maimon 2013). However, a growing body of literature started identifying the significance of neighborhood level factors – such as neighborhood socioeconomic disadvantage, neighborhood disorder, and neighborhood experience – as major determining forces of our mental health outcomes (Downey and Van Willigen 2005b; Kim 2010; Mair, Diez Roux, and Morenoff 2010; Ross and Mirowsky 2009). These studies argue that individuals living in poorer neighborhoods bear a greater burden of mental distress due to the higher prevalence of chronic neighborhood stressors (e.g., a lack of social cohesion and support, higher crime rates, a lack of amenities, etc.), all of which, they believe, are attributable to neighborhood socioeconomic disadvantage.

A neighborhood, however, is much more than just the sum of its socioeconomic attributes (Rollings et al. 2015). Among many other components of which a neighborhood is comprised, its physical environmental factors (e.g., the presence of green space, air and water quality, pollution, etc.) and their potential influences upon our mental health deserve our special attention. The chances are that individuals living in more environmentally favorable neighborhoods enjoy better mental health than their counterparts elsewhere. Though a growing body of research has recently started paying attention to the influence of an individual environmental factor (e.g., green space, park accessibility) on various physical health outcomes (i.e., obesity, health behavior, stress, anxiety, etc.) (Rollings et al. 2015), no attempt has yet been made to incorporate both socioeconomic and physical environmental factors together to comprehensively assess neighborhood mental health vulnerability.

In addition, it has been widely known that there exists a close relationship between neighborhood quality of life and racial/ethnic residential segregation. In the United States, for example, minority concentrations are often associated with socioeconomic disadvantage, a lack of social cohesion, neighborhood disorder (Massey and Denton 1989; Sampson et al. 1997), and environmental degradation (Chakraborty and Zandbergen 2007; Mohai et al. 2009). From a mental health perspective, all these factors could potentially influence minorities’ mental health in a very negative way. Though this relationship may sound obvious, a review of literature has revealed that there is still a lack of systematic understanding as to the ways in which the minority concentrations (or more generally, racial/ethnic residential segregation) and neighborhood mental health vulnerabilities are related to one another.

Finally, in mental health studies, stress is assumed to be the primary link through which neighborhood contexts eventually take their toll on residents’ mental health (Cutrona et al. 2006;

Mirowsky and Ross 2003). Perceptions of residents are also regarded as important preconditions for any stress-related responses (McEwen and Lasley 2002). This means that in order for neighborhood contexts to be relevant in mental health studies, they must be either directly experienced or perceived by their residents (Thomas and Thomas 1928). When measuring people's perceptions, previous mental health studies have mostly relied on interviews and survey questionnaires. However, one of the major limitations of such approaches is that only the theory relevant questions are addressed in those studies, thus failing to discover other potentially significant neighborhood contextual factors. For example, the presence of neighborhood green space, cultural diversity, gentrification, and the like may also play important roles in shaping people's mental health. However, none of these factors and their implications on mental health have been explicitly discussed in the existing body of literature.

Therefore, in light of these shortcomings, the following research objectives are addressed in the subsequent chapters of this dissertation. ***The first chapter*** primarily focuses on developing theoretically justifiable neighborhood mental health vulnerability typologies that are inclusive of both socioeconomic and physical environmental indicators. In addition to this, relationships among vulnerability indicators are also examined in order to investigate the validity of underlying assumptions and theoretical claims as to how different neighborhood contextual dimensions are related to one another. For this purpose, this study employs a method called a Self-Organizing Map (SOM). ***The second chapter*** of this dissertation aims to systematically examine the associations between racial/ethnic residential segregation and neighborhood mental health vulnerability indicators. This is accomplished by employing a multinomial logistic regression approach. Finally, ***the third chapter*** of dissertation intends to explore the perceptions of residents as revealed through neighborhood textual review data (retrieved from the website called 'Niche'). For this purpose, this study uses an exploratory topic modeling approach known as Latent Dirichlet Allocation (LDA). The intention here is to identify more of neighborhood contextual factors that are perceived to be important by residents. All things considered, results from this dissertation are expected to advance our current understanding of neighborhood effects on mental health.

CHAPTER I
DEVELOPING NEIGHBORHOOD MENTAL HEALTH VULNERABILITY
TYPES: INTEGRATION OF SOCIOECONOMIC AND PHYSICAL
ENVIRONMENTAL FACTORS

Abstract

Using Los Angeles County as a case study, this research aims to (1) develop neighborhood level mental health vulnerability typologies and (2) examine their spatial distribution and its associations to racial/ethnic residential segregation patterns. The whole process of developing mental health vulnerability typologies was driven by consultations with the existing theoretical frameworks. A total of 16 variables was identified, and they can be divided into five neighborhood domains: socioeconomic structure, residential stability, disorder, physical environmental quality, and pollution burden. Using Self-organizing map (SOM), an approach combining computational and geo-visualization techniques, the component planes were derived which were then used to systematically examine relationships among the variables. Next, a k-means clustering algorithm was employed to segment the multi-dimensional SOM output space into sub-typologies which neatly captured the neighborhood-level mental health vulnerability. Finally, the results were mapped in order to examine their spatial distribution patterns. By and large, the findings indicated that centrally-located and minority-concentrated neighborhoods tend to display higher level of mental health vulnerability compared to suburban White-dominant neighborhoods. It was also found that there exists interesting partial and non-linear relationships among the variables. The findings of this study offer useful insights in local governments' devising of efficient intervention plans when dealing with neighborhood mental health vulnerabilities.

1.1. Introduction

“Why does mental health matter?” It matters because mental health affects our overall quality of life. Center for Disease Control and Prevention (CDC, 2018) stated that mental health not only influences how we manage our stress, but it can also influence how we interact with others and how we make decisions. In 2014 alone, a total of \$186 billion was spent on treating mental health related disorders (Mark et al. 2016). The National Institute of Mental Health also reported that nearly one-fifth of adults (18 years or older) in the United States lived with some mental health related problems in 2017.

Traditionally, as for the causes of various mental illnesses, much emphasis has been given to individual level factors such as personal income level, educational achievement, epigenetic modification, or self-esteem. (Hill and Maimon 2013). However, a growing body of literature started identifying the significance of neighborhood contexts as the major determining forces of our mental health outcomes (Downey and Van Willigen 2005, Ross and Mirowsky 2009, Kim 2010, Mair et al. 2010). These studies argue that individuals living in poorer neighborhoods bear a greater burden of mental distress due to the higher prevalence of chronic neighborhood stressors (e.g., a lack of social cohesion and support, higher crime rates, a lack of amenities, etc.) They believe that all these problems are largely attributable to neighborhood socioeconomic disadvantage.

A neighborhood, however, is much more than just the sum of its socioeconomic characteristics (Rollings et al. 2015). Among many other components that comprise a neighborhood, its physical environments and their potential influences on mental health deserve some special attention. This is because a growing number of studies suggests that there may be a close relationship between neighborhoods' physical environments and residents' mental health outcomes (Beyer et al. 2014; Sugiyama et al. 2008; Van Den Berg et al. 2010). This implies a need for a more holistic approach to advance our current understanding of neighborhood mental

health vulnerability. The need for employing such an approach becomes more obvious when we consider the close interactions and interconnectedness between neighborhood physical and socioeconomic environments. Systematic examination of such relationships is expected to provide useful insights that will be helpful in developing more reliable statistical models for future mental health studies.

There have been several studies that already attempted to incorporate physical environmental factors to assess overall neighborhood quality of life (Delmelle et al. 2013; Li and Weng 2007; Lo and Faber 1997). Though these studies employed methodologically innovative approaches, they were limited in that i) their definition of ‘Quality of Life (QoL)’ was ambiguous, ii) that neighborhood QoL was not defined in any problem-specific context, and iii) that their selection of QoL variables was not guided by any existing theoretical frameworks, all of which inevitably rendered their studies less meaningful and applicable. Hence, the current study aims to overcome these shortcomings by addressing the following research objectives:

- i) Develop theoretically justifiable mental health neighborhood QoL typologies;
- ii) Incorporate neighborhoods’ physical environmental factors (i.e., green space, land surface temperature, and pollution burden) in the typology development process;
- iii) Systematically investigate the relationships between different mental health QoL indicators using an exploratory Self-Organizing Map (SOM) approach;
- iv) Visualize and examine the spatial distribution patterns of neighborhood mental health vulnerability using Los Angeles County as a case study.

The remainder of the paper is organized as follows. In section 2, the theoretical background and relevant empirical evidence pertaining to mental health are discussed, and this is followed by a study area overview, and data and methods descriptions. Findings and results are presented in section 6, followed by the discussion and conclusions.

1.2. Neighborhood contexts and mental health

1.2.1. Fundamental assumptions and the importance of neighborhood socioeconomic contexts

In the study of ‘neighborhood effects on mental health,’ the most fundamental question that one could ask is “why do neighborhood contexts matter in our understanding of residents’ mental health outcomes?” The existing theories attempt to answer this question based on the following two underlying assumptions:

- i) Stress is the major link between neighborhood environments and mental health” (Mirowsky and Ross 2003)
- ii) Perception is a precondition for stress-related response (McEwen and Lasley 2002).

Furthermore, it is also known that prolonged exposure to stress hormones could significantly impair the part of the brain that is responsible for developing various mental illnesses such as anxiety and depression (McEwen and Lasley 2002; Mirowsky and Ross 2003). As such, individuals living in a socioeconomically disadvantaged neighborhoods are more likely to experience chronic neighborhood stressors (e.g., high crime, a lack of social support, etc), which may make them increasingly more susceptible to various mental health problems. The detailed mechanism as to how *neighborhood socioeconomic contexts* eventually take their toll on

residents' mental health will not be discussed in this paper. For those who are interested in this are referred to Hill and Maimon (2013).

1.2.2. Physical neighborhoods' environments and mental health

In addition to socioeconomic neighborhood contexts, neighborhood physical environmental factors (e.g., availability of green space, public parks, air quality, toxic release, etc.) also deserve our consideration. It is intuitive to think that green space in a neighborhood can have some favorable impacts on our mental well-being. On the other hand, chronic neighborhood environmental stressors like pollution or noise can have quite the opposite effects. Despite these potential influences, however, not enough attention has been given to neighborhood physical environmental factors in neighborhood mental health studies. Most of the previous studies have simply equated neighborhood qualities with socioeconomic characteristics while altogether ignoring the implications of physical neighborhood environments on mental health. Though some studies have focused on isolated physical neighborhood qualities (such as green space) and their impacts on physical health outcomes, an effort to measure the effect of 'overall' physical neighborhood qualities on mental health is still lacking in the existing body of knowledge (Rollings et al. 2015). This study, therefore, attempts to integrate variables representing neighborhoods' green space, environmental pollution, and land surface temperature to better capture the overall quality of physical neighborhood environment. Hence, in the following sections, the implications of such factors on mental health are discussed along with some supporting empirical evidence.

1) Green space and mental health

Open green space and public parks are the most commonly available nature-type components in most of contemporary urban landscapes (Wood et al. 2017). They are also widely regarded as one of the most important health promoting attributes of neighborhoods' environments. In general, green space could benefit mental health by restoring residents from mental fatigue (Berman et al. 2008; Hartig et al. 1991; Hartig et al. 2003; Taylor and Kuo 2009), relieving stress (Roe et al. 2013; Thompson et al. 2012), promoting social support and cohesion (Kim and Kaplan 2004; Maas et al. 2009; Pretty et al. 1994; Prezza et al. 2001), and by acting as buffers between external stressors and health outcomes (Van Den Berg et al. 2010), etc.

Regarding the benefits of green space on mental health, Attention Restoration Theory (ART) suggests that exposure to nature can reduce mental fatigue and restore capacity for directed attention (Beyer et al. 2014). Directed attention refers to the kind of attention that one needs to focus on things of which in themselves do not attract our attention, thus requiring a good deal of mental endeavors to do so (Kaplan 1995). It has been argued that modern urban living – which is fast-paced, highly competitive, and stressful – demands much of our directed attention (Beyer et al. 2014), so it is more likely for urban dwellers to suffer from mental exhaustion or mental fatigue than their counterparts in rural areas.

Numerous empirical studies, especially in the field of environmental psychology, have shown that exposure to natural surroundings is positively related with stress reduction and attention recovery (Berman et al. 2008; Hartig et al. 2003; Kaplan 1995; Taylor and Kuo 2009). Sugiyama et al. (2008), for example, have shown that residents' '*perceptions*' of neighborhood greenness are positively related to better mental health outcomes. In addition, Van Den Berg et al. (2010)'s findings demonstrate that the objective quantity of neighborhood greenness (not perceptions) also positively contributes to better mental health outcomes and that residents

surrounded by greater amount of green space tend to be less influenced by external stressors. In the U.S., a recent study by Beyer et al. (2014) identified that neighborhood greenness is highly associated with the lower levels of stress, anxiety, and depression. Green space – especially public parks in a neighborhood – also plays a crucial role in promoting social interactions and consequently social cohesion (Bedimo-Rung et al. 2005; Wolch et al. 2014). This particular neighborhood quality (social cohesion), according to Hill and Maimon (2013), is one of the key elements through which neighborhood contexts influence residents' mental health. Thus, the potential benefits of green space discussed here certainly demands its integration into mental health research.

2) Environmental stressors and mental health

Neighborhood physical environments, in contrast, can have adverse impacts on residents' mental health. For example, environmental stressors such as industrial activities, water/air/noise pollution, traffic density, etc. are perceived to be harmful and noxious stressors, and people generally avoid living in close proximity to such stressors (Downey and Van Willigen 2005b). The 1993 General Social Survey revealed that more than half of the respondents studied viewed industrial pollution as major threats to their families' well-being (Davis et al. 1999). Another study also found that the awareness of residents' local environmental problems tends to be greater as their residential proximity to pollutants – such as industrial activities and hazardous waste sites/facilities – increases (Mohai and Bryant 1998).

Living in such neighborhoods and the reality of not being able to avoid such circumstances can be stressful and even be psychologically distressing if exposed chronically. Moreover, it may induce a sense of powerlessness that such environmental stressors take a final toll on residents' mental health. Often most of the important industrial decisions regarding pollution and pollution reduction are made without involvement of local communities, and in some cases, these decisions are carried out notwithstanding residents' strong opposition (Bullard 1994; Hofrichter 1993). Under such circumstances, people may start viewing their lives as being uncontrollable and helpless, which can possibly be worsened if residents lack enough financial resources to escape such situations (Ross and Jang 2000). If prolonged, they may develop a sense of fear or powerlessness, which in turn can affect their psychological well-being. Downey and Van Willigen (2005a)'s study used the Toxic Release Inventory (TRI) as a measure of 'visible industrial activity' and found that close proximity to such industrial activities had a negative impact on residents' mental health. Their findings also corroborate that the impact of industrial activity on mental health was significantly mediated by residents' perceptions of neighborhood disorder and their sense of powerlessness (Downey and Van Willigen 2005b).

In addition to pollution factors, heat (or high temperature) can also be an important element that can potentially influence residents' mental health. For instance, previous studies (Li and Weng 2007; Lo and Faber 1997) identified land surface temperature as one of the critical factors that can influence residents' overall quality of life. Another study conducted by the Office of Environmental Health Hazard Assessment (OEHHA) has shown that exposure to high temperature may increase emergency room visits related to mental health outcomes (Basu et al. 2018). Higher temperatures make many people feel ill-tempered, nervous, or listless which may make them more susceptible to various mental disorders like anxiety, depression, or even death (Cooper 2018). Increased heat may also escalate violence and assaults. One previous empirical analysis showed that increase in temperature is associated with increase in both interpersonal and intergroup assaults (Hsiang et al. 2013). Heat stress is also known to influence insomnia

(Okamoto-Mizuno and Mizuno 2012) as well as impairment in complex cognitive tasks like spatial and pattern recognition (Hancock and Vasmatazidis 2003). All these theories and empirical evidence call for the need of incorporating heat as a critical element in the development of neighborhood level mental health susceptibility typologies.

1.2.3. Summary

To sum up, neighborhood contexts matter in mental health study. Though socioeconomic factors are important, by themselves they are insufficient in capturing the totality of what a neighborhood is. As elaborated thus far, incorporation of neighborhood physical environmental variables is crucial given their ramifications on mental health outcomes - an aspect which has been largely overlooked in the past. It is also reasonable to argue that the effects of environmental stressors can greatly increase residents' vulnerability to mental health problems when confounded with other contributing factors such as poverty, lack of green space, lack of social cohesion, substandard housing, etc. As such, a more holistic approach is needed toward the development of mental health vulnerability typologies, and this comprises a major contribution of this study.

1.3. Study area description

Los Angeles County in California is selected as the case study site for this research. The County of Los Angeles is located in the southwestern part of California and comprised of 16 sub-regions (Figure1). It is also the most densely populated county in the United States with a population of almost ten million people (9,818,605), which, according to the 2010 census, comprised more than one quarter of the entire population of the state of California.

Among other characteristics, the county's diverse physical landscapes and complicated socioeconomic makeup offer an ideal setting to examine various aspects of mental health disparities. First, Los Angeles County encompasses a wide variety of physical landscapes (e.g., coastlines along the Pacific Ocean, mountain ranges, forests, valleys, rivers, and deserts) whose presence or adjacency, as discussed in earlier sections, can have significant impacts on residents' mental health. These physical features not only provide a wide variety of recreational opportunities to Angelenos, but also form a natural buffer against urban sprawl.

Los Angeles County is also known for its complicated socioeconomic makeup. While Los Angeles County had 14.4% of its families living under the poverty line, more than 24% of the population earned more than \$100K annually (Census 2010). Due to such gaps in income, the County of Los Angeles has become more fragmented and segregated over the last several decades. All these natural and socioeconomic dynamics are important factors to be considered since they are not only known to play critical roles in determining the overall quality of life for a neighborhood, but also believed to significantly shape residents' mental health outcomes.

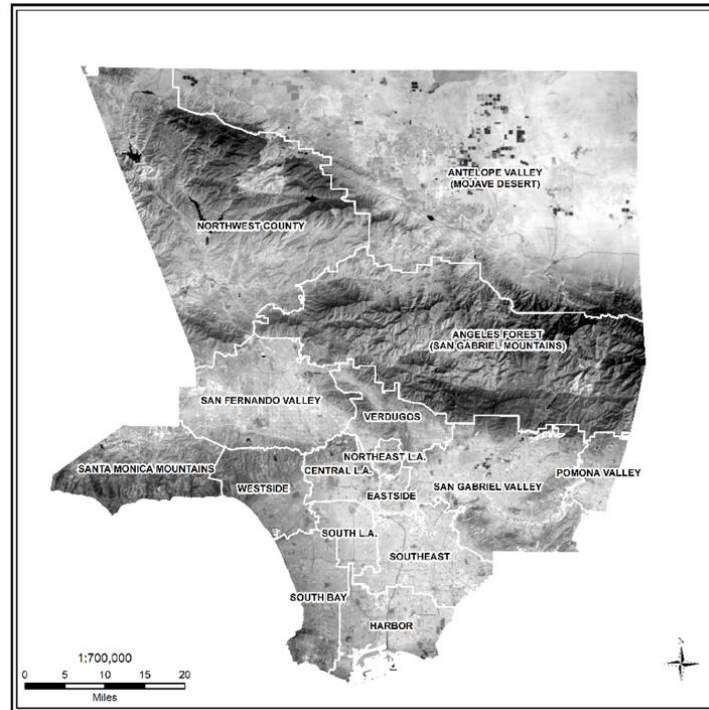


Figure 1. The Los Angeles County and its sub-regions

1.4. Data sources

The primary datasets used for developing neighborhood mental health susceptibility typologies are obtained from four different data sources: i) Demographic and socioeconomic variables are extracted from American Community Survey (ACS, 2011 ~ 2015, 5-year estimates); ii) crime datasets from the Los Angeles County Sheriff's Department (LASD); iii) neighborhood physical environmental variables from the United States Geological Survey (USGS); iv) neighborhood pollution indicators from the Office of Environmental Health Hazard Assessment (OEHHA).

First, the variables obtained from ACS are used for measuring 'neighborhood structure' which, in this study, is represented by its socioeconomic disadvantage, residential stability, and housing characteristics. The variables used for measuring each aspect are summarized in Table 1 below. The selection of variables here is consistent with the previous studies (Hill and Maimon 2013). Census tracts are chosen as surrogates for neighborhoods. The shapefiles for census tracts are downloaded from the Census TIGER (Topographically Integrated Geographic Encoding and Referencing) website, which then are joined with the tabular ACS data using the common census geographical entity codes.

Second, in order to measure neighborhood social and physical disorder, this study uses 2015 crime data retrieved from the Los Angeles County Sheriff's Department. The dataset is comprised of Part I and Part II crimes. Part I is designated for more serious crimes in nature while Part II crimes are considered to be less serious. The complete list of variables used for representing neighborhood disorder is shown in Table 1 below. Again, the variables are selected

in consultation with the existing theories (Ross and Mirowsky 2009). Next, all crime incident points are geocoded using ArcGIS Online Geocoding service. Finally, the crime density (the number of incidents divided by its corresponding areas in square miles) for each type is computed separately at the census tract level in order to make them comparable to other variables used in the study.

Third, as discussed in the previous section, greenness and heat stress can be important determinants of residents' mental health outcomes. As such, Normalized Difference Vegetation Index (NDVI) is used as a proxy for greenness, as is commonly done in other neighborhood studies (Li and Weng 2007; Lo and Faber 1997). Land Surface Temperature (LST) is used as a surrogate for heat stress. Both NDVI and LST are derived from Landsat 8 OLI images which are downloaded from USGS Earth Explore website. The images were originally obtained on June 15, 2015, and at the time of image acquisition, the atmospheric conditions were cloud-free. For those who are interested in data generation processes of NDVI and LST are referred to (Bingqing and Qihao 2011; Li and Weng 2007). After deriving the values from the original images, the mean NDVI and LST are computed at the neighborhood level using zonal statistics available in ESRI ArcGIS software.

Lastly, neighborhood environmental stressors are operationalized using the various pollution indicators obtained from the California Communities Environmental Health Screening Tool (CalEnviroScreen) - an interface created by OEHHA. The latest CalEnviroScreen tool incorporated 12 pollution variables, all of which are used for deriving overall neighborhoods' pollution burden scores. OEHHA has already calculated and made them available through CalEnviroScreen. However, they were calculated with respect to state-wide average and were not suitable for this study. Hence, employing the same procedures (the details and the list of variables used here are described in CalEnviroScreen 3.0 original document), the overall neighborhood level pollution burden scores are re-calculated with respect to Los Angeles County-wide average.

1.5. Methods

In order to accomplish the aforementioned research objectives, this study employs a geo-visual analytical method called self-organizing map (SOM). SOM was originally developed by (Kohonen 1990). This is an unsupervised learning algorithm and belongs to the family of artificial neural network (ANN). SOM projects multi-dimensional input data unto a low-dimensional (typically two dimensional) output space in such a way that similar samples across the input space are clustered closely together, hence this is a suitable method for developing coherent neighborhood QoL typologies – the first research objective of this study. For more details regarding its algorithm and applications, one is referred to Kohonen (1990) and Skupin and Hagelman (2005). Though there are other competing dimension reduction techniques available (e.g., PCA, factor analysis), SOM is preferred because of its powerful visualization capacity, which facilitates the discovery of not only latent structures of a dataset, but also complicated relationships (e.g., partial, non-linear) among the variables which may otherwise go unnoticed – another major objective of this study. This capacity is demonstrated in the following section. Finally, the results are also mapped using GIS software in order to examine the spatial distribution patterns of neighborhood mental health vulnerability in the study area.

Table 1. Mental health quality of life indicators

<i>Dimension</i>	<i>Variables used</i>	<i>Source</i>	<i>SOM label</i>
<i>Neighborhood socioeconomic status</i>	Percentage greater than high school degree	The U.S. Census Bureau	Education
	Percentage unemployment		Unemployment
	Percentage of female headed households		Female-headed
	Median household income		Income
	Percentage of residents living below the poverty line		Poverty
	Percentage manufacturing employment		ManuEmploy
<i>Residential stability</i>	Percentage owner-occupied household	The U.S. Census Bureau	HomeOwner
	Percentage of residents who lived in the same tracts more than 15 years		Duration
	Percentage of residents living in apartment units		Multiunit
<i>Housing characteristics</i>	Percentage of structures built more than 35 years ago	The U.S. Census Bureau	YrStrBuilt
	Percentage vacant housing units		Vacancy
	Median home values		HomeValue
<i>Neighborhood disorder</i>	<i>Part I crime:</i> criminal homicide, forcible rape, robbery, aggravated assault, burglary, <i>Part II crime:</i> disorderly conduct, DUI, prostitution, drunkenness, vagrancy, vandalism, weapon	Aggregated at the neighborhood level using crime density The Los Angeles County Sheriff's Department	Crime
Neighborhood physical environment	Average neighborhoods' NDVI	United States Geological Survey	NDVI
	Average neighborhoods' LST	United States Geological Survey	LST
	Pollution burden	California Office of Environmental Health Hazard Assessment	Pollution

1.6. Findings and results

1.6.1. Cross-sectional view of the mental health vulnerability indicators

In the SOM analysis, component planes (shown in Figure 2 below) visualize the relative contribution of each mental health vulnerability indicator over the final SOM output space. For instance, the first component plane (located in the top-left corner of Figure 2) depicts how the values of education variable vary over the output space - the yellow color indicates higher levels of educational attainment while the blue color indicates the opposite. In addition, components planes, by enabling us to compare the positions and the colorings of different variables, provide an effective way to explore the systematic cross-sectional relationships between all 16 variables used in this study.

1) Socioeconomic indicators

First of all, six variables are employed to capture the socioeconomic characteristics of a neighborhood. Two of them - % greater than high school degree and median household income – are positive indicators whereas the rest - % unemployment, % female-headed households, % below poverty line, % manufacturing employment – are negative indicators. As expected, educational attainment and household income display similar patterns (education and income in Figure 2). For both variables, higher values are more concentrated towards the top-left corner of the component planes while the values tend to drastically decrease towards bottom portion of the plane. Interestingly, all the negative indicators exhibit a completely opposite pattern: higher values are more concentrated towards the bottom portion of the component planes while decreasing in values towards the top portion of the planes. It should also be noted that the cells with higher concentration of manufacturing employment tend to display relatively lower rates of female headed households, unemployment, and below poverty line (Figure 2).

2) Residential stability and housing characteristics

Second, the residential stability aspect of a neighborhood is measured by three variables: % owner-occupied households, % residents who have lived in the same neighborhoods for more than 15 years, and % residents living in apartment units. The components planes display that the length of stay (duration) has a strong correlation with the homeownership variable. For both variables, higher values are more concentrated towards the top-right corner of the planes while the values tend to significantly decrease towards the bottom-left corner of the planes. Conversely, the percentage of multiunit residents display a largely opposite pattern. It should also be pointed out that the cells with higher residential stability do not necessarily overlap with the cells displaying better socioeconomic values (i.e., higher education and income level). There is certainly some degree of overlaps between the two aspects, but it is worth paying attention to their differences since they may have some theoretical implications, which are discussed in the following section.

3) Housing Characteristics

Third, % housing structures built more than 35 years ago (YrStrBuilt), % vacant housing units, and median home values are used as proxies for neighborhood housing characteristics. The high values for ysb 35 variables, in comparison to all other variables, are more evenly spread out over the SOM output space. However, there are two exceptions of hexagonal-shaped holes in the middle of the plot, which may be a sign of new (or re-) development. Next, the higher values for

median home value variable are mostly concentrated in the upper left-corner of the plane. Interestingly, however, those cells display a large degree of overlap with % vacant housing unit variable, explanations for which demand further investigation.

4) Neighborhood Disorder (Crime density).

Crime density indicator was operationalized to capture the degree of neighborhood social and physical disorder. The high values for this variable are mostly clustered in the bottom-right corner of the plane, which also largely overlap with areas showing socioeconomic disadvantage, residential instability, and higher level of environmental stress. Interestingly, the figure reveals that there is no strong and direct correlation between crime density and poverty.

5) Environmental Factors (pollution burden, NDVI, & LST)

The cells with higher scores of pollution burden are mostly located in the bottom half of the plane. This largely coincides with the concentrations of % manufacturing employment and female-headed households but displays much less overlap with % below poverty line and unemployment rate. Interestingly, pollution burden displays some degree of associations with both residential stability and instability of a neighborhood, whose theoretical implications are discussed in the following section.

The higher values for NDVI are more concentrated towards the top-left corner of the plane, while LST displays a largely opposite pattern. A closer examination of the LST plane reveals that a hexagonal-shaped-cluster in the middle of the plot coincides with the neighborhoods located in Antelope Valley which comprises the southwestern end of Mojave Desert (Figure1). Interestingly, its shape and location are almost identical with the bottom hexagon-shaped void (signifying a new development) identified in the ysb35 component plane. Further investigation reveals that Lancaster and Palmdale – two major cities located in Antelope Valley – have been the fastest growing cities in Los Angeles County. By and large, socioeconomically well-to-do neighborhoods tend to have significantly less pollution burden while enjoying much more favorable physical neighborhood's environment.

1.6.2. The spatial distribution of neighborhood mental health vulnerability

As a first step to examine the spatial distribution patterns of the mental health vulnerability in Los Angeles County, the multi-dimensional component planes needed to be simplified according to their homogenous characteristics. For this end, k-means clustering algorithm was applied to the final SOM output space. Prior to running a clustering algorithm, David-Bouldin analysis was run for each k in order to determine the optimal number of clusters. The result suggested that a k = 6 had the best discerning power, and its corresponding clustering results are depicted in Figure 2. An examination of the component planes and z-score means from the k-means clustering analysis is used to interpret the characteristics of each cluster and the following sub-sections describe the attributes of each cluster from a mental health vulnerability perspective. These will be supplemented by their spatial distribution patterns and racial/ethnic composition.

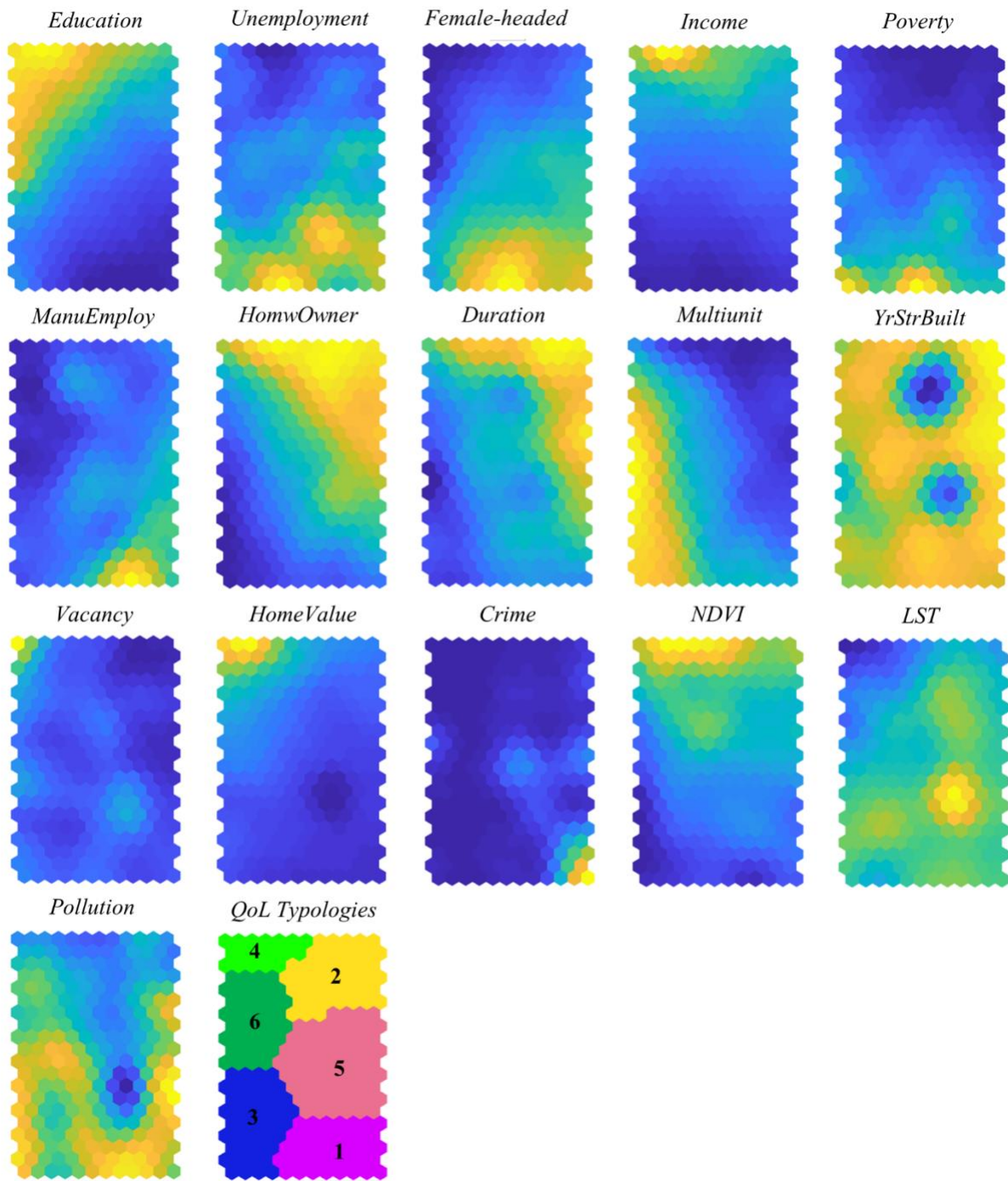


Figure 2. Self-organizing map component planes and the final QoL typologies

1) Highest QoL neighborhoods (Typology 4)

The neighborhoods in this typology possess characteristics associated with the least mental health vulnerability. These neighborhoods display the highest socioeconomic status as indicated by the highest educational achievement, exceptionally higher median household income, lowest representation of unemployment, female-headed households, manufacturing employment, and lower rates of residents living below the poverty line. They also show higher levels of residential stability as represented by higher % of homeownership and residents who have lived in the neighborhoods for more than 15 years, and lower % of residents living in apartment units. Their physical environmental qualities are comparatively much more favorable (indicated by higher NDVI, lowest LST, and less pollution burden) than other neighborhoods. In addition, they show almost no indication of neighborhoods' social and physical disorder. Given all these characteristics, therefore, this typology can be regarded as having the highest quality of life in terms of its mental health vulnerability.

There are a total of 134 neighborhoods that fall into this category. As Figure 3 shows, the first major concentration is found in the West Side and Santa Monica Mountains regions (the names and locations of sub-regions are shown in Figure 1). The neighborhoods that are located in the south and southwestern tip of the South Bay region comprise the second dominant cluster of this typology. Much of the Verdugo region also contains neighborhoods belonging to this category. In general, these neighborhoods are located in the outer suburban areas that are disjointed from the central downtown area. Racial/ethnic composition clearly indicates that these are mainly White-dominant neighborhoods (70.3%), with Asians (14.4%) comprising the second largest group followed by Hispanics (9.2%), and Blacks (1.9%) being the most under-represented.

2) High QoL neighborhoods (Typology 2)

As with the first one, the second typology displays higher quality of life (and thus lower mental health vulnerability), but the levels of their QoL indicators are not as high as those of typology four. These neighborhoods are characterized with relatively higher socioeconomic status, higher levels of residential stability, and favorable physical neighborhood environment. They also tend to have lower levels of social and physical disorder problems.

There are 393 neighborhoods that belong to this typology. First, as Figure 3 shows, these neighborhoods generally occupy the outer rim of the Los Angeles Basin area (along the western coastline and southeastern border of the county). They are also mostly disjointed from the central downtown areas. Second, the neighborhoods in this typology also comprise a significant portion of Santa Monica Mountains, San Gabriel Mountains, and the Northwest County regions as shown in Figure 3. Whites (43.4 %) are the dominant race group in these neighborhoods followed by Hispanics (26.2%) and Asians (22.2 %), but Blacks (4.4%) and other racial/ethnic groups (3.8 %) are significantly under-represented.

3) Above-average QoL neighborhoods (Typology 6)

This cluster shares very similar socioeconomic characteristics with the first two preceding typologies. Its educational attainment and housing values, for instance, are only second to those of typology 1. However, these neighborhoods display a significantly lower level of residential stability in comparison to the first two. Not only their homeownership rate is way below the county average, but also a large percentage of their residents moved in recently. Nor are their

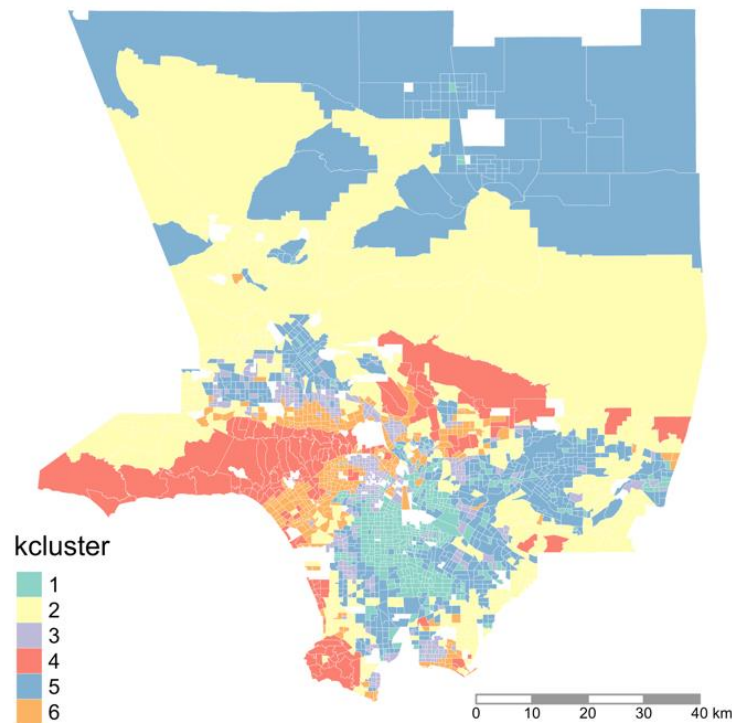


Figure 3. Mental health QoL typologies and their spatial distribution patterns

physical environmental qualities as favorable as the first two, and they have a significantly lower NDVI level and relatively higher pollution burden.

A total of 301 neighborhoods belong to this typology. As indicated in Figure 3, these neighborhoods are largely concentrated at the bottom half of the Westside region, a significant portion of which includes the neighborhoods along the coastline (e.g., Santa Monica, Venice). Another concentration is also identified in the southeastern part of the San Fernando Valley. This cluster displays a relatively large share of Whites (52.6%), Hispanics (22%) and Asians (14.8%), but their shares of Blacks (6.3%) and other racial/ethnic groups (4.3%) are significantly below the county average.

4) Average QoL neighborhoods (Typology 5)

Most of the socioeconomic indicators of this typology align with the county average. The only two exceptions to this tendency are educational attainments and median home values, both of which are significantly below the county average. Second, these neighborhoods display a relatively higher levels of residential stability as indicated by a smaller percentage of recent in-movers, higher percentage of owner-occupied households, and lower shares of apartment residents. In addition, they have a significant share of manufacturing employments. Having considered all these factors, it can be concluded that this typology resembles the typical characteristics of a stable suburban blue-color neighborhood. Third, in terms of physical environmental quality, their levels of pollution burden and NDVI are close to the county average.

However, their LST level is the highest among all six typologies indicating greater likelihoods of residents' exposure to heat stress.

The largest number of neighborhoods belong to this typology (a total of 605). A majority of neighborhoods in San Gabriel Valley and Pomona Valley as well as in the Southeast and Harbor region belong to this category (see Figure 3). A large portion of neighborhoods located in the northeastern and western part of the San Fernando Valley also belong to this typology. Unlike the first three typologies, these neighborhoods show a significantly higher concentration of Hispanics (60.1%) and an above average share of Blacks (7.5 %). White representation (16.6%) is the second lowest among all six typologies, and Asian percentage (13.3%) is below the county average.

5) Below-average QoL neighborhoods (Typology 3)

Overall, this typology displays below-average socioeconomic quality. In terms of residential stability, these are the least stable neighborhoods, and this is clearly indicated by the highest rate of recent in-movers, the highest percentage of apartment residents, and the lowest homeownership rate. Their physical environmental qualities are among the worst in the study area. However, their social/physical disorder indicator is below average.

A total of 381 neighborhoods belong to this category. Spatially, they are mostly concentrated in central L.A. as well as in the middle of San Fernando Valley (Figure 3). Other smaller concentrations can be identified across the Los Angeles basin area, but they are spatially disjointed from one another. They display a relatively higher representation of Hispanics (53.3%) and Blacks (9.5%), but their share of Whites (18.4%) is markedly below the county average.

6) Lowest QoL neighborhoods (Typology 1)

This typology possesses the lowest QoL in terms of mental health vulnerability. Their socioeconomic quality, residential stability, physical environmental quality, and the level of social/physical disorder are amongst the worst of all typologies in the study area. A total of 399 neighborhoods belong to this category. They are mostly concentrated in the central part of the Los Angeles Basin area (Figure 3). These neighborhoods have the highest concentration of Hispanics (78%), but their shares of Whites (3.1%) and Asians (4%) are the lowest among all six typologies.

1.7. Discussion and conclusions

As discussed in the earlier sections, the importance of neighborhood contexts cannot be overemphasized in the study of mental health. Although a growing body of literature has been investigating the relationships between neighborhood contexts and residents' mental health outcomes, their discussion on neighborhood contexts are limited to socioeconomic factors (Rollings et al. 2015). As such, neither the significance of neighborhoods' physical environment nor its associations to socioeconomic factors have received the attention they deserve. In light of these shortcomings, this paper has attempted to holistically assess neighborhood quality of life pertaining to mental health vulnerability by incorporating a neighborhood physical environmental dimension (i.e., NDVI, LST, and pollution burden). Its primary aims were developing theoretically justifiable QoL (or mental health vulnerability) typologies, examining their spatial distribution patterns in light of racial/ethnic segregation, and investigating relationships among the five major neighborhood QoL domains.

First, this study attempted to define neighborhood quality of life from the perspective of mental health vulnerability. According to the existing theories and previous empirical evidence, the five essential neighborhood domains have been identified. These include socioeconomic structure, residential stability, housing characteristics, social/physical disorder, and physical neighborhood environment, all of which are known to play significant roles in determining residents' mental health outcomes. Accordingly, a total of 16 variables are selected and used to develop neighborhood mental health QoL typologies. This theory-driven/context-specific approach, it can be argued, greatly eliminates semantic ambiguities (e.g., livability, desirability, competitiveness) which have been inherent problems in previous neighborhood QoL studies. Hence, this approach can render study results more relevant, effective, and practical to the specific problems at hand – in this case, neighborhood mental health vulnerability.

Second, one of the major advantages of using SOM is that it enables a more in-depth exploration of a dataset. For instance, the component planes from SOM analysis can reveal new patterns and relationships (e.g., non-linear, or partial relationship) among variables which could otherwise be overlooked. SOM, in this sense, not only enables discovery of new knowledge, but it can also help researchers to formulate more plausible hypotheses which could be tested in confirmatory statistical analyses later on.

This study, by employing SOM, has also discovered several new knowledges which have not been explicitly discussed in previous mental health literature. First, the existing theory views neighborhood structural disadvantage as a major contributor to social disorganization (Hill and Maimon 2013; Shaw and McKay 1942). They believe that this is largely due to the lack of necessary resources (e.g., social, institutional, or material) needed to develop meaningful social relationships (e.g., solidarity, informal social control). However, as shown in the previous section, this study reveals somewhat contradicting results to these claims, and hence it deserves further investigations in future study. The findings from this study show that:

- A higher neighborhood socioeconomic structure does not always indicate residential stability (e.g., typology 6)
- There is a large number of neighborhoods that display average or below average socioeconomic status, but with significantly higher residential stability (e.g., typology 5).
- There are also some high-income neighborhoods which display a relatively higher vacancy rate (e.g., typology 4)

Second, other existing theories (Massey and Denton 1989; Sampson et al. 1997) argue that there exists causal relationships between neighborhood structural disadvantage and neighborhood disorder, which, they believe, is attributable to the absence of residents' willingness to exercise informal social control (Hill and Maimon 2013). However, the findings from this study seemingly contradict such claims. For instance, this study shows that:

- Poverty concentration does not show significant overlaps with social disorder (crime).
- Socioeconomic disadvantage indicators (such as female-headed household, unemployment, and poverty, manufacturing employment) are not uniformly distributed across the SOM output space, indicating partial, non-linear, or even negative relationships among them.
- Third, there are some other interesting findings that deserve our attention, which include:
- Pollution burden displays strong correlations with both residential stability (e.g., typology 5) and instability (e.g., typology 6).

- SES advantage does not always indicate higher environmental quality (e.g., typology 6).

Finally, the results from SOM analysis were also mapped in order to examine their spatial distribution patterns in light of racial/ethnic segregation. In general, high QoL (low mental health vulnerability) neighborhoods are located in outer suburban areas with a relatively higher concentration of Whites and Asians while low QoL neighborhoods are mostly concentrated in the central L.A. basin area with a greater representation of Hispanic/Blacks/Others. However, as hinted from the preceding points, it is likely that a systematic examination would reveal more complicated relationships between mental health vulnerability and residential racial/ethnic segregation patterns, an aspect of which needs to be investigated in future research.

All these findings together suggest that the reality of mental health vulnerability is far more complicated than our present theoretical understanding. Neighborhood structure (socioeconomic disadvantage, residential stability, racial/ethnic composition), though it may be a major determining factor for social disorganization and neighborhood disorder, and possibly pollution burden, it is not without exceptions. And these exceptions do not seem negligible according to the findings of this study and certainly demand further investigation in future research.

However, when viewed from a different perspective, these findings can provide useful insights to policy makers and public health practitioners/investigators. For instance, the visualization of SOM results can help them to understand the spatial distribution pattern of mental health vulnerability much more clearly. This may be useful in fostering their communication processes, and it also can help them to come up with more targeted intervention plans. In addition, the new knowledge unearthed from this study (the relationships among the mental health indicators as discussed above) can greatly help with strategizing and prioritizing budget allocations to make mental health intervention much more effective and fruitful.

This study, however, also has some limitations. A major limitation is the absence of neighborhood-level mental health data with which the validity of QoL typologies could be tested. Though the process of developing typologies was guided by the existing theoretical frameworks and empirical evidence, their validity still needs to be tested before they can be implemented into practice. In addition, it will be helpful if future studies can utilize confirmatory statistical analyses to test the new hypotheses and causal relationships revealed in this study. Finally, this study makes important contribution by adding physical environmental dimension to the study of mental health; however, this does not mean that we have considered all the needed factors. For a better understanding of the whole dynamics of neighborhood effects on mental health, more investigations are warranted on identifying other potential neighborhood factors in future research. This could involve adding qualitative investigations such as individual case studies and focus groups that will add nuanced dimensions into the causal relationships between neighborhood quality and mental health vulnerabilities.

CHAPTER II
NEIGHBORHOOD MENTAL HEALTH VULNERABILITY AND ITS
ASSOCIATION WITH RACIAL/ETHNIC RESIDENTIAL SEGREGATION

Abstract

Neighborhood contexts matter in mental health study. In the U.S., minority concentrations have historically been associated with neighborhood disadvantage. This could mean that minorities living in disadvantaged neighborhoods are at greater risks for developing mental health related problems. Though this may sound obvious, knowledge on the ways in which they are related to one another has not yet been clearly known. This study uses Los Angeles County as a case study site to systematically examine the relationships between neighborhood mental health Quality of Life (QoL) and racial/ethnic residential segregation. First, the neighborhood mental health QoL typologies were developed by employing a Self-Organizing Map (SOM) and a k-means clustering algorithm. Second, seven levels of racial/ethnic segregation typologies were created, and their spatial distribution patterns were visually examined in light of mental health vulnerability typologies. Finally, the relationships between these two entities were systematically examined through a multinomial logistic regression analysis. The findings from this study indicated that minority neighborhoods, in general, have higher levels of socioeconomic disadvantage, crime density, and pollution burden, and that different minority-type neighborhoods were disadvantaged in different ways. These findings suggest that the actual relationships between the two entities are more complicated than our current theoretical understanding, a valuable insight that needs to be incorporated in future mental health study.

2.1. Introduction

Neighborhood Quality of Life (QoL) is an important topic in urban geography. The earliest attempt to define neighborhood QoL dates back to the early 20th century (Burgess 2008) by the Chicago School sociologists. However, empirical research on this topic has been somewhat limited. This is, in large part, due to the complexity and subjectivity involved in the process of defining neighborhood QoL. Neighborhood QoL is multifaceted, and its measurement usually involves “physical, spatial, economic, and social aspects of urban environment (Bingqing and Qihao 2011).” QoL can also be defined as “livability, desirability, and competitiveness” of a neighborhood (Delmelle et al. 2013).

In the United States, neighborhood QoL is closely associated with racial/ethnic residential segregation. According to the early neighborhood transition models, urban neighborhoods may go through a gradual process of deterioration when lower income social groups start moving into (or invade) a neighborhood (Burgess 2008) or when wealthier residents choose to move out to expanding suburban areas by trading-off housing qualities and commuting costs (Muth 1969). This process usually accompanies distinguishable changes in neighborhood QoL (e.g., population density, economic conditions, housing qualities, etc.) and racial/ethnic compositions (i.e., concentration of poor minorities in deteriorating inner-city neighborhoods whereas wealthier Whites live in higher quality suburban neighborhoods).

A growing body of literature also suggests that there is a link between neighborhood QoL, residential segregation, and residents’ mental health outcomes. In mental health literature, neighborhood QoL (in this study, we use the term ‘neighborhood mental health QoL’ instead) is defined by neighborhood structure, social disorganization, neighborhood disorder (Hill and Maimon 2013), and physical neighborhood environment. In general, minority concentrations suffer from overall socioeconomic disadvantages, residential instability, neighborhood disorders, and poor physical neighborhood environment, all of which could negatively influence residents’ mental health (Hill and Maimon 2013). Though this may sound obvious, we still do not know ‘in

what ways' residential racial/ethnic segregation and neighborhood mental health QoL are related to one another. This relationship may manifest in more complicated ways than our current theoretical understanding. For example, in cities with higher racial/ethnic diversity, some minority concentrated neighborhoods may display severe mental health vulnerabilities while others may not. A systematic examination of these relationships could benefit future confirmatory statistical approaches by helping them to tease out causal relationships between mental health and neighborhood contexts in a more precise way. This knowledge could also help urban planners to come up with more effective and strategic intervention plans.

Therefore, this study uses Los Angeles County as a case study site in order to systematically examine the relationships between neighborhood mental health QoL and racial/ethnic residential segregation by addressing the following research objectives:

- i) to visualize racial/ethnic residential segregation patterns using typology analysis;
- ii) to develop and visualize neighborhood mental health QoL typologies using a self-organizing map approach;
- iii) to examine relationships between neighborhood mental health QoL indicators and racial/ethnic residential segregation patterns through a multinomial logistic regression analysis.

The remainder of the paper is organized as follows. In section 2, the theoretical background and relevant empirical evidence pertaining to mental health are discussed, and this is followed by a study area overview, and data and methods descriptions. Findings and results are presented in section 5, which is then followed by discussion and conclusions.

2.2. Neighborhood contexts and mental health

There are two fundamental assumptions in the study of neighborhood effects on mental health, and they are:

- i) Stress is the primary link between neighborhood contexts and mental health (Mirowsky and Ross 2003)
- ii) Perception precedes most of the stress-related responses (McEwen and Lasley 2002).

In addition, prolonged activation of stress hormone can damage the part of the brain that is responsible for various mental illnesses (e.g., depression, anxiety) (McEwen and Lasley 2002; Mirowsky and Ross 2003). This means that individuals exposed to chronically stressful environment (e.g., high crime, open incivility, ambient noise, etc.) are more likely to suffer from mental health-related problems. For a deeper understanding of this mechanism, it is crucial to define and establish a clear link between neighborhood structure, social disorganization, and neighborhood disorder since these are the primary preconditions from which neighborhood contexts eventually take toll on residents' mental health.

2.2.1. Neighborhood structure

In previous mental health studies, neighborhood structure has been defined by neighborhood's socioeconomic (SES) disadvantage, a racial/ethnic composition, and residential stability (Hill and Maimon 2013). Neighborhood SES disadvantage refers to the level of concentration of individuals with lower socioeconomic status (Krieger et al. 2003). A racial/ethnic composition refers to the degree of minority groups' concentration (Acevedo-Garcia and Lochner 2003). This is an important indicator of neighborhood structure because minority

concentrations, in the U.S., have historically been related to unique socio-cultural environment and economic disadvantage (Acevedo-Garcia and Lochner 2003; Kwate 2008; Massey 2004). Residential stability is defined by the rate at which the demographic composition of a neighborhood changes (Ross et al. 2000). Neighborhood structure could negatively influence residents' mental health by constraining people's access to community resources (e.g., quality education, medical cares), or by limiting their opportunities for upward social mobility (Hill and Maimon 2013). Previous studies have shown that residents from disadvantaged neighborhoods are more likely to display higher levels of depression (Kim 2010; Wight et al. 2011), anxiety (Ross et al. 2000), and psychological distress (Ross et al. 2000).

2.2.2. Neighborhood organizations

According to Hill and Maimon (2013), neighborhood social organization can be defined by the "density of social ties and the level of collective efficacy (p 481)." The level of social ties is usually measured by the average number of residents' social connections and frequency of their interactions with others (Mair, Diez Roux, and Morenoff 2010; Sampson and Groves 1989). Collective efficacy is defined by the degree of cohesion among neighbors and their willingness to practice informal social control (Sampson et al. 1997). Based on these, 'social disorganization' can be defined as residents' inability to form such social ties or close interactions to such a degree that they could effectively exercise informal social control or form lasting and efficacious community organizations (Sampson et al. 1997). Residential instability, one of the main components of neighborhood structure, is a primary precursor of social disorganization. For example, when a neighborhood population composition quickly changes, people can be hampered from developing meaningful social relationships and collective efficacy (Sampson et al. 1997; Shaw and McKay 1942). In addition, socioeconomic disadvantage could also significantly undermine communities' efforts to establish (or maintain) necessary social institutions (i.e., schools, community organization) (Shaw and McKay 1942), which may in turn lead to even higher levels of neighborhood social disorganization (Wilson 1997, 2012). Previous empirical studies have shown that residents from neighborhoods with higher levels of social disorganization are more likely to suffer from depression (Mair, Diez Roux, Osypuk, et al. 2010).

2.2.3. Neighborhood disorder

Neighborhood disorder refers to a range of social and physical neighborhood conditions that indicate the disintegration of order and control in a neighborhood (Raudenbush 2003; Ross and Mirowsky 1999). Neighborhood structural disadvantage and social disorganization are believed to be the immediate forerunners of neighborhood disorder (Massey and Denton 1989; Sampson et al. 1997). First, structurally disadvantaged neighborhoods are often characterized by insufficient tax revenues and a lack of solid consumer base (Hill and Maimon 2013). Under such circumstances, local businesses tend to decline (Hanlon and Vicino 2007), and there may not be sufficient tax revenues for the upkeep and maintenance of a neighborhood (Haines 2010). This can lead to physical disorder, the signs of which may include abandoned buildings, ambient noise, graffiti, vandalism, garbage, and the like (Ross and Mirowsky 2009). Second, residents living in a disadvantaged and unstable neighborhoods often lack longstanding social ties and collective efficacy (Sampson et al. 1997), which are the primary causes of neighborhood social disorder, the signs of which include increasing criminal activities, open incivilities (i.e. open alcohol consumption and drug use), prostitution, etc. (Ross and Mirowsky 2009). Residents

living in such high-stress environments are more prone to developing various mental illnesses. Previous empirical studies have shown that neighborhood disorder is closely related with depression (Downey and Van Willigen 2005b; Mair, Diez Roux, Osypuk, et al. 2010) and psychological distress (Cutrona et al. 2000).

2.2.4. Physical neighborhood environment

In the study of neighborhood effects on mental health, neighborhood physical environments and their impacts on mental health also deserve our consideration. First, according to previous studies, neighborhood green space benefit mental health by restoring people from mental fatigue (Berman et al. 2008; Hartig et al. 1991; Hartig et al. 2003; Taylor and Kuo 2009), relieving stress (Roe et al. 2013; Thompson et al. 2012), promoting social support and cohesion (Kim and Kaplan 2004; Maas et al. 2009; Pretty et al. 1994; Prezza et al. 2001), or by acting as buffers between external stressors and health outcomes (Van Den Berg et al. 2010). In the U.S., Beyer et al. (2014) found that neighborhood greenness is strongly associated with the lower levels of stress, anxiety, and depression. In contrast, neighborhood physical environment could bring quite the opposite effect. For instance, residents may perceive pollution (e.g., industrial activities, water/air pollution, traffic density) as noxious and try to avoid living in close proximity to such environmental stressors (Downey and Van Willigen 2005b). Living in such environment can certainly be stressful and psychologically distressing. This could cause various mental illnesses if chronically exposed. In addition to pollution, heat (or high temperature) is also regarded as an important element that can potentially impact mental health. Previous studies (Li and Weng 2007; Lo and Faber 1997) identified 'land surface temperature' as one of the major factors comprising neighborhood QoL. Office of Environmental Health Hazard Assessment (OEHHA) has shown that exposure to high temperature may increase emergency room visits related to mental health outcomes (Basu et al. 2018). High temperature could also make people feel ill-tempered, nervous, or listless, which in turn may make them more susceptible to various mental disorders like anxiety, depression, or even death (Cooper, 2018).

2.2.5. Residential racial/ethnic segregation and neighborhood mental health vulnerability

In the U.S., racial/ethnic residential segregation is closely associated with mental health vulnerability, which can be represented by high levels of i) socioeconomic disadvantage, ii) residential instability, iii) social disorganization, iv) neighborhood physical/social disorder, and v) poor neighborhood environmental qualities. For instance, Massey and Denton (1989) argue that extreme residential segregation is associated with socioeconomic disadvantage. Black residential segregation has also been historically associated with high levels of neighborhood disorder (Massey and Denton 1989; Sampson et al. 1997). Shaw and McKay (1942) argue that ethnic diversity could also prevent residents from establishing effective social organizations. In addition, from an environmental justice perspective, hazardous sites (e.g., industrial activities, waste facilities) and pollution sources (e.g., air pollution, traffic noise) are more likely to be located in or in close proximity to minority concentrated neighborhoods (Chakraborty and Zandbergen 2007; Daniels and Friedman 1999; Davidson and Anderton 2000; Mohai et al. 2009). These environmental problems could be compounded by their socioeconomic disadvantage or social disorganizations. All these factors together may make minority populations (i.e., Blacks, Latinos, Native Americans) living in segregated neighborhoods more vulnerable to environmental threats and various health-related problems (Gee and Payne-Sturges 2004).

All in all, if perception is a precondition for stress, it can be reasonably argued that residents living in segregated neighborhoods are more likely to suffer from chronic stress and various mental health-related problems. However, as mentioned earlier, previous mental health studies provide little insight into ‘in what ways’ racial/ethnic residential segregation is related with multi-dimensional mental health QoL indicators - a systematic examination of which is the primary purpose of this study.

2.3. Study area description

As a case study site for this study, Los Angeles County was selected. The county is comprised of 16 sub-regions (Figure 4). This is one of the most densely populated areas in the United States. According to 2010 Census, the county alone had a population of approximately ten million people (9,818,605), comprising more than one-quarter of the total population of California. The county’s diverse physical landscapes, racial/ethnic composition, and socioeconomic makeup provide optimal contexts in which various aspects of neighborhood mental health disparities can be studied. First, the county possesses a wide variety of physical landscapes such as coastline along the Pacific Ocean, mountain ranges, forests, valleys, rivers, etc. Such neighborhood natural amenities could positively influence mental health by serving as a natural buffer against environmental stressors or by restoring people from mental fatigue. Second, Los Angeles County is a major port of entry in the United States and is also known for its racial/ethnic diversity. The county’s population was comprised of 48% Hispanic, 28% non-

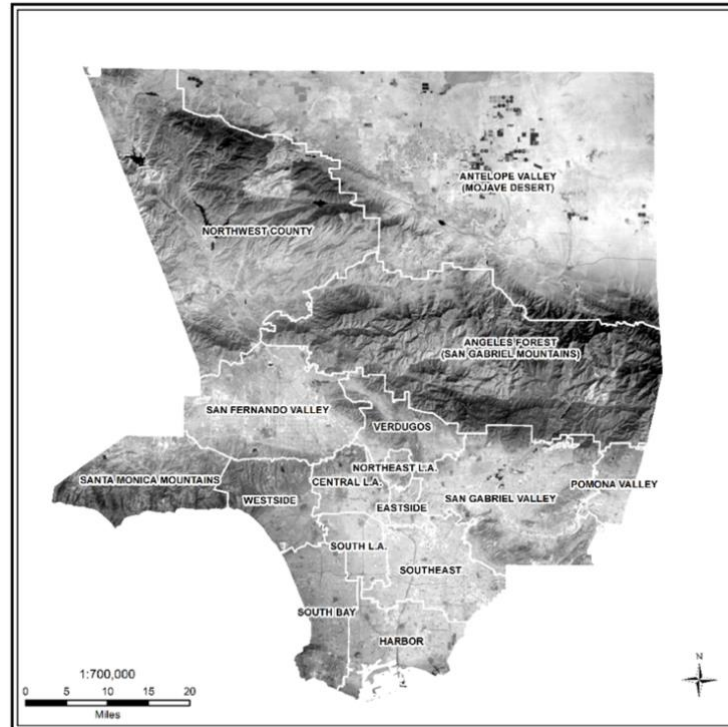


Figure 4. 16 sub-regions in the Los Angeles County

Hispanic White, 9% Asian, 8.6% African American, and 6.4 % others (Census 2010). Third, the county also displays diverse socioeconomic makeup. In 2010, county's median household income was \$52,684; nearly one-fifth of county residents lived below the poverty line; almost one-quarter of its population earned greater than 100K per year. Los Angeles County, as shown in the next section, is still heavily fragmented and segregated along the lines of race, ethnicity, and class. The interplay of these diverse factors determines neighborhoods' quality of life, which plays an important role in shaping residents' mental health outcomes.

2.4. Data description

The primary datasets used for this research were obtained from four different sources - American Community Survey (ACS, 2011 ~ 2015, 5-year estimates), the Los Angeles County Sheriff's Department (LASD), U.S. Geological Survey (USGS), and the California Communities Environmental Health Screening Tool (CalEnvironScreen).

First, ACS data were used for measuring neighborhood structure (i.e., neighborhood socioeconomic status, residential stability, and housing characteristics). Table 2 summarizes the list of variables used for measuring each aspect. This study used census tracts as an approximation for neighborhoods. For further spatial analysis, census tract shapefiles were obtained from the U.S. Census TIGER geodatabase. Then, the tabular ACS data and shapefiles were joined together using common census geographical entity codes.

Second, crime data from LASD were employed for measuring neighborhood social/physical disorder. This dataset is comprised of Part I and Part II crimes. Part I category includes more serious crimes in nature (e.g., homicide, forcible rape, arson, etc.), while part II crimes include less serious offenses (e.g., disorderly conduct, drunkenness, vandalism, etc.). The complete list of variables used for representing neighborhood disorder is shown in Table 2. Next, all crime incident points were geocoded and summarized at the census tract level using crime density approach (i.e., the number of incidents divided by its corresponding areas in square miles).

Third, as a proxy for neighborhood greenness and heat stress, this study used Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST), respectively. Both variables were derived from Landsat 8 OLI images downloaded from USGS Earth Explore website. The image was originally obtained on June 15, 2015. Next, the mean of NDVI and LST were computed at the neighborhood level in order to make them comparable to other variables used in this study. For those who are interested in more detailed variable extraction processes are referred to (Bingqing and Qihao 2011; Li and Weng 2007).

Fourth, 12 pollution variables were extracted from OEHHHA in order to calculate overall neighborhood pollution burden score. This score is a combination of 'exposure' and 'environmental effects' indicators. The variables used for 'exposure (i.e., the degree of residents' exposure to pollutants)' include ozone concentration, PM2.5 concentration, diesel PM emissions, drinking water contaminants, pesticide use, toxic releases from facilities, and traffic density; the variables used for representing 'environmental effects (i.e., the degree of environmental degradation in a neighborhood)' include cleanup sites, ground water threats, hazardous waste, impaired water bodies, solid waste sites and facilities. The procedures employed for calculating pollution burden score is described in the CalEnvironScreen 3.0 original document.

Table 2. Neighborhood mental health QoL indicators

<i>Dimension</i>	<i>Variables used</i>	<i>Source</i>	<i>SOM label</i>
<i>Neighborhood socioeconomic status</i>	Percentage greater than high school degree	The U.S. Census Bureau	Education
	Percentage unemployment		Unemployment
	Percentage of female headed households		Female-headed
	Median household income		Income
	Percentage of residents living below the poverty line		Poverty
	Percentage manufacturing employment		ManuEmploy
<i>Residential stability</i>	Percentage owner-occupied household	The U.S. Census Bureau	HomeOwner
	Percentage of residents who lived in the same tracts more than 15 years		Duration
	Percentage of residents living in apartment units		Multiunit
<i>Housing characteristics</i>	Percentage of structures built more than 35 years ago	The U.S. Census Bureau	YrStrBuilt
	Percentage vacant housing units		Vacancy
	Median home values		HomeValue
<i>Neighborhood disorder</i>	<i>Part I crime:</i> criminal homicide, forcible rape, robbery, aggravated assault, burglary, larceny theft, grand theft auto, arson <i>Part II crime:</i> disorderly conduct, DUI, prostitution, drunkenness, vagrancy, vandalism, weapon Aggregated at the neighborhood level using crime density	The Los Angeles County Sheriff's Department	Crime
<i>Neighborhood physical environment</i>	Average neighborhoods' NDVI	United States Geological Survey	NDVI
	Average neighborhoods' LST		LST
	Pollution burden	California Office of Environmental Health Hazard Assessment	Pollution

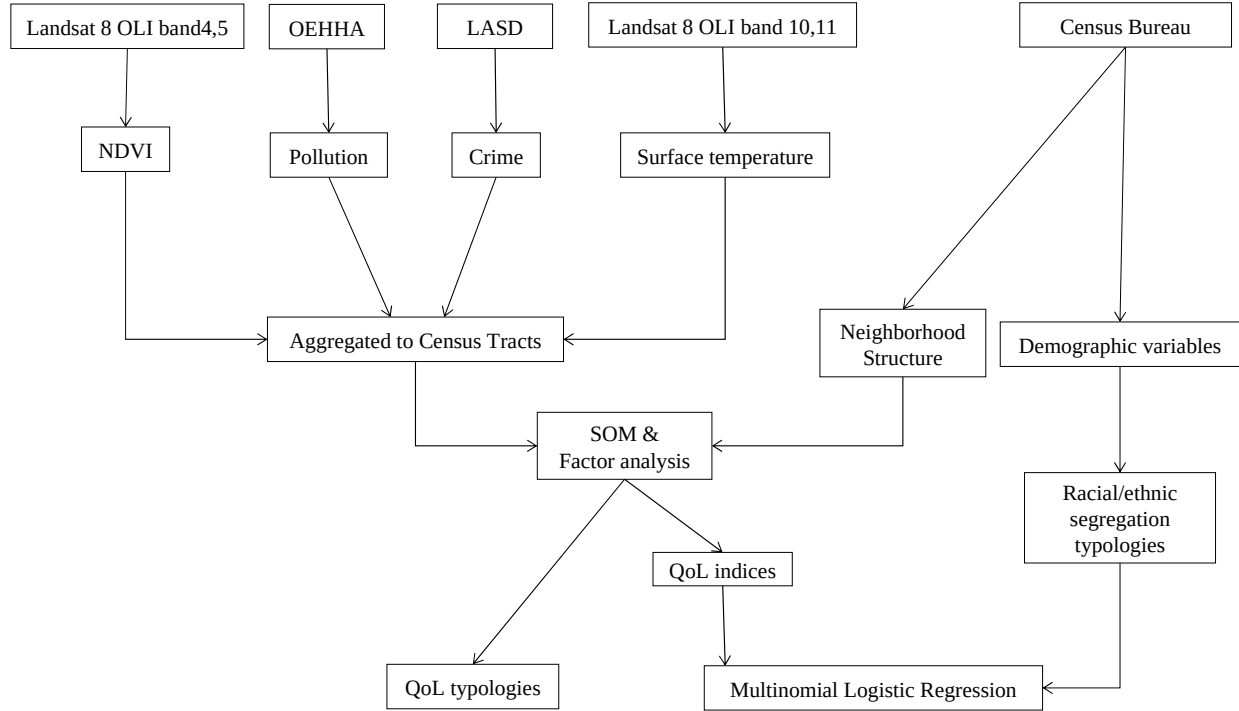


Figure 5. Overall analytical workflow

2.5. Methods

Figure 5 illustrates the overall workflow of measuring the relationships between mental health QoL indices and residential racial/ethnic segregation patterns. The followings are the explanations of analytical procedures used in this study.

2.5.1. Developing racial/ethnic residential segregation typologies

For visualizing racial/ethnic residential segregation patterns in the study area, the current study employs the typology analysis developed by Poulsen et al. (2001). This method, based on the ratio between majority and other minority groups, categorizes neighborhoods into six different segregation typologies:

- i) Type I (also called ‘isolated host communities’) where majority group takes up more than 80% of total population;
- ii) Type II (called ‘non-isolated host communities’) where majority group dominates (50 – 80 %) but with significant presence of racial/ethnic minority groups;
- iii) Type III (called ‘assimilation-pluralism enclaves’) where ethnic minority groups dominate (50-70%) with host society constituting a substantial minority;
- iv) Type IV (called ‘mixed minority enclave’) where minority groups predominate (more than 70%), but no single group dominates the other;

- v) Type V (called polarized enclave) where minority group predominate with one group being at least twice as large as the other groups;
- vi) Type VI (ghetto) where it satisfies the criteria for Type V with more than 30% of this minority group concentrated in these areas.

2.5.2. Developing neighborhood mental health QoL typologies using a Self-Organizing Map approach

For developing neighborhood mental health QoL typologies, this study employed a geo-visual analytical method called self-organizing map (SOM). This method was originally developed by Kohonen (1990). SOM is an unsupervised learning algorithm and belongs to the family of artificial neural network (ANN). SOM projects multi-dimensional input data unto a low-dimensional (typically two dimensional) output space in such a way that similar samples across the input space are clustered closely together, hence this is a suitable method for developing coherent neighborhood mental health QoL typologies. As a first step to develop the typologies, SOM component planes were visualized, which showed the relative contribution of each QoL indicator over the final SOM output space. Second, a k-means clustering algorithm was applied to the multi-dimensional SOM output space. Prior to this step, David-Bouldin analysis was run for each k in order to determine the optimal number of clusters, which suggested that a k = 6 had the best discriminating power. Third, a visual examination of component planes and interpretation of z-scores (from k-means clustering analyses) was performed in order to determine the characteristics of each QoL typology. For more details regarding SOM algorithms and applications, one is referred to Kohonen (1990) and Skupin and Hagelman (2005).

2.5.3. Developing QoL indices using factor analysis

In previous studies on QoL (Lo and Faber 1997; Li and Weng 2007; Bingqing and Qihao 2011), factor analysis has been the most frequently used methods for combining multidimensional QoL indicators. Factor analysis is a parsimonious technique that attempts to regroup observed variables into a set of latent factors based on shared variance. Its primary purpose is to summarize data so that underlying patterns and relationships can be more easily interpreted and comprehended (Yong and Pearce 2013). Factors are regarded as underlying dimensions and most variability among data are explained by these factors. Among different factor extraction methods, this study utilized the principal component method. First, socioeconomic disadvantage index was created by running factor analysis on educational attainment, unemployment rate, percentage manufacturing employment, percentage female-headed household, and median household income variable. In the same way, residential stability index was developed by using homeownership rate, length of stay, and percentage renter occupied housing unit variables. NDVI, LST, pollution burden score, and crime density variables were used as they are described in the data description section.

2.5.4. Multinomial logistic regression analysis

Finally, in order to examine the systematic relationships between mental health QoL indicators and the racial/ethnic segregation patterns, this study employed multinomial logistic regression (MLR) analysis. MLR is an extension of logistic regression, a classification method used when the dependent variable is binary. MLR, different from a logistic regression analysis, allows a model to have more than two categories. In this study, the response variable has seven

classes: I, II, III, IV, V(Hispanic), V(Asian), and V(Black), and the typology ‘I’ was chosen as a baseline category. Since the response variable has seven classes, the MLR can be represented with six different logistic regression equations, each of which models the probability of a neighborhood belonging to a particular typology divided by the probability of a neighborhood belonging to the baseline category (typology I). The MLR modeled the probabilities as an exponential function of all six mental health QoL indicators. Accordingly, regression coefficients were computed simultaneously using maximum likelihood estimation method.

$$\ln\left(\frac{P_{iII}}{P_{iI}}\right) = \alpha_{II} + \beta_{1II}SES_i + \beta_{2II}Stability_i + \beta_{3II}NDVI_i + \beta_{5II}Pollution_i + \beta_{6II}Crime_i \quad (1)$$

$$\ln\left(\frac{P_{iIII}}{P_{iI}}\right) = \alpha_{III} + \beta_{1III}SES_i + \dots + \beta_{6III}Crime_i \quad (2)$$

$$\ln\left(\frac{P_{iIV}}{P_{iI}}\right) = \alpha_{IV} + \beta_{1IV}SES_i + \dots + \beta_{6IV}Crime_i \quad (3)$$

$$\ln\left(\frac{P_{iV(H)}}{P_{iI}}\right) = \alpha_{V(H)} + \beta_{1V(H)}SES_i + \dots + \beta_{6V(H)}Crime_i \quad (4)$$

$$\ln\left(\frac{P_{iV(A)}}{P_{iI}}\right) = \alpha_{V(A)} + \beta_{1V(A)}SES_i + \dots + \beta_{6V(A)}Crime_i \quad (5)$$

$$\ln\left(\frac{P_{iV(B)}}{P_{iI}}\right) = \alpha_{V(B)} + \beta_{1V(B)}SES_i + \dots + \beta_{6V(B)}Crime_i \quad (6)$$

Where P_{ij} = the probability that an observation is from typology j, α_j = intercept

, β_{ij} = a vector of regression coefficients to be estimated

2.6. Findings and results

2.6.1. The typology analyses of mental health QoL and racial/ethnic residential segregation

(1) Highest QoL neighborhood (Typology 4)

Typology 4 (in Figure 7) possesses the highest neighborhood mental health QoL as shown in Table 3. First, the neighborhoods in this category display the highest socioeconomic status with the highest mean educational attainment (1.80) and income (2.08), the lowest means of unemployment (-0.80), female-headed households (-1.19), and manufacturing employment (-0.63), and lower means of residents living below the poverty line (-0.68). These neighborhoods also display higher residential stability as indicated by relatively higher homeownership (0.84), length of stay (0.63), and lower mean of multiunit (-0.40). They also possess favorable physical environmental qualities as indicated by the highest NDVI (1.52), the lowest LST (-1.74), and the lowest pollution burden (-0.64). The mean of crime density (-0.42) was also the lowest among all five categories. A total of 134 neighborhoods belonged to this category. As shown in Figure 7, the first major concentration of typology 4 is located in the West Side and Santa Monica Mountains regions (for the names and locations of sub-regions, refer to Figure 4); the second major concentration is found in the south and southwestern tip of South Bay region. Verdugo

region also contains a large number of typology 4 neighborhoods. The segregation typology analysis (Figure 6) clearly indicates that these highest QoL neighborhoods have significant overlaps with the type I and II segregation typologies (i.e., White-dominant neighborhoods)

Table 3. Cluster means

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6
Education	-0.99	0.68	-0.33	1.80	-0.49	1.07
Unemployment	0.86	-0.62	0.23	-0.80	0.12	-0.47
ManuEmploy	0.90	-0.21	-0.32	-0.63	0.15	-0.79
Female-headed	1.13	-0.70	0.31	-1.19	0.18	-0.84
Income	-0.82	0.99	-0.75	2.08	-0.18	0.20
Poverty	0.85	-0.73	0.49	-0.68	-0.13	-0.29
HomeOwner	-0.57	1.10	-1.10	0.84	0.41	-0.51
Duration	-0.21	0.72	-0.92	0.63	0.27	-0.55
Multiunit	-0.03	-0.80	1.14	-0.40	-0.53	0.86
YrStrBuilt	0.31	-0.45	-0.18	0.16	-0.06	0.06
Vacancy	0.02	-0.32	0.03	0.84	-0.08	0.18
Home Value	-0.63	0.30	-0.32	2.61	-0.47	0.65
Crime	0.55	-0.26	-0.38	-0.42	0.07	-0.32
NDVI	-0.61	0.81	-0.77	1.52	0.03	0.19
LST	0.33	-0.14	0.27	-1.74	0.52	-0.63
Pollution	0.50	-0.60	0.30	-0.64	-0.22	0.14

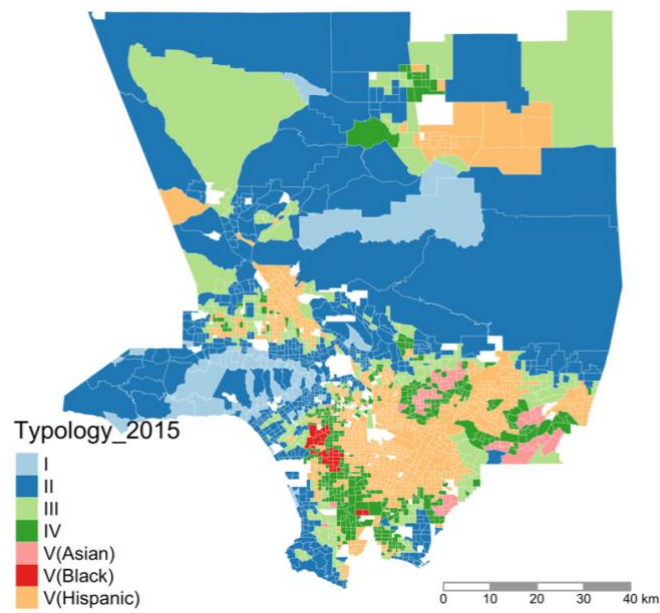


Figure 6. Racial/ethnic residential segregation typologies

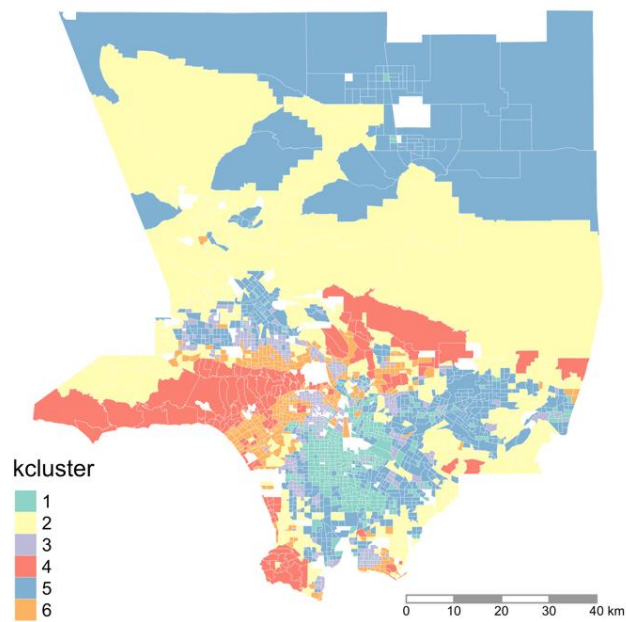


Figure 7. The spatial distribution of mental health QoL typologies

(2) High QoL neighborhoods (Typology 2)

Typology 2 (Figure 7) displayed the second highest mental health QoL. Table 3 shows that these neighborhoods possess a high level of socioeconomic status (Education = 0.68, Income = 0.99, Unemployment = -0.62, ManuEmploy = -0.21, Poverty = -0.73), a high level of residential stability (HomeOwner = 1.10, Duration = 0.72, Multiunit = -0.80), and favorable physical neighborhood environment (NDVI = 0.81, LST = -0.14, Pollution = -0.60). They also display below average crime density (Crime = -0.26). A total of 393 neighborhoods belonged to this typology. As Figure 6 shows, the typology 2 QoL neighborhoods are mostly found: i) along the southeastern border of the county; ii) in the upper half of Santa Monica Mountains region; iii) in the San Gabriel Mountains region; iv) in the Northwest County region. The segregation typology analysis (Figure 6) reveals that these high QoL neighborhoods are occupied by more diverse population groups (i.e., the segregation typologies of II, III, IV, and V(Asian))

(3) Above-average QoL neighborhoods (Typology 6)

Typology 6 neighborhoods display a relatively higher level of socioeconomic status (Education = 1.07, Income = 0.20, Unemployment = -0.47, ManuEmploy = -0.79, Poverty = -0.29). However, as shown in Table 3, their residential stability (HomeOwner = -0.51, Duration = -0.55, Multiunit = 0.86) is significantly lower than the first two typologies. They display an average level of NDVI (0.19) and pollution burden (0.19). Their crime density is below the county average (Crime = -0.32). A total of 301 neighborhoods belongs to this typology. These neighborhoods are mostly concentrated in the bottom half of the Westside region (Figure 6); another concentration is also identified in the southeastern part of the San Fernando Valley region. Figure 6 shows that this QoL cluster largely overlaps with the segregation typologies of II and III (i.e., a relatively higher proportion of White residents).

(4) Average QoL neighborhoods (Typology 5)

Overall, typology 5 displays an average level of socioeconomic status (Income = -0.18, Unemployment = 0.12, Poverty = -0.13) except education (-0.49) and median home value (-0.47). These neighborhoods display a relatively high level of residential stability (HomeOwner = 0.41, Duration = 0.27, Multiunit = -0.53). While their NDVI (0.03) and pollution burden (-0.22) are close to the county average, the mean level of their LST is highest among all six typologies. The largest number of neighborhoods belong to this typology (a total of 605). As Figure 7 shows, a majority of neighborhoods in the San Gabriel Valley, the Pomona Valley, the Southeast, and the Harbor regions belong to this typology. A large portion of neighborhoods located in the northeastern and western part of the San Fernando Valley also belong to this typology. These average-QoL neighborhoods largely overlap with the Hispanic-majority neighborhoods (i.e., V(H) typology in Figure 6).

(5) Below-average QoL neighborhoods (Typology 3)

Table 3 shows that the typology 3 displays below-average socioeconomic status (Education = -0.33, Income = -0.75, Unemployment = 0.23, Poverty = 0.49). Their level of residential stability (HomeOwner = -1.10, Duration = -0.92, Multiunit = 1.14) and physical environmental quality (NDVI = -0.77, LST = 0.27, pollution = 0.30) are lowest among all six typologies. In contrast, however, their social/physical disorder indicator (crime = -0.38) is below average. A total of 381 neighborhoods belong to this typology. Spatially, these neighborhoods are largely concentrated in the Central L.A. and in the middle of San Fernando Valley regions (Figure 7). The segregation

typology analysis shows that Hispanics (V(H)) comprise a majority of the population in those neighborhoods (Figure 6).

(6) Lowest QoL neighborhoods (Typology 1)

Overall, typology 1 neighborhoods display the lowest neighborhood mental health QoL among all six typologies. Table 3 shows that these neighborhoods have the lowest level of socioeconomic status (Education = -0.00, Income = -0.82, Unemployment = 0.86, Poverty = 0.85). Their level of residential stability (HomeOwner = -0.57, Duration = -0.21, Multiunit = -0.03) is below the county mean. Their physical environmental quality (NDVI = -0.61, LST = 0.33, pollution = 0.50) is significantly lower than the county average. Their crime density (crime = 0.55) was highest among all six typologies. A total of 399 neighborhoods belong to this typology. Spatially, they are largely concentrated in the South L.A., Eastside, and Southeast regions (Figure 7). Figure 6 shows that these lowest QoL neighborhoods have the highest concentration of Hispanic residents(V(H)).

2.6.2. Multinomial logistic regression analysis results

The results so far have suggested that there may be a close relationship between the neighborhood mental health QoL indicators and the racial/ethnic residential segregation patterns. For a more systematic examination of this relationship, the MLR analysis was carried out, and the results (as shown in Table 4) indicated that:

- (i) **(for socioeconomic disadvantage)** a one unit increase in ‘socioeconomic disadvantage (SES),’ the relative risks of a neighborhood belonging to typology II, III, IV, V(Asian), V(Black), and V(Hispanic) (relative to typology I) are expected to increase by a factor of 4.57, 16.75, 151.3, 12.06, 102.3, and 1809.54 respectively, holding all other variables constant. All SES coefficients were statistically significant ($p < 0.001$);
- (ii) **(for residential stability)** when the other variables in the model are held constant, given a one unit increase in residential stability (Stability), the relative risks for a neighborhood belonging to typology II, III, IV, and V(Hispanic) (relative to typology I) are expected to decrease by a factor of 0.76, 0.69, 0.75, and 0.93, respectively; all else being equal, a unit increase in residential stability, the relative risks for a neighborhood belonging to typology V(Asian) and V(Black) (relative to typology I) are expected to increase by a factor of 1.27 and 1.11, respectively. However, none of the coefficients were statistically significant;
- (iii) **(for NDVI)** For this variable, none of the coefficients were statistically significant; accordingly, all relative risk ratios (except the one for V(Hispanic)) for NDVI (relative to typology I) were close to zero;
- (iv) **(for pollution)** a one unit increase in ‘pollution burden (Pollution),’ the relative risks of a neighborhood belonging to typology II, III, IV, V(Asian), V(Black), and V(Hispanic) (relative to typology I) are expected to increase by a factor of 1.58, 2.12, 3.43, 2.98, 2.58, and 4.36 respectively, given the other variables in the model are held constant. All pollution coefficients were statistically significant ($p < 0.01$ for the typology II, $p < 0.001$ for all else);
- (v) **(for crime)** when the other variables in the model are held constant, given a one unit increase in crime density, the relative risks for a neighborhood belonging to typology II, III, IV, V(Asian), V(Black), and V(Hispanic) (relative to typology I) are expected to increase by

a factor of 1.32, 1.55, 1.82, 2.06, 1.82, and 1.59, respectively; all crime coefficients were statistically significant ($p < 0.05$ for the typology II, $p < 0.001$ for all else).

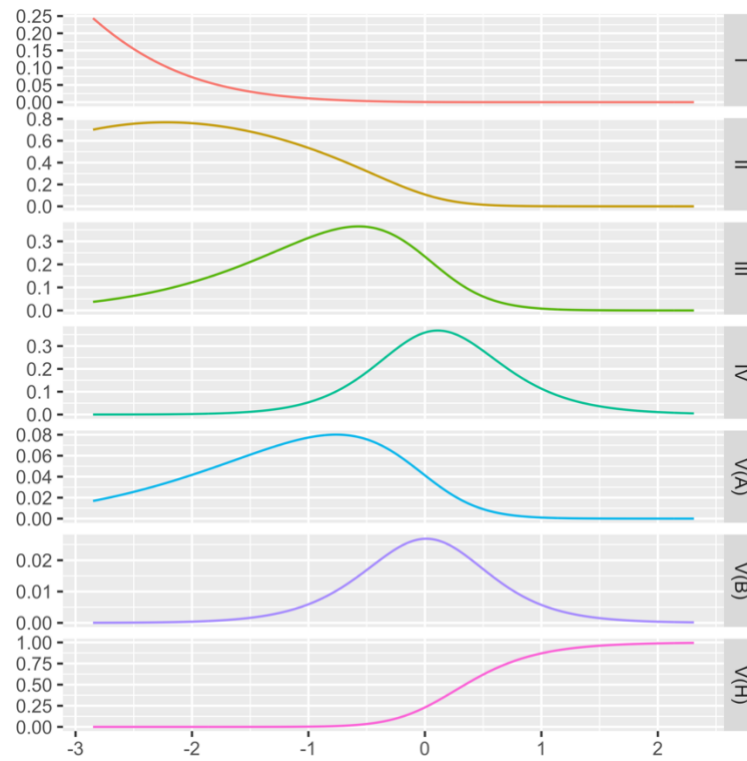


Figure 8. The predicted probabilities against ‘SES’ score for racial/ethnic segregation typologies

Table 4. Multinomial logistic regression model results

	II		III		IV		V(Asian)		V(Black)		V(Hispanic)	
	B(SE)	RRR	B(SE)	RRR	B(SE)	RRR	B(SE)	RRR	B(SE)	RRR	B(SE)	RRR
SES	1.52 (0.29)	4.57	2.82 (0.32)	16.7 5	5.02 (0.35)	151. 3	2.49 (0.36)	12.0 6	4.63 (0.51)	102. 3	7.50 (0.38)	1809 .54
Stability	-0.27 (0.22)	0.76	-0.37 (0.23)	0.69	-0.29 (0.24)	0.75	0.24 (0.27)	1.27	0.10 (0.34)	1.11	-0.07 (0.25)	0.93
NDVI	-6.59 (4.13)	0.00	-7.61 (4.68)	0.00	-6.47 (5.20)	0.00	-9.82 (5.95)	0.00	-2.57 (8.44)	0.08	1.24 (5.36)	3.46
Pollution	0.46 (0.17) **	1.58	0.75 (0.19)	2.12	1.23 (0.19)	3.43	1.09 (0.21)	2.98	0.95 (0.25)	2.58	1.47 (0.19)	4.36
Crime	0.28 (0.11) *	1.32	0.44 (0.12)	1.55	0.60 (0.12)	1.82	0.73 (0.13)	2.06	0.60 (0.15)	1.82	0.47 (0.12)	1.59
Intercept	2.60 (1.22) *		1.21 (1.34)		-2.09 (1.45)		-3.17 (1.67)		-3.34 (2.07)		-4.79 (1.48) **	

AIC = 4387.745, Residual Deviance = 4315.745, *** $p < .001$, ** $p < .01$, * $p < .05$

RRR = Relative Risk Ratio, Typology I is the baseline outcome

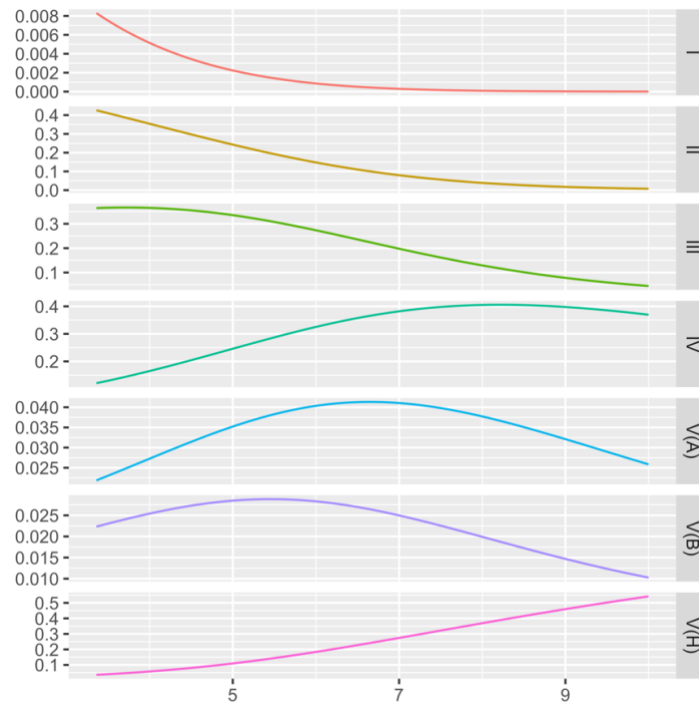


Figure 9. The predicted probabilities against ‘Pollution’ score for racial/ethnic segregation typologies

Next, in order to present the results in a more understandable way, the predicted probabilities for each segregation typology were computed over the range of QoL indicators. For visualization purpose, only the significant variables (i.e., SES, Pollution, Crime) were considered. First, small datasets for each variable were created. This was done by varying each indicator while holding others at their means. More specifically, for example, the SES variable was incremented in steps of 0.01 in the range of -2.85 (min) and 2.31 (max) while holding Stability, NDVI, Pollution, and Crime at their means (the same was done for the ‘Pollution’ and ‘Crime’ variable). Subsequently, the probabilities for each variable at different levels of the segregation typologies were predicted using the MLR model. The resulting plots are shown in Figures 8, 9, and 10. First, Figure 8 shows that there is a clear association between socioeconomic disadvantage and racial/ethnic minority concentrations; however, the V(A) typology was an exception to this tendency; the high levels of SES disadvantage is more closely related to the V(H) typology than to the V(B) typology; lastly, given the same level of SES disadvantage, a neighborhood is more likely to belong to the IV typology than to the V(B) typology. Second, Figure 9 indicates that there is also a close relationship between pollution burden and racial/ethnic minority concentrations; but with a closer look, the high levels of pollution burden seem to be more closely related with the V(H) and IV typology than it is to the V(A) and V(B) typology. Third, the same tendency was also observed from Figure 10 – the higher the concentrations of minority groups, the higher the neighborhoods’ crime density; but the plot also shows that the increase in crime density is negatively related to the V(H) typology while it is positively related to the IV, V(A), and V(B) typology.

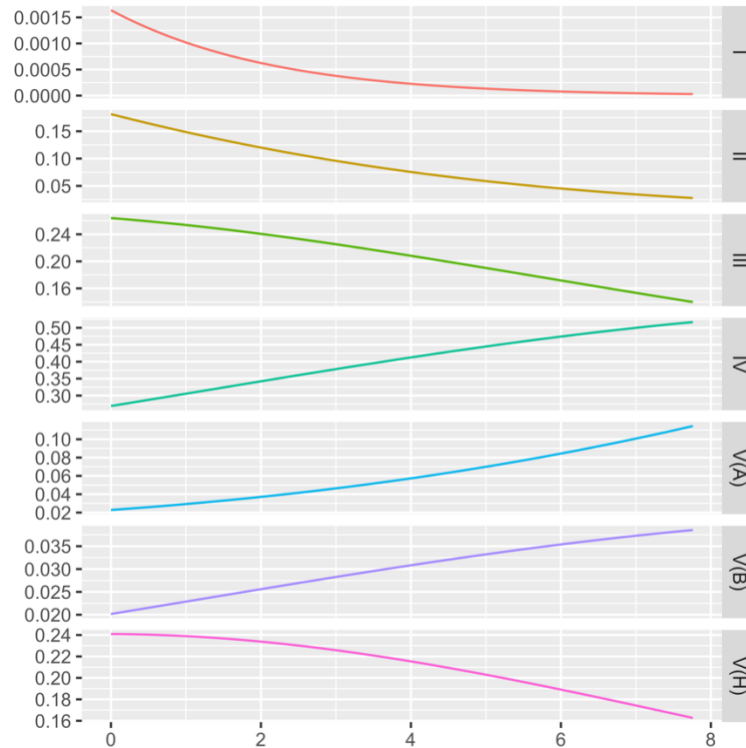


Figure 10. The predicted probabilities against ‘Crime density’ for racial/ethnic segregation typologies

2.7. Discussion and conclusions

The current study, using Los Angeles County as a case study, aimed to systematically examine the relationships between neighborhood mental health QoL indicators and racial/ethnic residential segregation patterns. As a first step, the spatial distribution patterns of residential segregation were visually examined in comparison to the mental health QoL typologies. Then, these relationships were statistically tested through a multinomial logistic regression analysis. The following are the major conclusions of this study.

First, as supported by the existing theories (Massey and Denton 1989), this study found that a high level of minority concentration is closely related with socioeconomic disadvantage. As the proportion of minorities increases, neighborhoods are more likely to be socioeconomically disadvantaged. However, this was not without exceptions. The Asian-concentrated neighborhoods in the study area were significantly less disadvantaged than other minority-concentrated neighborhoods. In addition, though the Black concentrations were expected to have the highest level of socioeconomic disadvantage, the findings from this study suggested otherwise – in Los Angeles County, the Black concentrated neighborhoods tend to be socioeconomically better off than their Hispanic and ‘mixed minority’ counterparts. Hispanic neighborhoods, in contrast, were socioeconomically most disadvantaged among all minorities.

Second, a lack of social organization (or collective efficacy), by increasing social disorder and stress level, may pose a significant threat to residents’ mental health outcomes (Mair, Diez

Roux, Osypuk, et al. 2010). Residential stability is one of the most important prerequisites for higher levels of neighborhood collective efficacy (Hill and Maimon 2013; Sampson et al. 1997). Racial/ethnic heterogeneity (one aspect of residential segregation) could also prevent residents from establishing social organizations (Hill and Maimon 2013; Shaw and McKay 1942). The findings indicated that there is no significant relationship between residential stability and minority concentrations. However, this result does not mean that ethnically diverse neighborhoods are equally likely to have the similar levels of collective efficacy. On the contrary, such neighborhoods, given the same level of residential stability, are expected to have lower levels of collective efficacy. This may be because language and cultural barriers among different racial/ethnic minority groups could significantly prevent them from establishing meaningful social relationships. Testing the validity of this hypothesis is outside the scope of this study. But this aspect still needs to be tested in future studies.

Third, neighborhood greenness (measured by NDVI) turned out to be not significantly related to minority concentrations. But, as expected (from an environmental justice perspective), there was a close relationship between pollution burden and minority concentrations; a high level of pollution burden is more closely related to racial/ethnic minority concentrations; interestingly, in Los Angeles County, the Asian- and Hispanic-concentrated neighborhoods tend to bear a greater burden of environmental pollution than the Black-concentrated neighborhoods. Based on this finding, it is reasonable to speculate that pollution burden, by increasing the likelihood of experiencing environmental stress, may make racial/ethnic minorities more vulnerable to mental health problems. In the meantime, it is worth noting that environmental problems and their effects on mental health can be significantly compounded by neighborhood socioeconomic disadvantage. Therefore, all these relationships need to be thoroughly tested in future mental health research.

Fourth, the findings from this study indicated that in general, minority concentrated neighborhoods tend to be more affected by social disorder (i.e., crimes). Thus, the minorities living in those neighborhoods are more vulnerable to stress and mental health problems. The results also indicate that increase in social disorder was more highly associated with the Asian-concentrated and mixed minority (IV) neighborhoods than it is with the Black- and Hispanic-concentrated neighborhoods. This finding was somewhat contrary to the initial expectation because, according to the existing theories, socioeconomic disadvantage (which is more prevalent in Black and Hispanic neighborhoods) is believed to be one of the primary preconditions for social disorder (Hill and Maimon 2013; Sampson et al. 1997). However, the results from this study clearly suggested otherwise, which warrants further investigation in future studies.

There are several important limitations in this study. First, this study used ‘residential stability’ as a proxy for neighborhood social organizations. Though it is true that a residentially stable neighborhood is more likely to develop necessary social capital (a precondition for neighborhood social organizations), this is not always the case. For instance, as mentioned earlier, ethnically diverse neighborhoods can be greatly discouraged from developing meaningful social relationships due to language barriers and cultural differences. The results from the topic modeling analysis (the primary focus of next chapter) also revealed that some residents perceived racial/ethnic diversity as a hindrance to further social integration. Therefore, I argue, future studies need to i) clearly define what social organization is (e.g., local churches, neighborhood watch, home-owners association, etc.), ii) measure the impact of such

organizations to local communities, and iii) incorporate this aspect into analysis. These may greatly enhance our understanding of the impact of neighborhood contexts on mental health. Second, it has been widely known that police crime statistics often suffer from under-counting and under-representation and thus carry risks of misrepresenting reality (Altbeker 2005). The crime data used in this study are not free from such risks. For example, the findings from this study indicated that the Asian-concentrated neighborhoods are more likely to be affected by crimes than other minority-concentrated neighborhoods. This may as well have been caused by data bias. However, addressing such issue is outside the scope of this study. Therefore, care must be taken when interpreting and implementing the findings from this study.

In conclusion, as the existing theory argues, this study found that there is a close relationship between neighborhood mental health QoL and minority concentrations. However, different from the theoretical expectations, the current study clearly revealed that racial/ethnic segregation and neighborhood mental health QoL are related to one another in a more complicated way; for instance, the current study revealed that:

- Hispanic neighborhoods, though socioeconomically and environmentally most disadvantaged, tend to have relatively lower crime rates;
- Asian neighborhoods, though socioeconomically better off than other minority neighborhoods, tend to have relatively higher levels of pollution burden and crime density;
- Black neighborhoods were socioeconomically less disadvantaged and bear less pollution and crime burden than their mixed minority and Hispanic counterparts;
- The mixed minority neighborhoods, in general, displayed relatively higher levels socioeconomic disadvantage, pollution burden, and crime density.

The findings from this study are expected to provide valuable insights into future confirmatory statistical analyses by helping them to tease out causal relationships (between mental health and neighborhood contexts) in a more precise way. I also believe that this study could help policy makers and public health practitioners/investigator to come up with more effective and targeted intervention plans.

CHAPTER III
NEIGHBORHOOD PERCEPRIONS AND MENTAL HEALTH:
EXPLORING RESIDENTS' PERCEPTIONS FOR THE DISCOVERY OF
MORE NEIGHBORHOOD CONTEXTUAL FACTORS

Abstract

In the study of neighborhood effects on mental health, perceptions play crucial roles in determining residents' mental health outcomes. This is because unless neighborhood problems are directly experienced or perceived by residents, these are not likely to affect people's mental health outcomes. This study used neighborhood textual review data in order to unearth new neighborhood-level contextual factors whose importance may have gone unnoticed by the previous mental health studies. The neighborhood review data for New York City were retrieved from the website called 'Niche' and included a total of 7,673 reviews. This study employed Latent Dirichlet Allocation (LDA) method in order to find out underlying public discourses that may have relevance in mental health studies. In addition, objective neighborhood-level mental health vulnerability typologies were developed using a k-means clustering algorithm in order to examine the spatial distribution patterns of topics within the study area. The LDA algorithm identified 6 new topics (out of 19 topics) – gentrification, diversity, natural disasters, neighborhood environmental quality, accessibility, and walkability. The spatial distribution patterns of topics also displayed close relationships with the objective neighborhood mental health vulnerability typologies. Overall, the new knowledge obtained from this study offers invaluable insights in our current theoretical understanding of the neighborhood effects on mental health.

3.1. Introduction

World Health Organization (WHO) in their 2013 report said: “there is no health without mental health (Kolappa et al. 2013).” Previous empirical studies have also indicated that individuals with mental illnesses (e.g., depression, anxiety) are more prone to suffer from chronic physical diseases such as cancer, heart disease, and diabetes (Bhattacharya et al. 2014; Clarke and Currie 2009). Severe mental health problems are also known to potentially reduce our life expectancy. For instance, Dr. Seena Fazel, a professor of forensic psychiatry at Oxford University, said in his interview: “We found that many mental health diagnoses are associated with a drop in life expectancy as great as that associated with smoking 20 or more cigarettes a day (Oxford. 2014, May 23).”

A growing body of literature started identifying the significance of neighborhood level factors – such as neighborhood socioeconomic disadvantage, neighborhood disorder, and neighborhood experience – as the major determining forces of our mental health outcomes (Downey and Van Willigen 2005a; Kim 2010; Mair, Diez Roux, and Morenoff 2010; Ross and Mirowsky 2009). These studies have argued that individuals living in poorer neighborhoods bear a greater burden of mental distress due to the higher prevalence of chronic neighborhood stressors (e.g., a lack of social cohesion and support, higher crime rates, a lack of amenities, etc.).

In mental health studies, stress is assumed to be the primary link through which neighborhood contexts eventually take their toll on residents' mental health (Cutrona et al. 2006; Mirowsky and Ross 2003). Perceptions, with few exceptions, are also assumed to be the fundamental prerequisites of any stress-related responses (McEwen and Lasley 2002). Thus, in order for neighborhood contexts to be relevant in mental health studies, they must be either directly experienced or perceived by their residents (Hill and Maimon 2013). Without this, residents' mental health is much less likely to be affected by their surroundings. For this point, Thomas and Thomas (1928) argue that situations have real consequences when they are perceived (or defined) as real.

When measuring people's perceptions, however, most of the previous studies have solely relied on interviews and survey questionnaires. One of the major limitations of such approaches is that only the theory relevant questions are addressed in those studies, thus failing to discover other potentially significant neighborhood-level factors and their influences on mental health outcomes. For instance, the presence of neighborhood green space, cultural diversity, gentrification, and the like may also play important roles in shaping people's mental health. However, none of these factors and their implications on mental health have been discussed in the existing body of literature.

To overcome this limitation, the current study, using New York City as a case study site, explores the neighborhood textual review data (i.e., residents' direct perceptions towards their neighborhoods) retrieved from a website called 'Niche.' By taking an exploratory topic modeling approach (i.e., Latent Dirichlet Allocation (LDA)), this study intends to unearth the underlying public perceptual discourses. These topics will essentially reflect different aspects of a neighborhoods that are perceived to be important by residents as they experience them. Therefore, it can be reasonably argued that many of those newly discovered topics are likely to have some consequences on mental health. This new methodological approach is expected to expand the horizon of the existing body of knowledge by discovering new neighborhood-level contextual factors whose importance may have gone unnoticed by the previous mental health studies. This study will also examine the spatial distribution patterns of LDA topics in light of objective mental health vulnerability typologies.

The remainder of this paper is organized as follows. In the following section, the theoretical background and relevant empirical evidence pertaining to the importance of perceptions in mental health studies are discussed, which is followed by a study area overview, and data/methods descriptions. Findings and results are presented in section 5, followed by the discussion and conclusions.

3.2. Neighborhood contexts, mental health, and the importance of perceptions

Perceptions matter in the study of neighborhood effects on mental health. Unless neighborhood problems are directly experienced or perceived by residents, these may not bring any real consequences on people's mental health outcomes (McEwen and Lasley 2002). Regarding this, Hill and Maimon (2013) argue that residents' stress levels are largely contingent upon how they define (or perceive) their neighborhood problems. There are several ways in which perceptions influence mental health outcomes.

First, 'a sense of powerlessness' is believed to be one of the primary links between stress and mental health outcomes. When people are constantly exposed to neighborhood disorder such as crime, harassment, pollution, or noise, they may start viewing their lives as unpredictable and out of control (Abeles 2003). If this continues, it may generate a sense of powerlessness in an individual's mind which may in turn negatively influence residents' mental health outcomes. A number of empirical studies have shown that neighborhood disorder is closely related to a sense of powerlessness (Downey and Van Willigen 2005a; Schieman and Meersman 2004), which is regarded as one of the primary causes of depression and anxiety (Benassi et al. 1988; Mirowsky and Ross 2003).

Second, a psychological disposition like 'mistrust' can also be a primary link between neighborhood perception and mental health. Similar to the circumstances in which a sense of powerlessness may develop, when neighborhoods have high levels of disorderly behaviors (e.g.

crime, drug addiction, open alcohol consumption), its residents may also start perceiving their neighbors or their neighborhood environments as perilous and threatening (Mirowsky and Ross 2003; Ross and Jang 2000). When this perpetuates over time in such neighborhoods, its residents are more likely to develop a very negative psychological disposition such as mistrust (or misanthropy) toward other people in general (Hill and Maimon 2013), often resulting in social isolation (Geis and Ross 1998; Kim 2010; Ross and Mirowsky 2009). Scholars have argued that this can have harmful impacts on one's mental health outcomes (Ross and Mirowsky 2009) since constantly perceiving others as enemies or threats can be psychologically distressing (Mirowsky and Ross 2003).

In sum, perceptions matter in the study of mental health. However, in the previous studies, residents' perceptions are mostly understood only within neighborhood socioeconomic contexts. For instance, in the existing theoretical frameworks, a neighborhood is only represented by its structure (i.e., socioeconomic disadvantage, racial/ethnic composition, and residential instability), social organization (i.e., social capital or collective efficacy), and its degree of social/physical disorder (i.e., structural dilapidation, criminal activities, open incivility, etc.) (Hill and Maimon 2013). This theory contends that a neighborhood structural disadvantage (especially its socioeconomic disadvantage) is a prerequisite that ultimately leads to neighborhood social disorganization (e.g., a lack of collective efficacy) and disorder (i.e., crime, open incivility, industrial activities) (Massey and Denton 1989; Sampson et al. 1997; Shaw and McKay 1942). Though their claims bear some truth, it can still be argued that i) a neighborhood is greater than the sum of its socioeconomic characteristics, ii) and that there are many other potential contextual factors (e.g., green space, diversity, gentrification, etc.) that can be perceived as important by residents. As mentioned earlier, however, neighborhood factors outside the scope of existing theoretical frameworks have been largely overlooked in previous studies. This is partly because of their dependence upon qualitative methodological approaches such as interviews and surveys. To be more specific, when measuring perceptions, previous studies have mostly used the following types of questions - these example questions are taken from the 'National Longitudinal Study of Adolescent to Adult Health (Add health) (Harris and Udry 2018)' survey.

- 1) (overall neighborhood satisfaction) On the whole, how happy are you living in your neighborhood?
- 2) (neighborhood safety) Do you usually feel safe in your neighborhood?
- 3) (neighborhood social ties) Do you know most of the people in your neighborhood?
- 4) (neighborhood social disorder) In this neighborhood, how big a problem are drug dealers and drug users?
- 5) (neighborhood physical disorder) In this neighborhood, how big a problem is litter or trash on the streets and sidewalks?

Though slightly varying from the above questions, other mental health studies have also employed similar types of questionnaires, largely emphasizing only on theory-based questions. Efforts to expand the existing knowledge through exploratory approaches are still lacking in mental health study. This study will address this shortcoming by exploring residents' perception data (i.e., neighborhood textual review data) in order to discover other significant neighborhood-level contextual factors that need to be addressed in the future mental health studies.

3.3. Study area: New York City

The study area selected for this research is New York City. The city itself is comprised of Manhattan, Brooklyn, Queens, the Bronx, and Staten Island. Since there is a strong tendency among people to equate New York City only with Manhattan, the term, ‘the five boroughs’, is often intentionally used in order to include all five boroughs that collectively represent New York City. Each borough also corresponds with the respective counties in the state of New York: Manhattan comprises New York County; Brooklyn, Kings County; Queens, Queens County; the Bronx, Bronx County; and Staten Island, Richmond County.

The analysis for this study was conducted at the neighborhood level as defined by Ontodia. Originally, the names of neighborhoods in the five boroughs were derived from independent villages, towns, and cities that were incorporated into the City of New York in 1898. However, since there is no officially agreed-on definition of neighborhood, boundaries are often fuzzy, overlapping with one another, and the hierarchical relationships among different neighborhoods are also unclear. As such, to effectively display various demographic, socioeconomic, and overall neighborhood grades, the ‘*Niche*’ website uses the neighborhood boundaries defined by ‘Ontodia.’ According to this definition, there were a total of 233 neighborhoods in the study area as of May 2017. However, there were 21 neighborhoods without any reviews; thus they were excluded from the analyses. Only the remaining 212 neighborhoods, each of which had at least one review, were considered for the subsequent analyses.

New York City has been one of the largest immigrant gateways in the U.S., and ranks very high in its racial/ethnic diversity. The city was comprised of 33% non-Hispanic Whites, 26% Hispanics and Blacks, and 13% Asians (2010 Census). Preliminary results suggest that different neighborhoods within each borough are marked by their own distinctive racial/ethnic makeup with varying degrees of socioeconomic status reflecting ongoing processes of residential segregation.

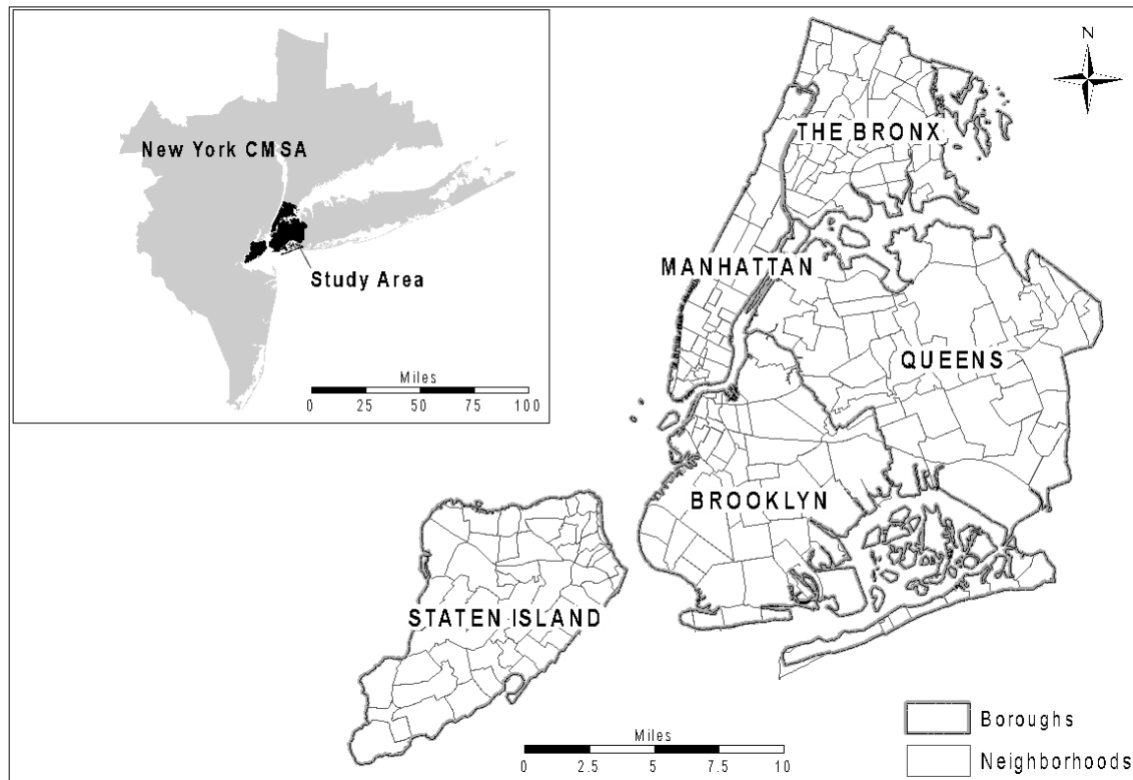


Figure 11. New York City and ‘Ontodia-defined’ neighborhoods

3.4. Data and methods

3.4.1. Data: neighborhood review data from Niche

The primary dataset used for discovering public neighborhood discourses in New York City was retrieved from the website called ‘*Niche*’ (<http://www.niche.com>). The company, Niche, was founded in August 2002 by Luke Skurman, and its original service was confined only to college prowling. During their rebranding process, however, they expanded their services to providing reviews and assessments of K-12 schools as well as neighborhoods throughout the United States. Since this study focuses on assessing residents’ perceptions of neighborhoods, only the latter was considered for further analyses. A total of 7,673 review texts from the 212 neighborhoods were retrieved from the website. The neighborhood with the highest number of reviews (278) was Harlem whereas neighborhoods with the lowest number of reviews (1) included Belle Harbor, City Island, Little Italy, etc. On an average, each neighborhood had about 33 reviews.

3.4.2. Method1: Topic modeling - Latent Dirichlet Allocation (LDA)

To unearth latent public discourses regarding residents’ neighborhood perceptions, this study employs the Latent Dirichlet Allocation (LDA) method, one of the most commonly used approaches for topic modeling. Fundamentally, LDA attempts to infer the latent (or underlying)

“topics” within a collection of documents based on the words that constitute each document. In this study, each neighborhood review is regarded as a single document, and for a collection of reviews, the LDA method is applied to infer a mixture of latent topics that could have generated those perceptions. These topics are later used for grouping reviews according to the words comprising each review.

LDA is based on two major assumptions: (i) each document is comprised of a mixture of topics; (ii) every topic is made up of a mixture of words. The LDA algorithm begins with specifying the number of k (topics) which should be determined a priori by a researcher. For this, a number of models with different values of k ranging between 5 and 100 (by increments of 5) are developed. A final model is selected based on the perplexity measure which attempts to evaluate model performance by calculating the inverse log-likelihood of previously unseen testing documents (Blei et al. 2003). Better models tend to have lower perplexity values, which indicate less uncertainties about the unseen testing dataset. After determining the suitable value of k for the model, the algorithm repeatedly samples the words from a corpus of documents for identifying associations among different words. Then the algorithm assigns every word to temporary topics in a probabilistic manner. In the following steps, by looping through each word in all documents, the algorithm continues to update topic assignments based on two criteria – 1) frequency of a word across topics and 2) proportion of topics in a given document where that word appears. Through this iterative updating, the model gradually becomes more internally consistent, and this process stops when the model reaches its equilibrium. For a higher-level technical discussion of LDA, one is referred to Blei (2012); Blei et al. (2003).

3.4.3. Method2: K-means clustering

As stated in the introduction, one of the major aims of this study is to examine the relationship between objective mental health vulnerability and residents’ subjective perceptions. For measuring objective mental health vulnerability, the neighborhood typologies are developed by employing a K-means clustering approach. The K-means method is one of the most commonly used unsupervised clustering algorithms, which aims to cluster data into the k -number (which must be specified a priori) of clusters based on feature similarity. For this study, the algorithm is based on the four sets of census variables that represent neighborhoods’ socioeconomic status, residential stability, housing, and demographic characteristics (see Table 5 for the complete list of variables). The variables selected for this analysis are consistent with the previous mental health studies (see Hill and Maimon, 2013).

Prior to this analysis, the issue of boundary discrepancy (between the census and Ontodia shapefiles) needs to be addressed. To that end, this study employs the apportionment-by-area approach which involves the following steps: first, the two boundary shapefiles are intersected, and the new geometries (shape areas) for newly divided census tracts are computed; second, the original census tracts, if crossed by the ‘Ontodia’ boundaries, are apportioned to new shapes according to proportionate shape area size (e.g., $\text{population 2010} * \text{new-shape-area} / \text{original-total-shape-area}$); third, these newly assigned census values are aggregated at the Ontodia-defined neighborhood level to which the K-means algorithm are applied for developing neighborhood typologies. All variables are standardized prior to the analysis. Finally, the results from the LDA analysis are summarized by the neighborhood typologies in order to compare objective mental health vulnerability with residents’ subjective perceptions. The workflow of this process is illustrated in Figure 12.

Table 5. Variables used to measure ‘neighborhood mental health vulnerability’

<i>Dimension</i>	<i>Variables used</i>	<i>Source</i>	<i>Label</i>
<i>Neighborhood socioeconomic disadvantage</i>	Percentage of residents who have less than high school degree	The U.S. Census Bureau	Education
	Percentage unemployment		Unemployment
	Percentage of female headed households		Female-headed
	Median household income		Income
	Percentage of residents living below the poverty line		Poverty
	Percentage manufacturing employment		ManuEmploy
<i>Residential stability</i>	Percentage owner-occupied household	The U.S. Census Bureau	HomeOwner
	Percentage of residents who lived in the same tracts more than 15 years		Duration
	Percentage of residents living in apartment units		Multiunit
<i>Housing characteristics</i>	Percentage of structures built more than 35 years ago	The U.S. Census Bureau	YrStrBuilt
	Percentage vacant housing units		Vacancy
	Median home values		HomeValue
Demographic Characteristics	Percentage White	The U.S. Census Bureau	White
	Percentage Black		Black
	Percentage Asian		Asian
	Percentage Hispanic		Hispanic
	Percentage Other		Other

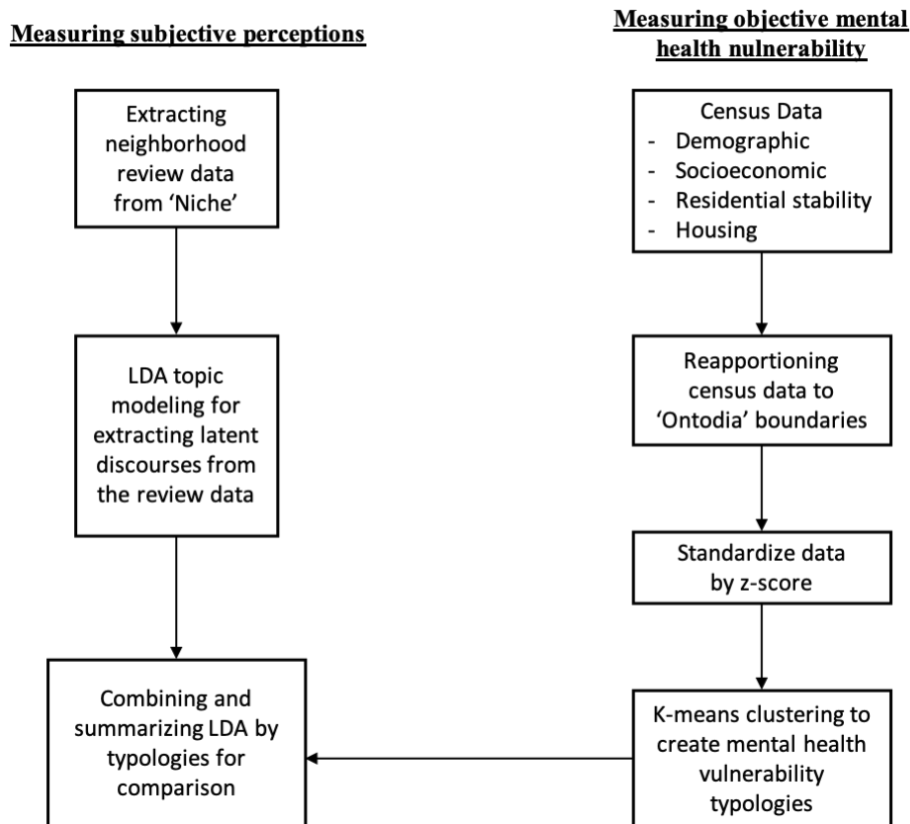


Figure 12. Workflow for comparing objective mental health vulnerability and subjective perceptions

3.5. Findings and results

The LDA algorithm has identified a total of 19 distinct topics. Main themes for each topic were determined by examining i) most common words for each topic and ii) reviews with higher topic probabilities. To identify new topics, these 19 topics were first examined in light of the existing theoretical frameworks (see Hill and Maimon, 2013). Accordingly, these topics were categorized into i) neighborhood structure, ii) social organization, and iii) neighborhood disorder categories. The results indicate that 5 topics (3, 14, 6, 8, and 13) fall into neighborhood structure category; 2 topics (2, 13) to neighborhood social organization category; 3 topics (4, 10, and 9) to neighborhood disorder category. In addition, there were 3 topics (1, 5, and 17) which can be categorized into an ‘overall neighborhood experience’ category. Finally, there were 6 topics (7, 11, 15, 16, 18, and 19) that did not neatly fit into any of the above categories, therefore those were classified as new topics – the discovery of which was the main objective of this study.

3.5.1. Topics regarding neighborhood structure (3, 14, 6, 8, 13)

1) Topic 3: local businesses, public service, and their qualities

Ten most frequent words for this topic included local, businesses, qualities, average, service, buildings, provide, and improve. Many reviews in this topic talked about the presence or availability of local businesses and public service. For instance, one reviewer from Bayside said

“There are a lot of local businesses in Bayside. Most of the residents depend on these local businesses. They are pretty decent and provide many good services.” This topic was classified into ‘neighborhood socioeconomic structure’ category because the existing theory closely connects socioeconomic disadvantage (i.e., not enough tax revenue, a lack of consumer bases) with low quality municipal services (Robert 1999) and less viable local businesses (Hanlon and Vicino 2007; Hill and Maimon 2013). This theory further argues that socioeconomic disadvantage could negatively influence residents’ mental health primarily by limiting their opportunities for upward socioeconomic mobility (Robert 1999).

2) Topic 14: small family-owned businesses; convenience

Ten most common words for topic 14 included stores, shops, store, grocery, shopping, convenient, supermarkets, drug, variety, and corner. Many reviews in this topic talk about a variety of family owned small stores in a neighborhood and the convenience they bring to residents. For instance, a reviewer from Jackson Heights said “We can pretty much get everything here. We have supermarkets, rite aid, drug stores, salons, clothing stores, retail store.” Similar to topic 3, the presence of a variety of small family owned businesses can also be greatly influenced by the socioeconomic disadvantage of a neighborhood. This aspect could potentially undermine residents’ mental health because having to travel a long distance for satisfying their daily needs can be stressful and frustrating especially for those who are with restricted mobility and disabilities. Furthermore, the presence of such small businesses in a neighborhood can be perceived as a sign of neighborhoods’ vitality and liveliness, which in turn may positively contribute to residents’ mental health outcomes.

3) Topic 6: neighborhood foodscapes

Ten most common words representing this topic included food, restaurants, fast, options, variety, bars, eat, Chinese, pizza, and healthy. Many reviews belonging to this topic talk about food availability, kinds of foods available in a neighborhood, and their qualities. For example, a reviewer from Williamsbridge said “the food and drink near this area is excellent.” Another reviewer from Concourse Village left a review regarding food quality, “Although many people enjoy and indulge on these tasty fast-foods, they are unaware how these foods can cause damage to their health if it is not eaten in moderation.” In general, neighborhood foodscapes are certainly related to and influenced by the viability of local businesses (as with topic 3 & 14) and neighborhood socioeconomic structure. In addition, the availability of healthy food and perceptions thereof can bring direct consequences on residents’ physical health, the well-being of which could also greatly affect residents’ mental health outcomes.

4) Topic 8: neighborhood employment opportunities

Ten most frequent words for this topic included job, jobs, opportunities, hard, employment, amount, college, retail, low, and decent. Many reviews in this topic were concerned about several different aspects of neighborhood employment opportunities (i.e., availability of jobs, pay grade, etc.). For instance, one reviewer from East Harlem said, “There do not seem to be many opportunities for employment around the area.” Another reviewer from Canarsie wrote “While, a job can be obtained in the area, the pay grade will not allow for anything above below average lifestyle.” As with the above three topics, this theme also falls into neighborhood structure category and can influence residents’ mental health in a very similar way.

5) Topic 13: school districts and their qualities; best neighborhoods to raise a family

Ten most common words representing this topic included family, school, schools, home, children, families, kids, middle, environment, and residents. This topic mostly concerns quality of school districts and if a neighborhood is family-oriented. These aspects of a neighborhood, like other topics in this category, are largely determined by neighborhood socioeconomic structure. A reviewer from Battery Park City said, “Today, it’s one of the best places in NYC, if not the US, to raise kids. The great schools, convenient parks, water views, little league - residents have convenient access to everything that once drove them to the suburbs, especially if they have kids.” Regarding school quality, another reviewer from Wakefield wrote “I want to move out the area. ... If you send your kids to the schools in the area, their personality will quickly change for the worse, and they will most likely graduate high school with a low GPA.”

3.5.2. Topics regarding neighborhood social organization (2, 12)

1) Topic 2: people in a neighborhood

Ten most common words for this topic included people, bad, friendly, tend, stay, worse, care, a lot, fine, and bit. According to the theory, people can be greatly hindered from developing meaningful social relationships (or social organizations) if they have negative attitudes (e.g., mistrust, indifference, or hostility) towards other residents (Hill and Maimon 2013). Also, an empirical evidence supports that neighborhood poverty is closely related to weaker social ties among neighbors (Ross et al. 2000). Many reviews in this topic indeed reflect this aspect. For instance, one reviewer from Arverne said “There are people with positive attitudes but for the most part that is not the case. I know the reason is because they are struggling too much, that they don’t have the ability to put up a fake smile and help others.” If this perpetuates over time, it may possibly result in further social isolation (Geis and Ross 1998; Kim 2010; Ross and Mirowsky 2009) or negative mental health outcomes (Mirowsky and Ross 2003).

2) Topic 12: a sense of community

Ten most common words for this topic included community, time, friendly, people, neighbors, events, sense, pets, pet, and strong. The main theme of this topic is “a sense of community,” which can be regarded as one of the most important prerequisites for collective efficacy (or social organization). Many reviewers, as the theory expects, talked about a sense of community within the context of residential stability – generally, the longer people live in a neighborhood, the stronger the sense of community. For instance, one reviewer from ‘Harlem’ wrote “this neighborhood is extremely family oriented. Most of us have known each other growing up, so through all negative circumstances we remain united.” Another reviewer from ‘Corona’ said “a sense of community is good. Everyone knows and respects each other.” Unlike negative psychological dispositions, a sense of community (or belonging) positively contributes to mental health (Stafford et al. 2011).

3.5.3. Topics regarding neighborhood (social/physical) disorder (4, 10, 9)

1) Topic 4 & 10: neighborhood social disorder, crime, and perceptions of safety

The topic 4 and 10 are mostly concerned about perceptions of safety in the context of neighborhood crime. Topic 4 is more about neighborhood crime itself while topic 10 concerns more about perceptions of safety. Topic 4 is largely represented by words such as crime, police, safety, rate, and happen. Topic 10 is represented by words like safe, feel, dangerous, night, and

walking. It has been known that individuals living in a high-crime neighborhood are more likely to perceive others as threats and enemies, which can have negative impacts on their mental health (Mirowsky and Ross 2003; Ross and Mirowsky 2009). For instance, one reviewer from ‘Concourse Village’ wrote “...it is a horrible experience living in a community where anything violent can unpredictably happen, even when there are small children around.” And regarding the perceptions of safety, a reviewer from ‘Brownsville’ wrote “The cops are always around which makes me feel safe especially when I am walking home from the train late at night. They make me feel safe, and they are there when you need them.” The longer the people live in a same neighborhood, the stronger the sense of community”

2) Topic 9: housing, housing qualities, signs of physical disorder

Ten most common words for this topic included houses, housing, building, rent, expensive, apartment, cost, affordable, apartments, and homes. Many reviews belonging to this topic talked about the generalities of neighborhood housing characteristics, and yet a large number of reviewers wrote explicitly about neighborhoods’ structural dilapidation, the presence of abandoned properties, street garbage, all of which can be regarded as indications of neighborhood physical disorder (Hill and Maimon 2013). Such signs and perceptions thereof could negatively influence mental health, and this can possibly happen through a sense of powerlessness as discussed earlier (Benassi et al. 1988; Mirowsky and Ross 2003). One reviewer from Williamsburg wrote “It doesn’t seem like there are vacant or abandoned properties, but it is not a clean area. A lot of garbage on the sidewalk... hope there are more cleaners who keep the neighborhood clean. There are a lot of old buildings that needs renovations.”

3.5.4. Topics regarding overall neighborhood experience (1, 5, 17)

1) Topic 1, 5, 17: things to do, tourist attractions, livability, overall experience

Ten most common words for topic 1 included city, York, living, Brooklyn, island, beautiful, NYC, located, and Staten. Many reviews in this topic concerned place names such as NYC, Brooklyn, Staten Island, etc., things to do, and major tourist attractions in those places. One of the most representative reviews (a reviewer from East Village) said “... there are inspiring places to go, like cultural hub that is Washington Square Park; and there are so many museums where you can learn new things and appreciate art and culture from all over the world...” The reviews belonging to topic 5 and 17 mostly concerned overall neighborhood experience. The most common words for both topics included live, living, neighborhood, and nice. For instance, one reviewer from Oakwood said “I grew up here, so I do like it a lot. I live in a pretty safe area with great choices for schools. I would definitely live here again...”

3.5.5. New topics (7, 11, 15, 16, 18, 19)

1) Topic 7: neighborhood change, gentrification

Ten most common words for topic 7 included neighborhood, Harlem, experience, moving, east, due, change, culture, and growing. Many reviews in this topic primarily concerned neighborhood changes and gentrification. Interestingly, people had varying sentiments and opinions about gentrification. Some were excited or neutral while others were threatened by it. For example, one reviewer from Harlem expressed positive sentiments about ongoing neighborhood changes, expressing “Growing up in Harlem was a fun and educational experience.... During the years there are a lot of changes from a rather dangerous neighborhood to an attractive place to live...” In contrast, another reviewer from East Harlem said “...but the

real issue is all the gentrification in NYC white people are moving into the parts of the city that were inhabited by black/Hispanics... are being changed drastically... people are being forced out of the neighborhood because white people are moving in and the rent is being raised due to this.” These results clearly indicate that gentrification is perceived by many residents (sometimes positively, sometimes negatively), and therefore it could bring real consequences on people’s mental health outcomes.

2) Topic 11: weather, natural disasters

Ten most common words for topic 11 included weather, bad, winter, summer, cold, pretty, snow, hot, natural, and due. Many reviewers in this topic expressed their feelings or perceptions about various weather-related events or natural disasters that they experienced in their neighborhoods in the past. For example, one reviewer from ‘Astoria’ said “It rains a lot, and when it comes to a storm, the removal takes up to two weeks.” Another reviewer from Elmhurst wrote “...summer gets really humid and hot, I hate the summer in NYC.” Regarding natural disaster, another reviewer expressed “I am not near the water, so I don’t have to worry about flooding.” These examples clearly show people’s awareness (or perceptions) of such events.

3) Topic 15: neighborhood diversity

Ten most common words for topic 15 included love, diverse, queens, heights, neighborhoods, amazing, Astoria, cultures, and world. Many reviewers within this category expressed their perceptions or opinions about neighborhood diversity or things to do with regard to diversity (e.g., cultural activities, exotic foods, festivals, etc.). Interestingly, a majority of them perceived diversity positively and as something to be celebrated. For instance, one reviewer from ‘Jamaica’ said “...the neighborhood reflect diversity. That is why I love Queens...” Another reviewer from ‘Flushing’ also wrote “...the best thing about living in Flushing is the diversity and culture. Knowing that there is a story behind every stranger you wave and being a part of the community.” As with other new topics, if diversity is perceived by residents, its implications for mental health need be examined in the future studies.

4) Topic 16: public parks, green space, and their qualities

Ten most common words for topic 16 included park, parks, clean, nearby, activities, gyms, enjoy, play, outdoor, and active. Many reviews in this topic talked about the presence of public parks and green space and their qualities. For instance, one reviewer from East Morrisania said “we do have several parks and recreational centers with fields, ... several events to promote good health are also things that may occur in our parks as well as free concerts supporting a good cause.” Sometimes, it could be the presence of green space (or natural environmental quality in a more general sense) itself that can promote better mental health. For instance, one reviewer from Flushing expressed “There are many beautiful trees and animals that can be seen...,” which clearly indicate that such natural amenities are perceived by residents, thus having implications for mental health studies.

5) Topic 18 & 19: transportation, walkability, accessibility

The most common words for topics 18 & 19 include transportation, train, easy, subway, bus, walk, street, traffic, and busy. These two topics mostly concerned transportation, accessibility, and walkability. Regarding public transportations, one reviewer from Springfield Gardens said “There are no trains that are less than a half hour bus ride away, and no busses less than a 5 min walk away. It may not seem like much, but in extreme weather, you can tell.” In addition, there

were some reviewers who also expressed their perceptions about neighborhood walkability. For instance, a reviewer from West Village said “what I like most about New York City is the walkability...” Another reviewer from Crown Heights also said, “It is easy to walk to places because there are so many stores nearby...” Peoples’ perceptions toward such aspects of a neighborhood could certainly influence their stress levels, therefore having implications for mental health, too.

3.5.6. The spatial distribution patterns of topics

Next, the spatial distribution patterns of these 19 topics were examined in light of neighborhood mental health vulnerability typologies. For developing the typologies, K-means clustering algorithm was applied to the variables listed in Table 5. The optimal value for k was determined by comparing the total within-cluster sum of squares (wss) for each k . The result suggested that a $k = 5$ had the best discriminating power, and its corresponding clustering results are depicted in Figure 13. Lastly, the frequency of 19 topics was summarized at the typology level (see Table 6).

1) Typology 1 (Low QoL - I)

Overall, this typology possesses lower quality of life in terms of mental health vulnerability. The neighborhoods within this category tend to display lower socioeconomic status (i.e., below-average educational attainment, higher rates of unemployment and female-headed household, etc.), higher residential instability (i.e., lowest homeownership rate, higher percentage of short-term residents), and low housing qualities (i.e., higher percentage of older housings, below-

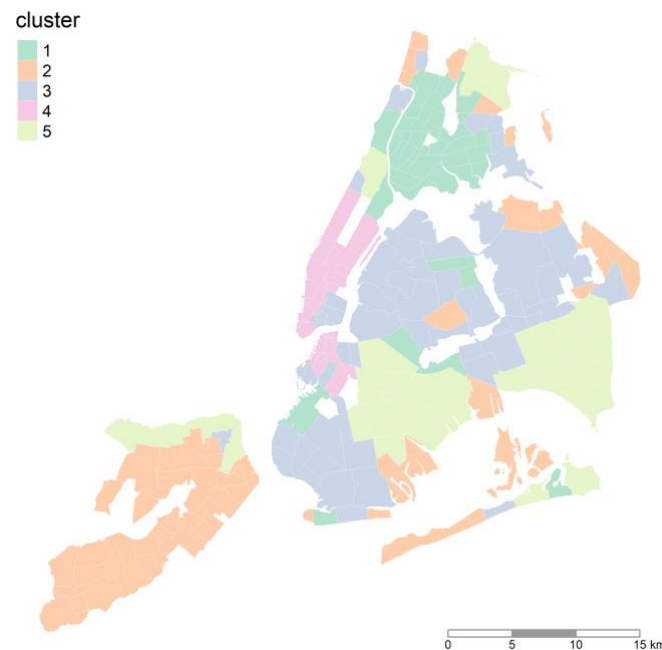


Figure 13. Neighborhood Mental health vulnerability typologies in New York City

average median housing values). This typology had significantly higher Hispanic and above-average Black representation. Spatially, the majority of typology 1 neighborhoods are clustered in ‘uptown’ Bronx area as shown in Figure 13 above. As Table 6 shows, a total of 1,823 reviews belonged to this typology. The topics that appear with relatively high frequency for this typology include topic 4 (crime, 175 reviews), topic 6 (neighborhood foodscapes, 119 reviews), and topic 8 (employment, 106 reviews). Among the new topics, topic 11 (weather & natural disasters, 77 reviews) and topic 16 (public parks & green space, 75 reviews) appeared with relatively high frequency.

2) Typology 2 (High QoL)

In general, the neighborhoods in this typology tend to display lower mental health vulnerability (therefore, high QoL) as indicated by relatively higher socioeconomic status, residential stability, and average housing characteristics. This typology has the highest concentration of Whites. Figure 13 suggests that a majority of typology 2 neighborhoods is concentrated in Staten Island. A total of 531 reviews belonged to this typology. Two most frequently discussed topics were topic 4 (crime, 43 reviews) and topic 6 (neighborhood foodscapes, 27 reviews). Among the new topics, 5.3 % of reviews (highest among the new topics) belonged to topic 11 (weather & natural disasters, 28 reviews).

3) Typology 3 (Average QoL)

Typology 3, in general, displays an average level of neighborhood mental health vulnerability except for its relatively higher representations of manufacturing employments and older housing structures. Asians are the majority racial/ethnic group in this typology. Spatially, those neighborhoods are mostly concentrated in Queens and in the southern half of Brooklyn borough (Figure 13). As shown in Table 6, a total of 2,497 reviews came from typology 3 neighborhoods. Residents from this typology talked most frequently about family-owned businesses (topic 14, 130 reviews) and neighborhood crime (topic 6, 174 reviews). Three of the most frequently discussed new topics included topic 11 (weather & natural disasters, 116 reviews), topic 18 (transportation & accessibility, 113 reviews), and topic 15 (diversity, 94 reviews).

Table 6. Topic distribution according to the vulnerability typologies

<i>Dimension</i>		<i>Number (%) of reviews for Typologies</i>				
<i>Topics</i>		<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>
	<i>Total Reviews</i>	1,823	531	2,497	488	2,257
<i>Topics regarding neighborhood socioeconomic structure</i>	Topic 3: local businesses, public service	58 (3.2)	16 (3)	67 (2.7)	15 (3.1)	66 (2.9)
	Topic 14: family-owned businesses	68 (3.7)	22 (4.1)	130 (5.2)	23 (4.7)	94 (4.2)
	Topic 6: neighborhood foodscapes	119 (6.5)	27 (5.1)	115 (4.6)	22 (4.5)	119 (5.2)
	Topic 8: employment	106 (5.8)	19 (3.6)	105 (4.2)	20 (4.1)	103 (4.6)
	Topic 13: places to raise a family, school	44 (2.4)	21 (4)	54 (2.2)	11 (2.3)	52 (2.3)
<i>Topics regarding neighborhood social</i>	Topic 2: people in a neighborhood	47 (2.6)	12 (2.6)	56 (2.2)	7 (1.4)	54 (2.4)
	Topic 12: sense of community	67 (3.7)	19 (3.6)	75 (3)	12 (2.5)	87 (3.9)
<i>Topics regarding neighborhood social/physical disorder</i>	Topic 4: crime	175 (9.6)	43 (8.1)	174 (7)	22 (4.5)	170 (7.5)
	Topic 10: perceptions of safety	53 (2.9)	20 (3.8)	85 (3.4)	18 (3.7)	83 (3.7)
	Topic 9: housing qualities	70 (3.8)	17 (3.2)	109 (4.4)	16 (3.3)	115 (5.09)
<i>Topics regarding overall neighborhood experience</i>	Topic 1: things to do, city life	36 (2)	23 (4.3)	72 (2.9)	31 (6.4)	49 (2.2)
	Topic 5: overall experience	47 (2.6)	7 (1.3)	70 (2.8)	8 (1.6)	59 (2.6)
	Topic 17: livability, living quality	29 (1.6)	16 (3)	64 (2.6)	9 (1.8)	55 (2.4)
<i>New topics</i>	Topic 7: neighborhood Change	29 (1.6)	5 (1)	44 (1.8)	23 (4.7)	68 (3)
	Topic 11: weather, natural disasters	77 (4.2)	28 (5.3)	116 (4.6)	18 (3.7)	105 (4.7)
	Topic 15: diversity	39 (2.1)	7 (1.3)	94 (3.8)	13 (2.7)	39 (1.7)
	Topic 16: public parks, green space	75 (4.1)	15 (2.8)	100 (4)	29 (5.9)	74 (3.3)
	Topic 18: transportation, accessibility	46 (2.5)	20 (3.8)	113 (4.5)	21 (4.3)	77 (3.4)
	Topic 19: walkability	42 (2.3)	12 (2.3)	60 (2.4)	14 (2.9)	43 (1.9)

4) Typology 4 (Urban High QoL)

The neighborhoods in typology 4 displayed the highest socioeconomic status, median home values, and a higher percentage of newly constructed buildings. However, their residential stability was very low. A majority of typology 4 neighborhoods were located in Manhattan borough (Figure 13). Racially, Whites comprised a majority of its population. A total of 488 reviews belonged to the typology 3 neighborhoods. One of the most frequently discussed topics was topic 1 (things to do & city life, 31 reviews). Among the new topics, topic 7 (neighborhood change, 23 reviews) and topic 16 (public parks & green space, 29 reviews) appeared with relatively higher frequency.

5) Typology 5 (Low QoL - II)

Typology 5 neighborhoods displayed socioeconomic disadvantage, average residential stability and housing characteristics. Spatially, typology 5 neighborhoods were largely concentrated in the eastern part of Queens as well as in the northern-half of Brooklyn borough (Figure 13). Blacks comprised a majority of its population. As shown in Table 6, a total of 2,257 reviews belonged to this typology. Residents from this typology talked most frequently about neighborhood crimes (topic 2, 170 reviews), foodscapes (topic 6, 119 reviews), housing qualities (topic 9, 115 reviews), and employment opportunities (topic 8, 103 reviews). Among the new topics, topic 11 (weather & natural disasters, 116 reviews) was the most frequently mentioned public discourse.

3.6. Discussion and conclusions

This study, by employing a topic modeling approach, explored the neighborhood textual review data in order to unearth more of neighborhood contextual factors that are perceived to be important by residents. As stated earlier, unless the reality is perceived as important by residents, it is less likely to bring real consequences upon their mental health outcomes (McEwen and Lasley 2002). Thus, identifying more of such perceptions – the primary purpose of this study – could have significant implications for expanding our current understanding of neighborhood effects on mental health. The LDA algorithm employed in the current study unearthed a total of 19 topics. When they were examined through the existing theoretical frameworks (see Hill and Maimon 2013), 6 of them turned out to be new topics: neighborhood change, diversity, weather and natural disasters, public parks and green space, transportation and accessibility, and walkability.

First, this study found that a large number of reviewers talked about gentrification. As clearly expressed by some reviewers, gentrification, by transforming a neighborhood into a more attractive place to live, may bring positive influences on people's mental health. In contrast, gentrification, by causing displacement of socioeconomically vulnerable populations, may also bring adverse effects on their mental health. In fact, one recent study conducted in New York City area found that displaced people (through gentrification) are twice more likely to be hospitalized for mental illnesses than those who stay in their neighborhoods (Lim et al. 2017).

Second, neighborhood diversity (e.g., diverse culture, foods, festivals, etc.) was also perceived to be one of the important aspects of a neighborhood by many reviewers. A majority of reviewers expressed diversity with positive sentiments. The existing theories, however, do not explicitly talk about diversity and its effects on mental health outcomes. The closest connection to diversity is found in their discussion of residential segregation. For example, Shaw and

McKay (1942) viewed ethnic heterogeneity (in its relation to socioeconomic disadvantage) as one of the key factors that may lead to social disorganization. Others viewed minority concentration (in conjunction with neighborhood poverty) as a predecessor of neighborhood social and physical disorder (Massey and Denton 1989; Sampson et al. 1997). In fact, some reviewers expressed their concerns about language/cultural barriers as potential hindrances to further social integration. However, as hinted by a majority of other reviewers, it is possible that diversity (or ethnic heterogeneity) could also bring positive impacts on mental health.

Third, the discourses regarding natural disasters and extreme weather events (e.g., hurricanes, flooding, a heat wave, etc.) were also identified as new topics by the LDA algorithm. Though such events take place at scales greater than a neighborhood, residents' perceptions toward such external stresses could significantly vary depending on the preparedness (e.g., collective efficacy and social organization) or the available resources within a neighborhood. Thus, this theme also has relevance in the study of 'neighborhood effects' on mental health. Next, from a mental health perspective, natural disasters, by causing the destruction of one's properties or the loss of loved ones, can have devastating effects on people's mental health. Studies have found that natural disaster is associated with an increase in post-traumatic disorder (PTSD) (Scaramutti et al. 2019; Boscarino et al. 2013). According to American Psychiatric Association (APA), the typical symptoms of PTSD may include ongoing fear, distressing dreams, or negative thoughts and feelings. Also, disasters can potentially bring damage to mental health through substance abuse. For instance, in New Orleans after Hurricane Katrina, the annual hospitalization rate due to substance abuse disorders significantly increased (Moise and Ruiz 2016). In addition, as discussed earlier, it may be through 'a sense of powerlessness' (when feeling overwhelmed by traumatic disasters) or 'mistrust' (by hurting social trust that is necessary to effectively cope with such events) that natural disasters can take their toll on mental health.

Fourth, neighborhood physical environmental quality (e.g., green space, public parks) and neighborhood accessibility (e.g., transportation availability, walkability) were also identified as new topics. All these factors can also be regarded as important mental-health-promoting neighborhood attributes. For example, green space is known to benefit mental health by restoring us from mental fatigue (Berman et al. 2008; Hartig et al. 1991; Hartig et al. 2003; Taylor and Kuo 2009), relieving stress (Roe et al. 2013; Thompson et al. 2012), promoting social support and cohesion (Kim and Kaplan 2004; Maas et al. 2009; Pretty et al. 1994; Prezza et al. 2001), and by acting as buffers between external stressors and health outcomes (Van Den Berg et al. 2010), etc. Likewise, a positive association was found between accessibility and mental health. In particular, Sarkar et al. (2013) found that higher-level neighborhood accessibility was associated with reduced psychological distress. Berke et al. (2007) also found that depressive symptoms (in men) were significantly related with neighborhood walkability.

As Thomas and Thomas (1928) argue, situations have real consequences when they are perceived (or defined) as real. This study shows that all these new themes (i.e., gentrification, diversity, natural disasters, neighborhood environmental quality, walkability) are clearly perceived by residents. Therefore, it can be reasonably argued that those factors are highly likely to bring substantial impacts upon people's mental health outcomes. As hinted above, all these factors (with exceptions of gentrification and racial/ethnic diversity) and their impacts on mental health have already been tested by different bodies of literature. However, what is still lacking is a comprehensive approach to incorporate all relevant control variables in a single study. In future mental health studies, an all-inclusive/comprehensive approach is warranted in order to gain a

more holistic understanding of neighborhood-level mental health vulnerability and also to obtain statistically unbiased estimates of neighborhood effects on mental health.

There are several important limitations to this study. First, the dataset used for this study suffers from sampling biases. As a result, some neighborhoods are overly represented while other neighborhoods are significantly under-represented. As such, the results for the spatial distribution patterns of topics (as described in 5.6) should only be regarded as suggestive rather than conclusive. Second, due to the absence of demographic and socioeconomic profiles of the reviewers, it is not possible to examine perception differences among different population groups. Sampson and Raudenbush (2004)'s study, for example, showed that whites, younger, divorced, and female residents tend to perceive more of neighborhood disorders, whereas blacks tend to perceive less of neighborhood disorder. Such aspects cannot be tested using the current dataset. However, this lack of representativeness in no way nullifies the significance of these findings. This study, with the sample size of 7,673 reviews and an average of 33 reviews per neighborhood, may have already reached a saturation point – the point at which no additional information is discovered from the data (Guest et al. 2006)". In general, for grounded theory research, a sample size of 20 ~ 30 is recommended in order to sufficiently address the research questions (i.e., reaching saturation point) (Creswell 1998). After manually examining most of the reviews, no additional new themes were identified than those already discovered by the LDA algorithm.

In conclusion, this study brings significant contributions to the existing body of literature by highlighting the values of neighborhood textual review data for the study of people's perceptions; by unearthing the new neighborhood contextual factors as initially intended; and by examining the spatial distribution patterns of topics in light of objective neighborhood mental health vulnerability. Most importantly, the new knowledge obtained from this study is expected to offer valuable insights for the enhancement of our current theoretical understanding of the neighborhood effects on mental health.

CONCLUSION

Chapter I “Developing neighborhood mental health vulnerability typologies: integration of socioeconomic and physical environmental factors”

There is a growing body of literature that examines the impact of neighborhood environment on mental health. However, as identified through a review of the literature, their discussion on neighborhood contexts are mostly limited to socioeconomic factors. As such, neither the significance of neighborhoods’ physical environment nor its associations to socioeconomic factors have received the attention they deserve. In light of these shortcomings, the first chapter of this dissertation has attempted to holistically assess neighborhood mental health vulnerability by incorporating a neighborhood physical environmental dimension (i.e., NDVI, LST, and pollution burden). Its primary aims were to develop theoretically justifiable QoL (or mental health vulnerability) typologies and investigate relationships among the five major neighborhood QoL domains.

A self-organizing map analysis has revealed new patterns and relationships among different vulnerability indicators whose importance have largely been overlooked in previous mental health studies. The study results show that:

- neighborhood structural disadvantage is not always related with residential stability;
- neighborhood socioeconomic disadvantage does not always lead to social disorder;
- pollution burden displays strong correlations with both residential stability and instability;
- socioeconomic advantage does not always indicate higher environmental quality.

To sum up, this study contributes to literature by proposing a more comprehensive way to assess neighborhood mental health vulnerability. The findings from this study suggest that the reality of neighborhood mental health vulnerability is far more complicated than our current theoretical understanding. In other words, though neighborhood structure may be a major determining factor for social organization and neighborhood disorder, and possibly pollution burden, this is not without exceptions. And these exceptions do not seem negligible and certainly demand further investigation in future mental health research.

Chapter II “Neighborhood mental health vulnerability and its association with racial/ethnic residential segregation”

In the United States, minority concentrations have usually been associated with socioeconomic disadvantage, a lack of social cohesion, neighborhood disorder, and environmental degradation. From a mental health perspective, all these factors could potentially influence minorities’ mental health in a very negative way. Though this relationship may sound obvious, a review of the literature has revealed that there is still a lack of systematic understanding as to the ways in which the minority concentrations and neighborhood mental health vulnerabilities are related to one another. Hence, the second chapter of this dissertation aimed to systematically examine the relationships between neighborhood mental health QoL indicators and racial/ethnic residential segregation using Los Angeles County as a case study. As a first step, the spatial distribution patterns of residential segregation were visually examined in comparison to the mental health QoL typologies. Then, these relationships were statistically tested through a multinomial logistic regression analysis.

As expected, minority concentrations were significantly related to socioeconomic disadvantage, pollution burden, and crimes. However, different from our theoretical expectations, these relationships were manifested in a more complicated way. For instance:

- Hispanic neighborhoods, though socioeconomically and environmentally most disadvantaged, tend to have relatively lower crime rates;
- Asian neighborhoods, though socioeconomically better off than other minority-concentrated neighborhoods, tend to have relatively higher levels of pollution burden and crime density;
- Black neighborhoods were socioeconomically less disadvantaged and bear less pollution and crime burden than their mixed minority and Hispanic counterparts;
- The mixed minority neighborhoods, in general, displayed relatively higher levels socioeconomic disadvantage, pollution burden, and crime density.

These findings are expected to offer valuable insights into future confirmatory statistical analyses by helping them to tease out causal relationships (between mental health and neighborhood contexts) in a more precise way. Results from this study could also help policy makers and public health practitioners to come up with more effective and targeted intervention plans.

Chapter II “Neighborhood perceptions and mental health: exploring residents’ perceptions for the discovery of more neighborhood contextual factors”

Previous mental health studies, in their attempts to measure residents’ perceptions, have mostly relied on interviews and survey questionnaires. However, one of the major limitations of such approaches is that only the theory-relevant questions are addressed in a study. This has hindered them from discovering other potentially important neighborhood contextual factors that may help enhance our understanding of neighborhood effects on mental health. In light this shortcoming, the third chapter of this dissertation, using New York City as a case study, aimed to explore the neighborhood textual review data for the purpose of unearthing more of neighborhood contextual factors that are perceived as important by residents. Topic modeling algorithm employed in this study has identified a total of 19 topics. When these were examined through the existing theoretical frameworks, 6 of them turns out to be new topic, which include: ***neighborhood change, diversity, weather and natural disasters, public parks and green space, transportation and accessibility, and walkability.***

As explained before, situations have real consequences only when they are perceived (or defined) as real. This study shows that all these new themes are clearly perceived by residents. Therefore, it can be reasonably argued that these factors are also highly likely to bring substantial impacts on residents’ mental health outcomes. It should be noted that all these factors (with exceptions of gentrification and racial/ethnic diversity) and their impacts on mental health have already been discussed by different bodies of literature. However, what is still lacking is a comprehensive approach to incorporate all relevant control variables in a single study. In future mental health studies, an all-inclusive/comprehensive approach is warranted in order to gain a more holistic understanding of neighborhood-level mental health vulnerability and to obtain statistically more accurate estimates of neighborhood effects on mental health.

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VITA

Donghee Koh was born and raised in Jeju, South Korea. He received his Bachelor of Arts degree in Geography from Jeju National University in 2011. He came to the United States in 2012 and received his Master of Arts degree in Geography from Western Illinois University in 2014. He moved to Knoxville, TN, in 2015 to pursue his Doctor of Philosophy degree in Geography. Donghee Koh's research interests center around GIS, mental health, and racial/ethnic residential segregation.