Spatial Analysis of Geographic Variation in Mental Health Visits and Its Association with Social and Built Environment in Toronto Neighbourhoods

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Authors Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Introduction: Mental health is a growing concern in Canada. Existing studies that examine mental health related factors generally focus on individual-level characteristics, which often neglect contextual and spatial effects. This study explores the geographic variation in mental health visits (MHV) in Toronto and identifies the social and built environment factors associated with MHV at the neighbourhood level adopting spatial analytical methods.

Methods: MHV are defined as individuals aged 20+ having had a mental health and addictions related primary care visit according to physicians' billing claims during the 2011 and 2012 fiscal years. MHV data were retrieved from the Toronto Community Health Profiles; social and built environment factors derived from various original data sources were obtained from the Toronto Community Health Profiles and Toronto Open Data. The Global Moran's I Statistic and Kulldorff's Spatial Scan Statistic were applied to evaluate the overall geographic variation in MHV and detect the locations of high and low risk clusters for MHV, respectively. This study quantified the effects of social and built environment on MHV fitting two spatial regression models, the spatial error model and the spatial lag model. All-subset selection using BIC as the selection criterion was employed as an ancillary tool to help determine which factors are most important to the relationships between social and built environment and MHV.

Results: Overall, the geographic distribution of MHV exhibited a clustering pattern, and the locations of hot and cold spots for MHV were further identified and visualized in Toronto neighbourhoods. Two social factors and two built environment factors were identified as the most salient factors affecting MHV. Income inequality and the proportion of households in need of major repairs were associated with increased MHV, while the proportion of East Asian residents and the number of health providers per 10,000 residents were negatively correlated with MHV. The spatial regression models showed superior performance compared to the non-spatial OLS model, and the spatial lag model provided the best model fit as indicated by BIC.

Conclusions: This study indicates that both social and built environment factors can contribute to variation of population mental health. The results can provide useful strategy basis for both locally tailored and general population mental health promotion programs. The cluster maps that visualized specific areas of high mental health concern can be utilized to target neighbourhoods in need of more focused investigations and mental health initiatives. Stakeholders may develop appropriate campaigns that serve to improve mental health in neighbourhoods with high levels of income inequality and deliver culturally tailored mental health services in East Asian communities. The findings also point to the need to improve housing quality and supply of general healthcare providers for addressing population mental health problems. Limitations related to data, the modifiable areal unit problem, and ecological fallacy are also discussed. Future studies can conduct attitude surveys among Toronto residents to gain better understandings of neighbourhood mental health.

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Chapter 1 Introduction

According to the World Health Organization (WHO), mental health is a fundamental part of health and not merely the absence of mental disorders or disabilities (WHO, 2018). One in five Canadians suffer from mental health problems, resulting in $42.3 billion direct and $6.3 billion indirect costs a year (Smetanin et al., 2011). The health burden caused by mental health problems is further exacerbated by the frequent co-occurrence of multiple diseases and injuries with mental disorders. It was estimated that the burden of mental illness and addictions, quantified by health-adjusted life years lost, is over 1.5 times greater than all cancers, and over 7 times upon that of all infectious diseases in Ontario (Ratnasingham, Cairney, Rehm, Manson, & Kurdyak, 2012). It was surprising that mental health issues had not received sufficient attention from the public health sector in Ontario and the whole society (Ratnasingham et al., 2012). In response, the federal government plans to provide Ontario with an additional $1.9 billion to support mental health care over the next decade (Canadian Mental Health Association, 2017).

Previous studies have revealed that mental health (Isaranuwatchai et al., 2014; Veldhuizen, Urbanoski, & Cairney, 2007) and mental health services (Ngamini Ngui & Vanasse, 2012) are not evenly distributed in Canadian large cities. Recognition of geographic variation in mental health can be the first step to achieve mental health equity. Identification of the locations of hot and cold spots can help maximize health system efficiency by formulating needs-based policies in specific areas to ultimately address issues of inequity.

In 2012, the Mental Health Commission of Canada (MHCC) released the first national mental health strategy: *Changing Directions, Changing Lives*, in which "reduce disparities in risk factors and access to mental health services" has been identified as one of six strategic directions (Mental Health Commission of Canada, 2012). Despite a large body of literature investigating individual risk factors of mental health by analysing national health survey data, only a small number of research accounts for contextual and spatial effects. Fowler and Christakis (Fowler & Christakis, 2008), in their innovative and widely cited study, followed a cohort of 4739 individuals for over 20 years and found that happiness can be transferred from one person to another. More importantly, the spread of happiness largely depends on geographic proximity (Fowler & Christakis, 2008). Like happiness, levels of well-being may be contagious within a certain proximity. It is therefore reasonable to hypothesize that where you reside and people who live nearby can impact how you feel mentally. Hence it is important for researchers to evaluate mental health issues from a population perspective while taking "place" into consideration. Such findings will provide the basis to develop suitable policies for both the general population and the regions with greater needs.

Using data from the Toronto Community Health Profiles (Toronto Community Health Profiles Partnership, 2012) and Toronto Open Data (City of Toronto, 2014), the main goal of this study is to identify hot and cold spots of mental health visits (MHV) as well as factors associated with MHV at the neighbourhood level in the City of Toronto. The two research questions can be presented as follows:

1) Is there any geographic variation in MHV across Toronto neighbourhoods? If geographic variation exists, where are clusters of high and low MHV rates?

2) What social factors and built environment factors could be associated with MHV at the neighbourhood level?

1.1 The Mental Health System in Ontario

Ontario's mental health and addictions care system delivers a wide range of essential services in three separate but connected settings: community-based, primary care and specialized physician's offices, and hospitals (Brien, Grenier, Kapral, Kurdyak, & Vigod, 2015). Community-based programs provide various mental health and addictions care at distinct levels, from low-intensity services such as peer support networks to high-intensity services like Assertive Community Treatment (ACT), to meet needs for patients with both mild-to-moderate mental illness and severe and complex mental illness (Canadian Mental Health Association, 2018). Hospitals offer mental health inpatient beds for patients with intensive and long-term care needs; patients experiencing an urgent crisis or having unmet needs at the other two settings usually end up with a visit to emergency departments.

As core providers of mental health care, family doctors and mental health specialists provide care for at least two million Ontarians each year, among which two-thirds visit primary care physicians and the other third are taken care of by psychiatrists (Brien et al., 2015). However, the results from National Physician Survey in Canada showed that 35% of family physicians considered access to psychiatrists as poor, which is almost 9-fold higher than that of internal medicine specialists (Kurdyak et al., 2014). The psychiatrist workforce is unevenly distributed across Canada. Compared with a recommendation of 15 psychiatrists per 100,000 residents made by the Canadian Psychiatric Association, the Toronto Central Local Health Integration Networks (LHIN) had a substantially high supply of 62.7 psychiatrists per 100,000 residents, whereas low-supply LHINs such as Central and Central East had less than 10 psychiatrists per 100,000 residents (Kurdyak et al., 2014). Poor access to psychiatrists, at least in high-supply regions like the Toronto Central LHIN, is not simply a result of the psychiatrist shortage. Evidence from a study that examined supply and practice patterns of psychiatrist in Ontario has shown that 40% of Toronto psychiatrists saw less than 100 unique patients annually and 24% of Toronto psychiatrists saw their patients more than 16 times annually; the equivalent proportions were 10% and 2%, respectively, in LHINs with the lowest psychiatrist supply (Kurdyak et al., 2014). It is not hard to imagine how infrequently psychiatrists will accept new patients in Toronto.

Consequently, family physicians and general practitioners have to take more responsibility since they are generally the first contact with mental health patients. Family physicians provide basic consultation, early detection and treatment for mild-moderate mental health problems (Lin et al., 2015). In addition, the majority of referrals to psychiatrist are made by primary care providers (Steele, Glazier, Agha, & Moineddin, 2009). Although nearly ninety-five percent of Ontarians with mental health conditions have a family doctor, more than half of them find it very or somewhat hard to get care after hours without accessing to emergency care (Brien et al., 2015). Thus, it is not surprising that one-third of Ontarians reported having unmet or partially unmet mental health or addiction needs, and one-third of mental health patients who visited emergency department had no prior contact with a physician (Brien et al., 2015).

Poor access to mental health services is partially a function of inequality. In other words, Ontarians do not have equal access to mental health services. In Canada, health services are financially based on a publicly funded fee-for-service reimbursement scheme that provides unlimited and fully covered physician consultations and hospital care services. The existing healthcare system, however, does not, or at least does not fully cover some consultations and psychotherapies provided by psychologists, or social workers. Patients who need these services either have an extended insurance plan from an employee benefits package, or pay out-of-pocket money to receive treatment. This deters lower-income groups from receiving quality evidence-based mental health services. Qualitative evidence suggested other access barriers included a fear of social stigma and not knowing where to find help (Brien et al., 2015). In Canada, mental health services are planned by LHINs while primary care services are planned by separate entities (MOHLTC, 2015). This has potentially resulted in a fragmented mental health care system and created a major challenge in navigating the system for patients with complex needs. To establish a more coordinated continuum of care, the Ontario government passed *Patients First Act, 2016* by which LHINs were given expended responsibilities to plan and manage primary care (MOHLTC, 2015).

All these evidence indicates considerable unmet needs, inequality, and the necessity for improvement of mental health care. This study analysed primary care mental health data at the neighbourhood level, which is a lower-level planning unit nested within LHIN. The findings can provide insights to help LHINs improve planning and integration of mental health services. By locating hot-spots and identifying specific populations at risk, the answers to the research questions have important policy implications for ensuring all Ontarians receive appropriate mental health services.

1.2 Study Rational

Most studies focused on mental health related contextual factors look at a limited range and number of variables, which potentially fail to reflect the complexity of neighbourhood environments. One salient characteristic of this study is the comprehensive examination on a considerable number of promising risk factors that are classified into various categories, especially certain objective measures of built environment that have been rarely evaluated in previous research. This study adds to the existing body of knowledge in regards to contextual factors associated with mental health by examining neighbourhood characteristics with a wealth of quality data covering the entire City of Toronto.

Most mental health research is developed from an epidemiological perspective, which typically neglects the integration of spatial concepts. The current study performed local cluster analysis to locate and visualize hot spots and used spatial regression models to improve model performance through accounting for spatial autocorrelation in the MHV data. From a practical point of view, the study distinguishes itself from many small-area analyses by choosing a planning-relevant geographic unit. A large number of spatial studies analyse census data, however, interventions may actually be enacted at a different scale other than census tract or dissemination area. This is particularly important if the ultimate goal of a study is to introduce changes to policies. Findings of this study can directly contribute to the delivery of effective local-based prevention and intervention programs of mental health.

On the other hand, compared to individual-level studies, where population surveys are often needed, ecologic designs have nature advantages of timesaving and cost-effective. A wide range of census and administrative databases are available and can be integrated with each other at the same geographic unit of analysis (i.e. Toronto neighbourhood), which is not usual for individual-level data. Additionally, ecologic findings in a spatial context can be easily conveyed to non-professional audience by displaying in maps with GIS techniques.

Chapter 2 Literature Review

Before proceeding to examine and seek for explanations for geographic variation in MHV, it is necessary to establish a complete understanding of what we have already known. The following section will present a literature review structured into two parts: mental health geography and factors associated with mental health.

For the second part, we first introduced a model for the determinants of population health that was used as a guiding framework in identifying factors associated with MHV at the neighbourhood level. In the remaining section, the focus is to present a review of current knowledge about social and built environment factors associated with mental health. Given the complexity of causes of mental health, this literature review covered a diverse range of factors examined at both the individual level and the population level. All reviewed mental health related factors were grouped into two broad domains: social factors and built environment factors. The built environment factors are referred to characteristics of the environment made or maintained by urban planners, architects and urban geographers, which include, but are not limited to land use patterns, features of urban design (e.g. green space), access to amenities and services (e.g. health providers), and transportation systems (Diez Roux & Mair, 2010; Halpern, 1995).

2.1 Geography and Mental Health

In spite of a growing body of mental health studies, only a few have explored mental health problems through a geographic lens. The very first attempt on this topic was made by Faris & Dunham (1939), who examined the distribution of psychiatric hospital admission in Chicago with manual cartographic methods in 1939 and found a decreasing trend of schizophrenia rate from socially disorganized inner-city communities to affluent outskirts. Inspired by promising initial findings, British scholars started to unlock the great potential of mental health geography by exploring the geographical spread of mental illness in Bristol (Hare, 1955), Nottingham (Giggs, 1973) and Plymouth (Dean & James, 1981) and consistently revealed that the distribution of schizophrenia was associated with social class.

In the 21st century, medical geography and spatial epidemiology have developed rapidly. Technically, the development of Geographical Information System (GIS) enables researchers to better manage, integrate, visualize and analyse spatial data. In public health, the growing volume of spatial data allows routinely assessing geographic inequalities in health status or service utilization, which can have direct implications for achieving equitable and efficient source allocation.

In the Canadian context, a few research works have compared rates of mental health indicators across geographic areas. Through mapping drug use and mental health among Ontario high school students, Isaranuwatchai et al. (2014) found that Toronto Central LHIN had an elevated proportion of students with poor mental health. A major limitation of this study is that it simply mapped mental health outcomes collected from a survey with no attempt to perform cluster detection analysis. Moreover, LHIN is a rough scale with 1-2 million people, and the sample sizes were considerably small in several LHINs. In a nationwide large-scale spatial analysis, Veldhuizen et al. (2007) identified significant clusters of high prevalence of problematic substance use in Toronto and Montreal using SaTScan. However, this study similarly relied on self-reported data from the CCHS and looked at an even larger area (province and census metropolitan areas). In addition, none of these studies have evaluated potential risk factors contributing to geographic disparities in mental health and addictions problems. The current study advances the field by applying spatial scan test to quantify geographic variation in the administrative mental health data at a fine scale while investigating possible risk explanations for the variation.

Until recently, a number of geographic inequalities in mental health remain unexamined owing to a lack of studies on this topic. Most mental health studies applying GIS techniques were carried out in the United States (Brown, 2013). Therefore, more Canadian mental health studies adopting a spatial method can be expected in the future to fill the knowledge gap.

2.2 Conceptual Framework

The development of chronic disease, especially mental illness, is multifactorial, with risk factors from a variety of aspects operating at numerous levels. Several models of health determinants have been developed to guide researchers formulating and testing hypotheses on the etiology of different health outcomes. The theoretical framework of this study (see Figure 2.2) is adapted from the widely cited Dahlgren-Whitehead 'rainbow' model of the main determinants of health (Dahlgren & Whitehead, 1991). The centred genetic characteristics are surrounded by a series of theoretically modifiable determinants. The innermost layer is individual health behaviour, followed by mutual interaction between individuals, their peers and communities. For this study, the layer we focus on is the influence of living and working conditions such as socioeconomic status, built environments, etc. The broad socioeconomic, cultural and environmental conditions also shape the population health.

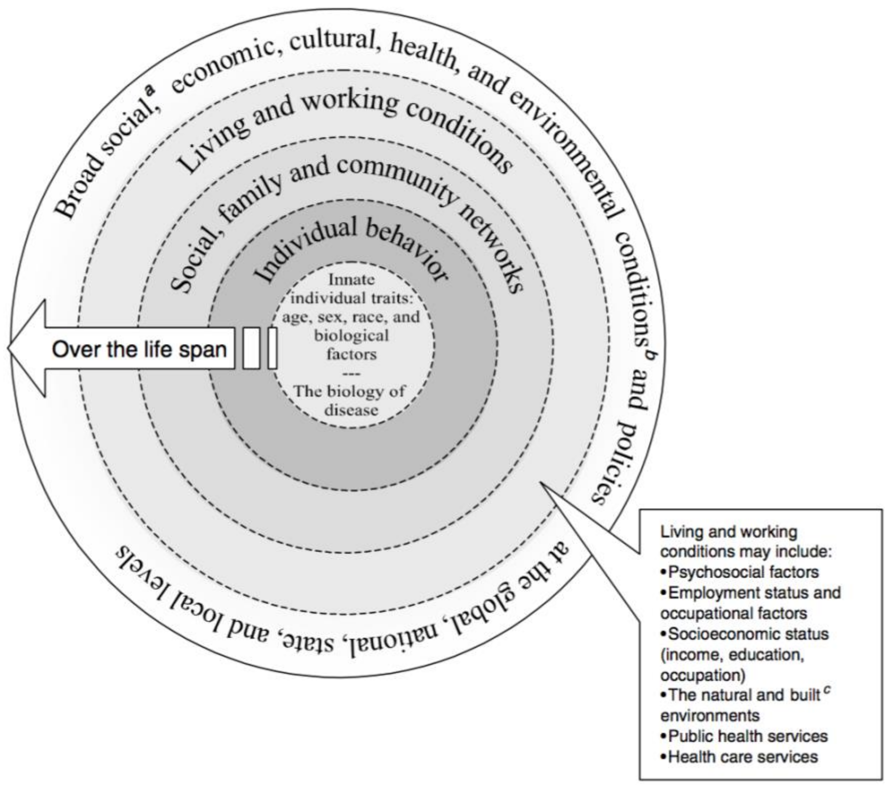

Figure 2.2 A guide to thinking about the determinants of population health
Reprinted from The Future of the Public's Health in the 21st Century, by Institute of Medicine (U.S.). Committee on Assuring the Health of the Public Health in the 21st Century, 2003, Washington, D.C. : National Academic Press. Copyright 2003 by the National Academy of Sciences (Institute of Medicine (U.S.), 2003).

Notes: Adapted from the model developed by Dahlgren and Whitehead, 1991 (Dahlgren & Whitehead, 1991).

[a]Social conditions include, but are not limited to: economic inequality, urbanization, mobility, cultural values, attitudes and policies related to discrimination and intolerance on the basis of race, gender, and other differences.

[b]Other conditions at the national level might include major sociopolitical shifts, such as recession, war, and governmental collapse.

[c]The built environment includes transportation, water and sanitation, housing, and other dimensions of urban planning.

2.3 Social Factors Associated with Mental Health

2.3.1 Socioeconomic Status

The social-mental health relationship is best documented for socioeconomic status (SES). However, SES is frequently treated as confounding factors in health research, or examined using diverse composite indices (Koppel & Mcguffin, 1999), making it even harder to compare results across studies. In her critique entitled *Socioeconomic Status in Helath Research: One Size Does Not Fit All*, Braveman et al. (2005) highlighted the importance of assessing specific but overall socioeconomic factors and including as much relevant measurements as possible. Furthermore, specific and precise definition of neighbourhood characteristics are fundamental to investigation into causal inference of neighbourhood effects on mental health (Diez Roux & Mair, 2010). Nevertheless, composite measurements of SES are useful considering the inherently multidimensional definition of SES and the complex relationship between SES and mental health (Maselko et al., 2018). In this review, the focus is on effects of specific socioeconomic factor on mental health, whereas both single (e.g. education) and multiple (e.g. marginalization index) SES measurements were analysed in the following regression analysis.

Indicators of adverse SES such as low income (Fone et al., 2013; Sundquist & Ahlen, 2006), unemployment (Koppel & Mcguffin, 1999) have all been shown to negatively affect mental health. The evidence for education attainment and mental health is mixed after adjusting for other socioeconomic variables, with some (Araya, 2003; Ludermir & Lewis, 2001; Melis, Gelormino, Marra, Ferracin, & Costa, 2015) but not all (Lewis et al., 2003) studies finding a significant association.

Unlike absolute income, income inequality has received less attention, but there is substantial evidence suggesting the critical role it plays in shaping mental health (Kahn, Wise, Kennedy, & Kawachi, 2000; Pickett & Wilkinson, 2010; Weich, Lewis, & Jenkins, 2001). Preliminary evidence came from the comparison of aggregate data at the national level by Pickett and Wilkinson (2010), who identified a link between income inequality and the prevalence of mental illness among rich societies. Specifically, more equal countries like Germany, Spain and Japan had the lowest proportion of adults with mental illness, followed by Canada and Australia, while the United States, often known as a considerably unequal society, had the highest rate of mental illness (Pickett & Wilkinson, 2010). The analysis was replicated using statewide data from the United States and found that illegal drug misuses were more common in unequal states (Pickett & Wilkinson, 2010). More studies at individual level have confirmed the negative effect of income inequality on mental health after controlling for household income (Kahn et al., 2000; Weich et al., 2001), but not all studies reported a significant association (Sturm & Gresenz, 2002). One possible explanation for these inconsistent conclusions is the varying ecological levels. A multilevel study in Wales concluded that income inequality had less effect on neighbourhood mental health, but that effect became pronounced at a larger regional level (Fone et al., 2013). Some important social factors related to mental health, like income inequality, are properties of populations and not reducible to individual persons, which remind us to think about and test social factors beyond the scope of individual level.

2.3.2 Demographic Factors

Ethnicity and Immigration

Findings about the influence of ethnicity on mental health appear to be country specific as ethnic composition and diversity differ across nations. Data from the Canadian Community Health Survey (CCHS) and National Population Health Survey (NPHS) have consistently suggested that South Asian, Chinese and black Canadians were less likely to report mental health problems compared to their white counterparts even after controlling for socioeconomic factors (Chiu, Amartey, Wang, & Kurdyak, 2018; Wu, Noh, Kaspar, & Schimmele, 2003).

In a major immigrant-receiving country like Canada, immigration largely shapes ethnic structure, thus is also closely linked to mental health. A scoping review of Canadian research on immigrant mental health revealed that immigration can pose a risk to mental health in three pathways: through acculturation related stressors, economic uncertainty and ethnic discrimination (George, Thomson, Chaze, & Guruge, 2015). Nevertheless, the impact of immigration on mental health is complex and does not always follow the predicted direction that immigrants as disadvantaged groups are more vulnerable to mental health problems. Ali (2002) found that rates of both depression and alcohol dependence were significantly lower among recent immigrants who arrived less than four years as compared to their Canadian-born counterparts. The health advantage held regardless of demographic and socioeconomic factors, but disappeared as time of residence increased (Ali, 2002). This phenomenon is the well-documented “healthy migrant effect”, and has been confirmed by many other Canadian studies (Salami et al., 2017; Xu & McDonald, 2010). Furthermore, previous studies demonstrated that mental health differed in immigrant groups according to own-group ethnic density (Xu & McDonald, 2010) and immigrant concentration (Menezes, Georgiades, & Boyle, 2011). Living in neighbourhoods with high density of same-ethnicity population and proportion of immigrants had mental health benefits for immigrants (Salami et al., 2017; Xu & McDonald, 2010).

Unlike the majority of Canadian studies that adopted self-reported mental health data derived from the CCHS (Ali, 2002; Chiu et al., 2018; Menezes et al., 2011; Xu & McDonald, 2010) or Canadian Health Measure Survey (Salami et al., 2017), administrative mental health data were used to assess mental health status in this study. Meanwhile, this study avoided broadly classifying culturally diverse population into one single category like “Asian”. Instead, three distinct ethnic subgroups: East Asian, South Asian, and Southeast Asian were included to separately represent Asian ethnicity.

Family Structure

Family structure is another frequently assessed demographic charasteristic, notably in studies of child and maternal mental health. Research on various populations in North America (Barrett & Turner, 2005; Bramlett & Blumberg, 2007; Wade, Veldhuizen, & Cairney, 2011), South America (Araya, 2003) and Western Europe (Bijl, Ravelli, & van Zessen, 1998) has reported a consistent association between single-parent family and worse mental health. Living in families headed by lone mother is a strong predictor of poor mental health for both children (Bramlett & Blumberg, 2007) and lone mothers per se (Cooper et al., 2008). However, the influence of lone-father family appears to be different for children and fathers. Children in families headed by lone father had comparable adjusted mental health with those in two-parent families (Bramlett & Blumberg, 2007), whereas the risk of having a common mental disorder was nearly four times higher for lone fathers than other man (Cooper et al., 2008). Moreover, the adverse mental health conditions of lone mothers were primarily driven by limited income, which was not the case for lone fathers, whose elevated mental health risk remained after controlling for income, debt and social support (Cooper et al., 2008).

Living alone has also received some attention as a possible risk factor for mental health with great emphasis being put on the elderly population (Chou, Ho, & Chi, 2006; Hughes & Gove, 1981; Lim & Kua, 2011; Russell & Taylor, 2009; Stahl, Beach, Musa, & Schulz, 2017). An exception is a study followed the entire Swedish population of 4.5 million men and women aged 25-64, in which researchers found individuals living alone had increased risks of both depression and psychosis (Lofors & Sundquist, 2007). Furthermore, the association between living alone and mental health is demonstrated to be contingent on gender (Chou et al., 2006), ethnicity (Russell & Taylor, 2009) and marital history (Hughes & Gove, 1981). Certain psychological factors such as perceptions of social quality (Stahl et al., 2017) and loneliness (Lim & Kua, 2011) can amplify the negative impact of living alone on mental health.

2.3.3 Neighbourhood Safety

There is a large body of literature on the relationship between crime and mental health, while most of them has focused on direct sufferers including victims or witnesses (Clark et al., 2008; Norris & Kaniasty, 1994). There is only a handful of studies looking at the ecological impact of neighbourhood safety on indirect sufferers who live in the area where illegal activities take place. Longitudinal evidence indicated a positive link between local crime rate and psychological distress with proposing that the damage to local built environment was a potential pathway of psychological distress elevation (Astell-Burt, Feng, Kolt, & Jalaludin, 2015). Another UK study examined the effects of different types of violent crime (robbery, sexual offences, violence against person) and property crime (burglary, criminal damage, fraud and forgery, offences against vehicles, other theft offences) on mental health with panel data (Dustmann & Fasani, 2016). Results showed a strong and negative effect of local crime, primarily derived from property crime, on residents' mental health (Dustmann & Fasani, 2016).

As a supplement to the dominant quantitative analyses in relevant literature, O'Campo et al (O'Campo, Salmon, & Burke, 2009) used concept mapping, a useful semi-qualitative method, to gain understanding of pathways by which neighbourhoods influenced mental health. Residents from Toronto were recruited and asked about their perceptions on neighbourhood characteristics potentially affecting mental well-being. Findings revealed that violence, crimes, and vandalism were rated as the most significant contributors to poor mental well-being (O'Campo et al., 2009). This study was replicated by involving a sample of participants living in downtown Toronto three years later, and crime was still on the top of the list of poor mental well-being determinants, highlighting the importance of neighbourhood safety (Sheppard et al., 2012).

2.3.4 Summary

It is extremely difficult to disentangle the relationships between multifaceted social environment and a broad range of mental health problems. Literature presents great heterogeneity in terms of methodology as well as measurements of both mental health outcomes and social factors.

It is worth noting that the vast majority of studies are conducted at the individual level. A few studies adopted a multilevel analytical approach (Fone et al., 2013; Menezes et al., 2011;

Sundquist & Ahlen, 2006) to quantify contextual factors, however, all of them used traditional multilevel models with no controlling for spatial effects. It is argued that standard multilevel models are unable to completely account for spatial dependence as spatial models do since they merely consider spatial correlation within areas and neglect spatial correlation across areas (Chaix, 2005). In spite of a growing interest in spatial analysis, geographic location is not among those characteristics considered as high priority to social science and public health researchers. Nearly all of the studies reviewed above are non-spatial, leaving place effects excluded from the investigation into social effects on mental health. Failing to incorporate spatial dependence that inherently exists can yield biased estimates and subsequently problematic recommendations for policy decisions. This study attempts to fill this gap by exploring the association between social context and population mental health through a spatial lens.

2.4 Built Environment Factors Associated with Mental Health

2.4.1 Neighbourhood Physical Surroundings

Green space is one of the built environment factors that has been most intensively examined with different study designs. A twin study assessing within-pair effect between green space and mental health among monozygotic twins showed that access to green space had a protective effect on depression after controlling for genetic, deprivation, and physical activity factors (Cohen-Cline, Turkheimer, & Duncan, 2015). Longitudinal (Alcock, White, Wheeler, Fleming, & Depledge, 2014) and ecological (Nutsford, Pearson, & Kingham, 2013) evidence also demonstrated a link between green space and better mental health. Interestingly, based on the findings from two studies using perceived mental health data (van den Berg, Maas, Verheij, & Groenewegen, 2010) and administrative data (Nutsford et al., 2013), respectively, this positive relationship was only significant for residential surrounding green space within a 3 km radius, but not for a smaller radius (1 km and 300 m, respectively).

Apart from green space, only few attempts have been made to analyse mental health in relation to neighbourhood built environment, most of which failed to show convincing evidence of significant associations. For example, Berke et al. (2007) and Sallis (2009) identified significant but opposite relationships between neighbourhood walkability and self-rated mental health, while Tomey et al. (2013) reported no association. Duncan et al. (2013) found a protective effect of recreational open space on depressive symptoms, but this effect was only significant among Asian groups. In a qualitative study among Toronto residents, participants cited the accessibility to neighbourhood amenities as important to their mental well-being (Sheppard et al., 2012), which was consistently found in a similar study in the UK (Guite, Clark, & Ackrill, 2006). However, these findings are vulnerable to small sample size (Sheppard et al., 2012) or low response rate (Guite et al., 2006).

2.4.2 Housing

Research on mental health correlates of housing type has converged upon the conclusion that residents of high-rise buildings are likely to have more mental health problems than residents of low-rise buildings or houses (Evans, Wells, & Moch, 2003). While McCarthy et al. (1985) concluded that housing location, specifically the area type where people resided, had closer association with mental health than housing type.

Several studies have consistently pointed to a positive relationship between housing quality and mental health (Evans, Saltzman, & Cooperman, 2001; Evans et al., 2003; Leclair & Innes, 1997;

Pevalin, Reeves, Baker, & Bentley, 2017). In a very recent longitudinal study, poor housing condition was found to do long-term harm to mental health (Pevalin et al., 2017). The study conducted by Leclair & Innes (1997) in Windsor, Ontario, Canada revealed a significant ecological relationship between low housing quality and high rate of referral for mood/conduct/stress-related concerns among children and adolescents.

It should be noted that these studies are vulnerable to certain methodological problems. For instance, many of the studies are restricted to deprived population such as homelessness. This can limit the variability of housing covariates, leading to underestimation of housing-mental health associations (Evans et al., 2003). Furthermore, the associations between self-reported mental health and subjectively measured housing conditions are particularly suspicious as they might be the production of report bias.

2.4.3 Transportation

Transportation is a key component of urban built environment. High accessibility of public transport was found to have a protective effect on depressive symptoms as measured by prescriptions for antidepressants, and this effect persisted after adjusting for individual socioeconomic indicators (Melis et al., 2015).

On the other hand, its undesired consequences, such as traffic noise can potentially act as environmental stressors that may have adverse effects on mental health. Jensen, Rasmussen & Ekholm (2018) reported a positive association between exposure to traffic noise and poor mental health. However, this association was only observed among individuals experiencing poor sleep quality in the study by Sygna et al. (2014). An intervention study in the UK found no evidence that the traffic noise reduction by the introduction of a bypass had effects on common mental disorders (Stansfeld, Haines, Berry, & Burr, 2009).

Traffic volume, as measured by daily vehicle miles traveled, was shown to raise the level of self-rated stress at the neighbourhood level (Yang & Matthews, 2010). A multilevel analysis revealed that persons who reported higher level of traffic stress and who lived in census tracts with greater vehicular burden also experienced greater depressive symptoms Gilbert (Gee & Takeuchi, 2004). However, this study presents several limitations: including a limited number of census tracts may reduce statistical power of contextual findings; the measurement of traffic stress showed a relatively low reliability; and results from the Chinese Americans sample may not generalize to other populations (Gee & Takeuchi, 2004).

In general, the relationship between transportation and mental health has been underexplored, and the current evidence is mixed. With respect to methods, all studies adopted a non-spatial analytical approach, except for one study (Yang & Matthews, 2010) which included one GIS-derived explanatory variable in analysis.

2.4.4 Summary

People spend a large amount of time in their residences. It can therefore be assumed that residents in the same neighbourhood tend to be similarly exposed to certain risk factors of mental health. Halpern (1995) described four pathways in his book that potentially linking built environment with mental health, specifically: 1) as a source of stress; 2) as an influence over social networks and support; 3) through symbolic effects and social labelling; 4) through the action of the planning process itself.

However, there is a relatively small body of published research that is concerned with built environmental impacts on mental health. Additionally, unlike literature focusing on social factors, more population-based and spatial studies are presented when assessing built environment factors. This is not surprising given the ecological study design and GIS analytical techniques enable more efficient and reliable measurements of environmental risk factors (Haining, 2003).

Chapter 3 Data

3.1 Unit of Analysis

3.1.1 Health Planning Units in Ontario

In Ontario, the government divides the area into several planning units of varying sizes, from large unit like LHIN to small unit like neighbourhood, to ensure planners better identify and prioritize local health needs. The *Local Health System Integration Act, 2006* was passed by the Government of Ontario to transfer Ontario's health care system by creating 14 LHIN with a mission to achieve an integrated delivery of health care at the local level (Bhasin & Williams, 2007). The handover of responsibilities from the Ontario Ministry of Health and Long Term Care (MOHLTC) to LHINs included planning, coordinating and funding hospitals, Community Care Access Centres, Community Support Services, Long-term Care, Community Health Centres, and most importantly, Mental Health and Addiction Services (Bhasin & Williams, 2007).

However, sometimes it can be difficult for each LHIN to effectively manage a highly diverse and rapidly growing population of approximately one to two million. In response to the MOHLTC's *Patients First Act, 2016*, 76 sub-regions were developed within each LHIN as the "focal point for local planning and service management and delivery" (MOHLTC, 2015). LHIN sub-regions are smaller geographical planning regions with a median population size of around 140,000, which help identify and tackle health inequalities through a more focused lens (Central LHIN Providers and Partners, 2017).

To achieve a more in-depth understanding about the unique needs of residents, sub-regions are further organized into a more refined geographic scale, neighbourhood, which is the level we have been focused on in this study. The launch of neighbourhoods enables more detailed health system planning, specific to the communities and individuals they serve. In addition to the basic health planning function, various area-level health and health-related indicators data were aggregated to LHIN, sub-region, as well as neighbourhood level and made available to the public. Through generating, visualizing, and analysing geographic data, researchers and health planners can work together to understand health patterns, identify areas of concern, and ultimately make Ontarians have equal access to best possible health services.

Figure 3.1.1 displays geographic boundaries of neighbourhoods as well as LHINs within the City of Toronto. The City of Toronto is shared between five LHINs, that are Toronto Central, Central East, Central, Central West, and Mississauga Halton LHIN, among which the Toronto Central LHIN lies entirely within the heart of the City of Toronto. The Toronto Central LHIN also contains the largest number of neighbourhoods and has the highest density of health services in Ontario.

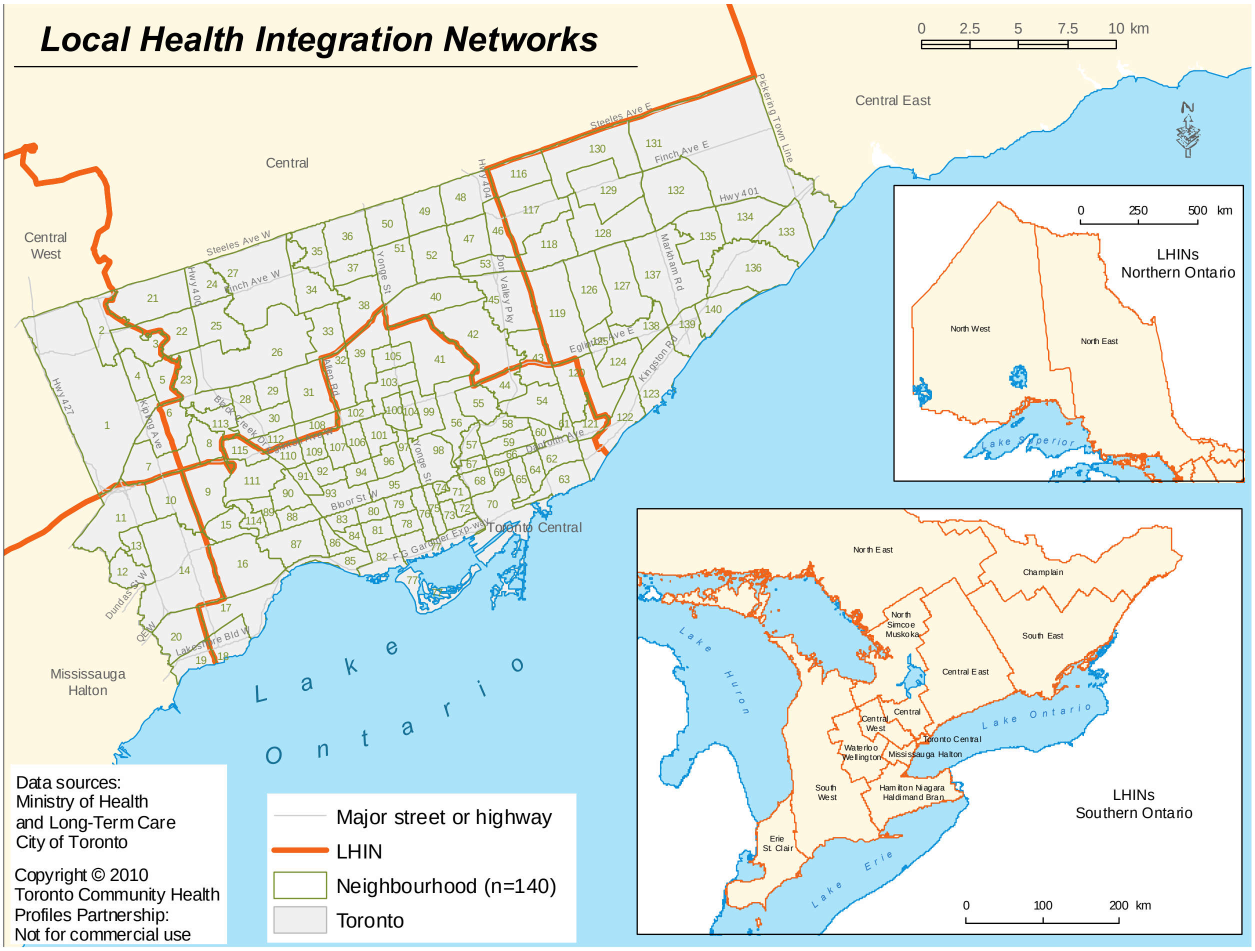

Figure 3.1.1 Map of geographic boundaries of 140 Toronto neighbourhoods overlaid with LHIN boundaries and major street or highway
Sources: Ministry of Health and Long-Term Care, by Toronto Community Health Profiles Partnership, City of Toronto, 2010, Retrieved from: http://www.torontohealthprofiles.ca/a_documents/TM_allCateg_maps/TM_maps_TopM/0_LHIN_of_Toronto_map.pdf. Copyright 2010 by Toronto Community Health Profiles Partnership.

3.1.2 Unit of Analysis: Neighbourhood

The study region, the City of Toronto, is the largest and most populous city in Canada with numerous economically and culturally diverse neighbourhoods, making it an ideal setting for exploring health variations. The city is split into 140 neighbourhoods by Toronto Social Development & Administration Division with the assistance of Toronto Public Health (Toronto Community Health Profiles, 2016). The geographic unit of analysis is the neighbourhood, which is aggregate of census tracts (CTs) into meaningful geographic area with the purposes of service planning and statistical reporting. In respect of existing boundaries, two to five census tracts are combined to form a neighbourhood with at least 7,000-10,000 population as well as similar percentage of low income households (City of Toronto).

As a key planning tool for the City of Toronto, a series of place-based programs were designed and implemented across the 140 neighbourhoods to reduce unnecessary, unjust and unfair differences, ultimately improving residents' well-being (City of Toronto, 2015). For instance, the first Toronto Strong Neighbourhoods program was launched in 2005 with more than 1,200 initiatives being implemented across the city; the current Toronto Strong Neighbourhood Strategy 2020 (TSNS 2020) continues working on building equal and thriving neighbourhoods (City of Toronto, 2015). In the project Urban HEART @ Toronto, researchers identified a total of 31 neighbourhoods as Neighbourhood Improvement Areas (NIAs) based on five different domains: economic opportunity, social and human development, governance and civic engagement, physical environment and infrastructure, and population health whereby mental health was used as one of the four key indicators (Centre for Research in Inner City Health, 2014; City of Toronto, 2015). However, in this project, mental health outcome was determined by self-reported data from the CCHS, and the impacts of other domains (e.g. economic opportunity, physical environment and infrastructure) were not accounted for. This study can benefit neighbourhood planning by providing a comprehensive and deep understanding on how mental health distributes and relates to neighbourhood environment.

Adopting neighbourhood as the level of analysis has several advantages: compared to LHINs and sub-regions, neighbourhoods are the smallest planning regions in Ontario that ensure homogeneous in regards to social and physical environment characteristics; population size of each neighbourhood is relatively similar and large enough to generate statistically stable results; unchangeable boundaries allow comparability over time; a wealth of census data can easily be aggregated to this level; in most cases, neighbourhoods, sub-regions and LHINs are neatly nested within each other, which allows intervention implemented at flexible levels. Additionally, and most importantly, created with the purposes of planning and service delivery, neighbourhood is exactly the level at which stakeholders tailor and implement policies. Research findings can be directly used by health planners.

3.2 Outcome Variable: Mental Health Visits

MHV data were retrieved from the Toronto Community Health Profiles (Toronto Community Health Profiles Partnership, 2012), a website making detailed area-level health data available to the public with primary goal of reducing health inequalities in Toronto.

Individuals aged 20 or older, who were eligible for Ontario Health Insurance Plan (OHIP) based on MOHLTC Registered Persons Database (RPDB), and who had used services in the previous 5 years were included in the study population (Toronto Community Health Profiles, 2015). MHV cases are defined as having had a doctor's visit for a mental health related symptom as indicated by the occurrence of a general service code as well as a mental health diagnostic code in primary care physicians' billing claims during the 2011 and 2012 fiscal years (Toronto Community Health Profiles, 2015). The data were aggregated based on the residence address of individuals rather than the location where the MHV had occurred. Not only psychotic, non-psychotic, and substance use disorders but also a range of social problems that are less severe but still significant were recorded as MHV purposes. A full list of service and diagnostic codes is available in Appendix Ⅰ. The MHV data have been shown to have a sensitivity of 81% and a specificity of 97% in terms of accurately identifying mental health and addictions related visits in primary care. For simplicity, "mental health visits" rather than "mental health and addictions related visits" was used in the current study to refer the outcome variable.

Moreover, prevalence of mental health illness has been known to differ among age groups. Consequently, comparisons of crude MHV rates across neighbourhoods with different underlying age structures could be misleading. To remove the effects of age from crude rates, the MHV data were standardized by the data provider using the direct standardization approach and the 1991 Canada population as the standard population. The outcome variable was initially mapped to a choropleth map for visualizing the geographic distribution of MHV across 140 Toronto neighbourhoods (see Figure 3.2).

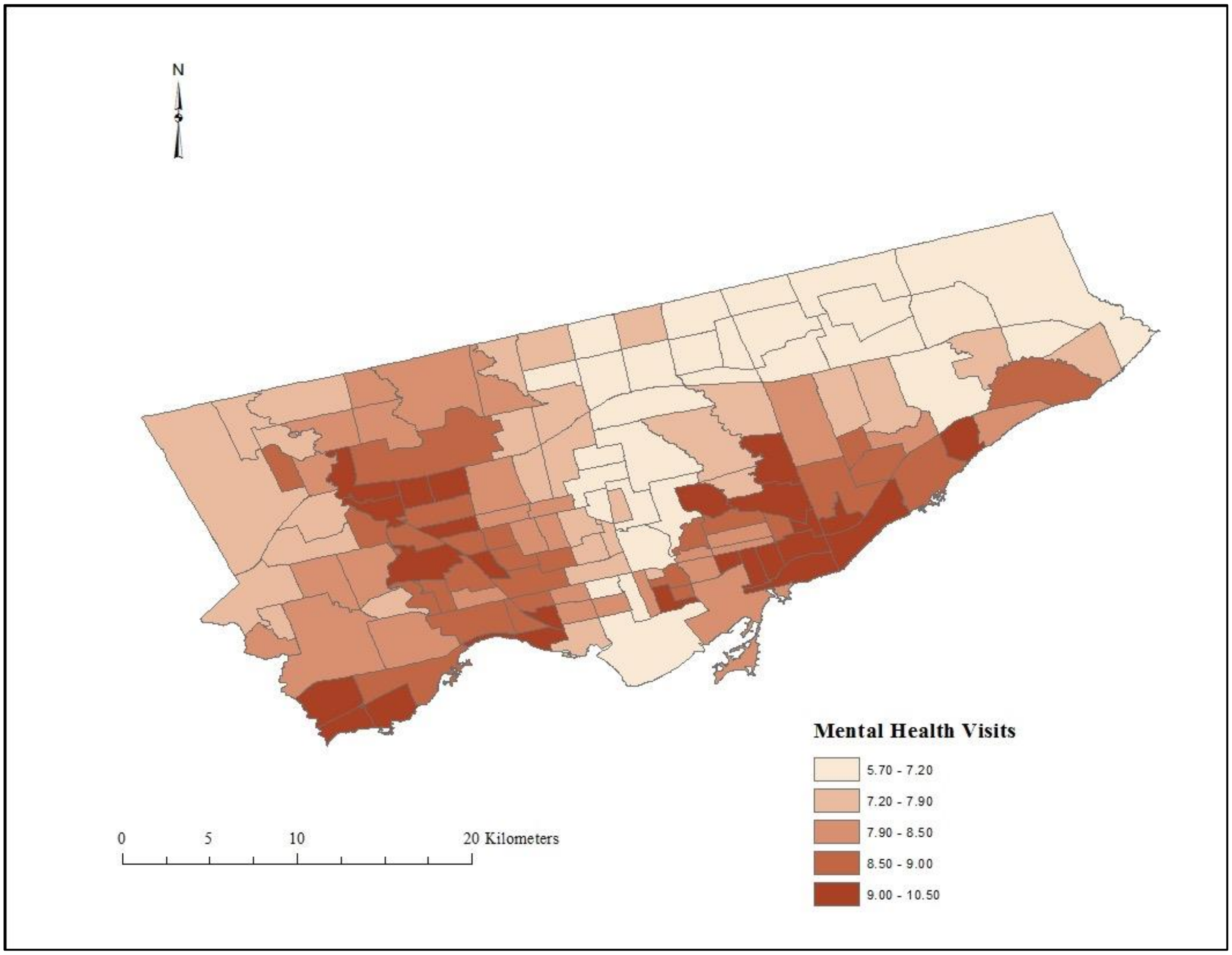

Figure 3.2 Quantile map of age-standardized mental health visits rates among population age 20+ in the City of Toronto by neighbourhood
The MHV rates were classified into five categories based on a quantile classification method. Darker colours indicate high MHV prevalence; while lighter colours represent low MHV prevalence.

By visually inspecting the quantile map of MHV (Figure 3.2), there appeared to be high risk clusters located in the west and southeast of Toronto as well as a low risk cluster located in the northeast of Toronto. However, visual examination is an unreliable method to detect clusters since displayed patterns largely depend upon which method is used to create categories, the number of categories, and even what colours are chosen to represent different categories for mapping results. For instance, Figure 3.2 adopted a quantile classification method that distributed MHV rates into five intervals that contain an equal number of neighbourhoods. Maps using another cut point to create intervals, such as equal-sized subranges (i.e. equal interval classification method), can give very different patterns. For these reasons, the Global Moran's I and Kulldorff's Spatial Scan Statistic were performed to quantitatively assess the geographic variation in MHV data.

3.3 Explanatory Variables

A great variety of social and built environment factors were included in the analysis to reflect neighbourhood context. The explanatory variables were extracted from the Toronto Community Health Profiles (Toronto Community Health Profiles Partnership, 2012) and Toronto Open Data (City of Toronto, 2014). Some of the variables took into account population size or neighbourhood area, when appropriate. Table 3.3 provides brief description for each of the explanatory variables. Detailed information about the measurements and data sources can be found in Appendix Ⅱ.

Table 3.3 Brief Description of Explanatory Variables

Variable	Description
Social Factors - SES	
Median Household Income	Median household income after tax
Income Inequality	Gini Coefficient ranges from 0 to 1 (perfect inequality)
Marginalization Index	Composite indicator of neighbourhood marginalization
Education	Proportion of people with post-secondary education
Social Factors – Demographic Factors -Ethnic Diversity	
Non-Visible Minorities	Proportion of people who are not visible minorities
Minority Groups	Proportion of people who identify themselves as South Asian, East Asian, Southeast Asian, and Black
Social Factors – Demographic Factors - Population Mobility	
Recent Movers	Proportion of people who have moved 5 years prior to the 2011 Census
Recent Immigrants	Proportion of immigrants landed between 2006-11
Social Factors – Demographic - Family Composition	
Lone Parent Families	Proportion of families with children that are headed by a lone parent
Population Living Alone	Proportion of people that are living alone
Social Factors – Demographic - Language	
Linguistic Diversity Index	Measure of neighbourhood linguistic heterogeneity
No Knowledge of English or French	Proportion of people who are unable to communicate in English or French

Table 3.3 Brief Description of Explanatory Variables (Continued)

Variable	Description
Social Factors – Social Aid	
Social Assistance Recipient	Proportion of people receiving social assistance
Social Factors – Neighbourhood Safety	
Property Crime	Incidents of property crime per 10,000 residents
Violent Crime	Incidents of violent crime per 10,000 residents
Drug Arrests	Incidents of drug arrests per 10,000 residents
Built Environment Factors – Neighbourhood Physical Surroundings	
Community Places for Meeting	Population-weighted average number of meeting places within a 10-minute walking distance
Health Providers	Number of health related businesses per 10,000 residents
Sports Facilities	Number of sports facilities per 10,000 residents
Walk Score	Walkability score ranges from 0 to 100 (very walkable)
Green Space	Green space per km^2 in a 1km buffer
Built Environment Factors – Housing	
Rented Households	Proportion of rented households
Households Need Major Repairs	Proportion of dwellings in need of major repairs
Population in Mid-Century Household	Proportion of people living in mid-century high-rises

Table 3.3 Brief Description of Explanatory Variables (Continued)

Built Environment Factors – Transportation	
Variable	**Description**
Overcrowded Routes	Number of overcrowded routes per kilometre of road
TTC Stops	Number of TTC stops per kilometre of road
Road Volume	Collector roads average 24-hour volume per collector

3.4 Descriptive Statistics

Table 3.4 provides descriptive statistics for the outcome variable, the prevalence of MHV, and all social and built environment independent variables. Median household income is the confounder variable used to adjust for material deprivation. The MHV rates were age-standardized using the direct method. The average prevalence of age-standardized MHV among individuals aged 20+ was 8.1% for the City of Toronto, and 8.4% for Toronto Central LHIN during the 2011 and 2012 fiscal years. The maximum was found in O'Connor-Parkview (10.5%), while the minimum was found in Steeles and Milliken (5.7%). The MHV data were approximately normally distributed across 140 Toronto neighbourhoods. For independent variables, property crime, violent crime, and drug arrests cases, the number of sports facilities and health providers were divided by neighbourhood population based on 2011 census to account for population differences.

Table 3.4 Descriptive statistics for dependent variable and independent variables (n = 140)

Variable	Mean	Minimum	Maximum	Standard Deviation
Dependent Variable				
Mental Health Visits %	8.13	5.70	10.50	1.00
Social Factors - SES				
Median Household Income /100,000	0.55	0.31	1.61	0.16
Income Inequality	0.39	0.20	0.56	0.04
Marginalization Index	2.40	1.00	3.40	0.56
Education %	68.80	37.50	91.70	12.78
Social Factors – Demographic Factors - Ethnic Diversity				
Non-Visible Minorities %	55.49	4.93	89.33	22.07
South Asian %	10.43	1.15	49.48	10.69
East Asian %	11.15	0.52	71.26	13.26
Southeast Asian %	6.62	0.77	21.58	4.48
Black %	8.13	0.29	38.68	7.33
Social Factors – Demographic Factors - Population Mobility				
Recent Movers %	40.86	20.17	72.49	9.42
Recent Immigrants %	8.22	1.51	24.43	4.81

Table 3.4 Descriptive statistics for dependent variable and independent variables (n = 140) (Continued)

Variable	Mean	Minimum	Maximum	Standard Deviation
Social Factors – Demographic Factors - Family Composition				
Lone Parent Families %	32.16	13.90	52.40	7.72
Population Living Alone %	13.05	2.90	39.80	7.38
Social Factors – Demographic Factors – Language				
Linguistic Diversity Index	0.65	0.25	0.88	0.15
No Knowledge of English or French %	4.89	0.20	23.40	4.01
Social Factors – Social Aid				
Social Assistance Recipient %	9.80	0.40	29.10	6.25
Social Factors – Neighbourhood Safety				
Property Crime / 10,000 residents	59.79	22.30	151.61	22.27
Violent Crime / 10,000 residents	108.95	21.97	374.77	58.83
Drug Arrests / 10,000 residents	20.27	0.00	185.16	21.46
Built Environment Factors – Neighbourhood Physical Surroundings				
Community Places for Meeting	14.99	3.40	39.90	7.92
Health Providers / 10,000 residents	19.06	1.00	97.00	17.51
Sports Facilities / 10,000 residents	13.01	0.00	28.31	5.69
Walk Score	72.27	42.00	99.00	12.79
Green Space	45.47	11.30	113.50	23.93

Table 3.4 Descriptive statistics for dependent variable and independent variables (n = 140) (Continued)

Variable	Mean	Minimum	Maximum	Standard Deviation
Built Environment Factors - Housing				
Rented Households %	44.10	6.66	93.37	16.81
Households Need Major Repairs %	8.22	2.28	17.56	3.03
Population in Mid-Century Household %	20.12	0.00	76.90	16.99
Built Environment Factors – Transportation				
Overcrowded Routes	4.82	0.04	22.34	3.41
TTC Stops	2.02	0.77	4.79	0.80
Road Volume	4372.33	0.00	13491.50	2033.09

Chapter 4 Methods

4.1 Geographic Variation in Mental Health Visits

4.1.1 Global Moran's I Statistic

In order to test the proposition of research question one that whether or not MHV vary across neighbourhoods in the City of Toronto, a global index of spatial autocorrelation is needed to determine the existence or absence of a geographic pattern and summarize the general geographic structure over space. Global Moran's I statistic (Moran, 1950) was used to measure the average degree of spatial autocorrelation throughout the entire study region, expressing how similar a value at a given location is to its defined neighbours. Neighbours were specified via a binary spatial matrix based on Queen-Contiguity method (that is, those neighbourhoods sharing a common border or corner are considered neighbours in the matrix). Global Moran's I value is given by (Cromley & McLafferty, 2012; Pfeiffer et al., 2008):

$$\mathrm{I} = \left(\frac{N}{\sum_i \sum_j w_{ij}}\right)\left(\frac{\sum_i \sum_j w_{ij}\,(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}\right)$$

where N is the total number of areal units, w_{ij} is the spatial weight matrix that defines the proximity of area *i* and *j* (is 1 if *i* and *j* are neighbours and is 0 otherwise), x_i is the value of variable of interest at area *i*, x_j is the value of variable of interest at area *j*, and $\bar{x}$ represents the global mean of *x*.

In general, Moran's I statistic lies between -1 and +1, where positive values indicate a clustered pattern that areas near together have similar values, while negative values indicate a dispersed pattern that neighbouring areas have dissimilar values. A perfect example of negative spatial autocorrelation is the checkerboard pattern which has a Moran's I value of -1. A Moran's I value of zero indicates the null hypothesis that there is no spatial autocorrelation in the study region.

4.1.2 Kulldorff's Spatial Scan Statistic

While Global Moran's I statistic is useful in assessing overall tendency of clustering, it is unable to specify the location or size of individual clusters. To locate clusters of neighbourhoods with significantly high or low prevalence of MHV, Kulldorff's Spatial Scan Statistic was applied.

This spatial scan statistic constructs a circular or an elliptic scanning window with continuously increasing radius that moves across the study region (Kulldorff, 2018). An infinite number of candidate clusters are created as a result of constantly changing size and location of the scanning window (Kulldorff, 2018). A likelihood ratio is calculated for each window by comparing the likelihood of the data under the alternative hypothesis of clustering to the likelihood under the null hypothesis of constant risk while adjusting for multiple testing problems (Waller & Gotway, 2004). The window with the maximum likelihood ratio captures the most likely cluster.

The likelihood ratio is calculated with the following equation (Kulldorff, 2018):

$$\mathrm{L} = \left(\frac{c}{E[c]}\right)^{c}\left(\frac{C-c}{C-E[c]}\right)^{C-c}$$

where C is the total number of cases in the study region, while c is the number of observed cases inside a specific scan window. $\mathrm{E}[c]$ represents the expected number of cases. Under the Poisson model, $\mathrm{E}[c]$ is assumed to be proportional to the population size within the window. $\mathrm{C}-\mathrm{c}$ is the observed number of cases outside the window and $\mathrm{C}-\mathrm{E}[c]$ is the expected number of cases outside the window.

A purely spatial scan statistic based on a discrete Poisson model was carried out to detect neighbourhoods with significantly higher or lower than expected prevalence of MHV among all adults age 20 and older. Additional analyses were conducted for the three age groups (20-44, 45-64, 65+) to investigate age-specific clusters. The statistical significance of the cluster was determined by conducting Monte Carlo simulation with 999 permutations. SaTScan, a free programme developed by Martin Kulldorff (1997) was used to complete the analyses.

4.2 Factors Associated with Mental Health Visits

Once the geographic variation of MHV has been examined, the focus now turns to potential risk factors that can explain such spatial variation. Ordinary Least Squares (OLS) is the classical approach and a good starting point when analysing the relationship between an outcome and its key factor(s). A multiple OLS regression model is given by:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_n x_{ni} + \varepsilon_i$$

where y_i is the dependent variable, $x_{1i}, x_{2i}, \cdots, x_{ni}$ are the independent variables, and n is the total number of independent variables. β_0 denotes the intercept parameter, $\beta_1, \beta_2, \cdots, \beta_n$ denote the regression coefficients for $x_{1i}, x_{2i}, \cdots, x_{ni}$, respectively, and ε_i is the independent and identically distributed (i.i.d.) error term at location i.

The usefulness of OLS is limited by its relatively strict assumptions, one of which is uncorrelated error terms. If there is evidence of spatial autocorrelation in the residuals, a non-spatial method like OLS, in some cases, is unable to perform satisfactory estimation (Beale, Lennon, Yearsley, Brewer, & Elston, 2010; Pfeiffer et al., 2008). The following sections will describe how the spatial error model and spatial lag model provide solutions for this issue by incorporating spatial dependence in different ways.

4.2.1 Spatial Error Model

One method to take into account spatial effects is through adding a spatially lagged error term to a linear regression model. The spatial error model is given by the equation below, where λ is the autoregressive coefficient for the error lag W_ξ. ξ_i is the independent and identically distributed (i.i.d.) error term (Anselin, 1988).

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_n x_{ni} + \lambda W_\xi + \xi_i$$

Spatial autocorrelation can derive from unobserved or unmeasurable explanatory variables in model specifications, in which case it is often relegated to the error term as a nuisance (Anselin & Lozano-Gracia, 2009). The spatial autoregressive parameter λ does not have a meaningful and substantive interpretation, but is included to ensure better estimation of regression coefficients (Anselin & Lozano-Gracia, 2009). As such, spatial error model is the optimum solution when appropriate explanatory variables are unavailable for some reason (Haining, 2003).

4.2.2 Spatial Lag Model

The spatial lag model, also referred to as a spatial autoregressive model (Anselin, 1988), is described as:

$$y_i = \rho W_y + \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_n x_{ni} + \varepsilon_i$$

where y_i is the dependent variable, $x_{1i}, x_{2i}, \cdots, x_{ni}$ are the independent variables, and n is the total number of independent variables. β_0 denotes the intercept parameter, $\beta_1, \beta_2, \cdots, \beta_n$

denote the regression coefficients to be estimated, and ε_i is the i.i.d. error term at location i. ρ is the spatial autoregressive coefficient and W_y is the spatially lagged dependent variable.

Essentially, the spatial lag model is referred to as the linear regression model with a spatially lagged dependent variable (Haining, 2003). In the context of this study, the introduction of the spatially lagged dependent variable takes into account the fact that the prevalence of MHV can be a function of mental health status in a wider area but not limited to the neighbourhood itself.

Theoretically, there could be a mismatch between the geographic unit of analysis and the real-life spatial context of the health outcome. Specifically, an administratively defined scale like neighbourhood may be unable to appropriately reflect the true social and built environment experienced by residents in the City of Toronto. The spatial lag model, with the inclusion of spatially lagged dependent variable, helps to correct for such mismatch and makes the model more interpretable (Anselin & Bera, 1998).

4.2.3 Spatial Regression Modelling Procedure

Research question 2 asked: What social and built environment factors could be associated with MHV at the neighbourhood level? A series of spatial regression analyses and variable selection procedure were conducted in order to identify prominent factors associated with MHV. Given the large number of independent variables, social factors were further categorized into SES, demographic (ethnic diversity, population mobility, family composition, language), social aid, and neighbourhood safety; built environment factors were broken into neighbourhood physical surroundings, housing, and transportation.

As the Global Moran's I ($I = 0.659$, $p = 0.001$) was statistically significant indicating strong positive spatial autocorrelation in MHV data, spatial regression models (as opposed to OLS) were applied to account for spatial dependency. Both the spatial error model and the spatial lag model were used to estimate the associations between MHV and social and built environment. Throughout the spatial regression modelling procedure, the variable median household income was kept in the models to adjust for income deprivation. The reason is that economic deprivation is considered as an important confounder related to a variety of health outcomes, and mental health is without exception.

The modelling procedure started with repeated bivariate regression analyses examining the independent correlation between MHV and each single explanatory variable after adjusting for deprivation. Multiple regression analyses were then carried out separately for each variable subcategory (i.e. SES, neighbourhood safety, housing, etc.). Any variables with a liberal p-value < 0.2 from both the bivariate and within-subcategory regressions fitting either one of the spatial models were selected for subsequent analysis. This variable screening process helps to reduce the number of independent variables to prevent over-fitting problems.

The variable screening process initially generated 13 candidate explanatory variables, but yet it was not feasible to include all in one model. Unnecessary and highly correlated explanatory variables will make it hard to identify influential factors of MHV to answer the second research question. We then built two models, one for the social factors and the other for the built environment factors, in which covariates with a $p < 0.05$ were jointly introduced in the final model. The final model was fitted using both the spatial error model and the spatial lag model, and the one with a lower BIC value was deemed as a better model.

In the end, spatial autocorrelation in regression residuals of the final model was quantified with Moran's I statistic. This is to confirm that the model has accounted for any possible spatial dependency. All spatial regression analyses were completed using R version 3.3.3 with the spdep package.

4.2.4 Automated Variable Selection: All-Subset Selection

It is not sufficient, we believe, to make decisions about what subset of explanatory variables can best explain the response variable based on their statistical significance alone. Thus more effort needs to be put into variable selection process. Automated model-building procedures are commonly performed as an addition to regression modelling. Stepwise method has been among the most popular variable selection methods in health-related publications due to the fact that it is a less computationally intensive approach that is built in to most standard statistical software packages. Stepwise method is a combination of forward selection and backward elimination. The forward selection method starts with a null model that has no variables, and adds a single variable that is most statistically significant at a time until certain "stopping rule" is reached, for instance, when all entered variables have a p-value greater than a defined significance threshold. Reversely, the backward elimination method starts with a full model that has all variables and drops variables in decreasing order of significance until all remained variables are significant based on a defined significance criteria.

In spite of its common usage in public health literature, the stepwise procedures have received extensive criticisms from statisticians (Burnham & Anderson, 2002; Harrell, 2015). Pitfalls of this approach thoroughly reviewed by Harrell (2015) include but not limited to the following: biased high R^2 values, biased large coefficient estimations, falsely narrow confidence intervals, problems of multiple comparisons, and exacerbated collinearity problems (p.68). In addition to the stepwise procedures per se, p-value based variable selection was considered dubious (Burnham & Anderson, 2002; Harrell, 2015). As alternatives to the p-value, information-theoretic criteria such as the Akaike Information Criterion or AIC (Akaike, 1974) and the Bayesian Information Criterion or BIC (Schwarz, 1978) are widely used to assist with variable selection. Burnham & Anderson (2002) mentioned that null hypothesis testing and information-theoretic approaches were two fundamentally distinct theories that can generate fairly different selection results when many candidate models were presented. Furthermore, the choice of the optimal entry and removal significance level α can be tricky as we don’t know what cut-off works best and there is no theory to guide such choices (Harrell, 2015).

In the light of the foregoing discussion, it is not wise to solely rely on p-value as the variable selection criterion. And thus information-theoretic criterion was used to be the basis of variable selection in this study. It is noteworthy that different information-theoretic criteria might be better-suited for specific purpose of model selection. The application context of AIC and BIC was demonstrated by Shmueli's (2010) that BIC was suited to explanatory modelling whereas AIC performed better in predicting modelling. BIC was preferred over AIC given the goal of this study was to “explain” rather than to “predict”. The model(s) with the lowest BIC value was deemed as the best model(s).

With the improvement of computing speed, statistical software packages like R or SAS allow automated model selection with every possible combination of explanatory variables, namely all-subset selection. According to Judd, McClelland & Ryan (2009), examining all-subset models was recommended over the stepwise procedures if automated model selection was applied (p.125). However, the total number of candidate models (2^{29}) built from combinations of 29 variables exceeds the maximum limit size of data that R can handle. Therefore, a subset of 13 variables selected from the variable screening process were introduced to the automated model selection procedure, yielding 2^{13} different subsets of explanatory variables. Medium household income was consistently included in each candidate model as a confounder. The spatial lag model was used to model all variable subsets since it showed better performance than the spatial error model in spatial regression analyses. BIC values were calculated to obtain a ranking list for all candidate models. It must be clear here that simply picking up a model with the lowest BIC value and concluding it is the "best" model will always miss valuable information. Following Raftery's (1995) guidelines, a difference of BIC lower than 2 is considered "weak", a difference of BIC between 2 and 5 is "positive", a difference between 5 and 10 is "strong", and a BIC difference greater than 10 is a "very strong" evidence in favour of the model with the lower BIC. Therefore, making comparisons between models with a negligible difference in BIC (i.e. <2) is meaningless. Nonetheless, this ranking list still gave us a clue as to which subset of explanatory variables is important to explain MHV. The all-subset selection was performed using R version 3.3.3 with the spdep package.

Chapter 5 Results

5.1 Geographic Variation in Mental Health Visits

5.1.1 Global Geographic Variation in Mental Health Visits

Figure 5.1.1 exhibits the Moran's I scatterplot for MHV dataset. Random permutation approach with 999 permutations was implemented to test the significance of the Moran's I statistic. The Global Moran's I of MHV rates was 0.659 and was statistically significant at the 5% significance level (p=0.001), indicating a positive spatial autocorrelation. The Moran's I value was quite close to +1, confirming that there was a strong clustered pattern of MHV data. Most of the points are situated at high-high or low-low quadrants, demonstrating clusters of high and low prevalence of MHV. Specifically, neighbourhoods with high/low prevalence of MHV tend to be adjacent to neighbourhoods with high/low prevalence of MHV in the City of Toronto.

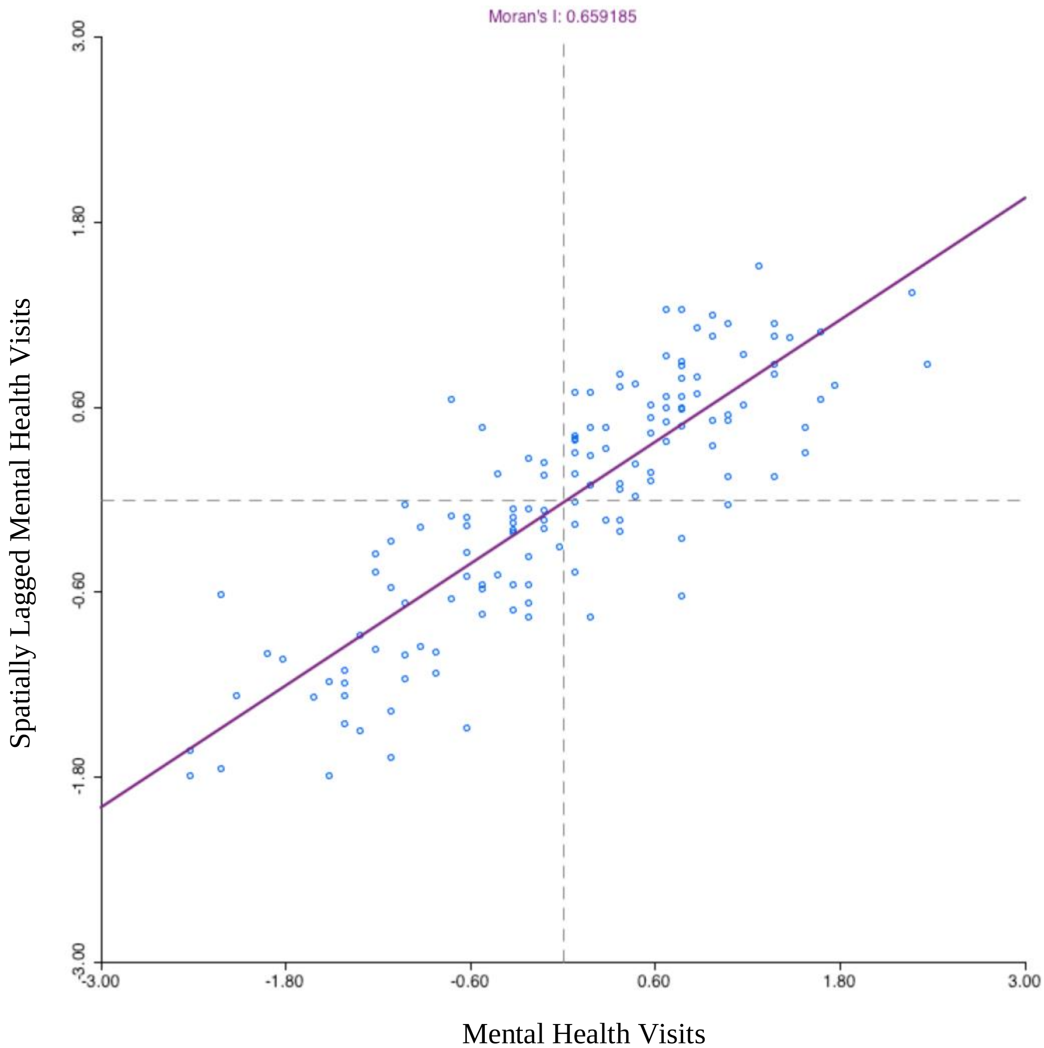

Figure 5.1.1 Moran's I scatterplot for MHV data
The values on the x-axis are the original variable (that is, MHV rates) and the values on the y-axis are the spatially lagged MHV (that is, average values of MHV in surrounding neighbourhoods). Both values are standardized (given in standard deviational units).The slope of the regression line is Moran's I value. The plot is divided into four quadrants: high-high (upper right), low-low (lower left), for positive spatial autocorrelation; high-low (lower right) and low-high (upper left), for negative spatial autocorrelation.

5.1.2 Cluster Analysis: Hot and Cold Spots of Mental Health Visits

Hot and cold spots detected by Kulldorff's Spatial Scan Statistic for MHV among adults age 20+ were mapped using ArcMap 10.6.1 as shown in Figure 5.1.2.1. Maps of clusters for the three different age groups can also be found in Figure 5.1.2.2 (age 20-44), Figure 5.1.2.3 (age 45-64), and Figure 5.1.2.4 (age 65+). The hot and cold spots were overlaid with a map of sub-regions rather than neighbourhoods due to the consideration that using a medium-size scale is easier to locate the clusters than using a small (i.e. neighbourhood) or large scale (i.e. LHIN).

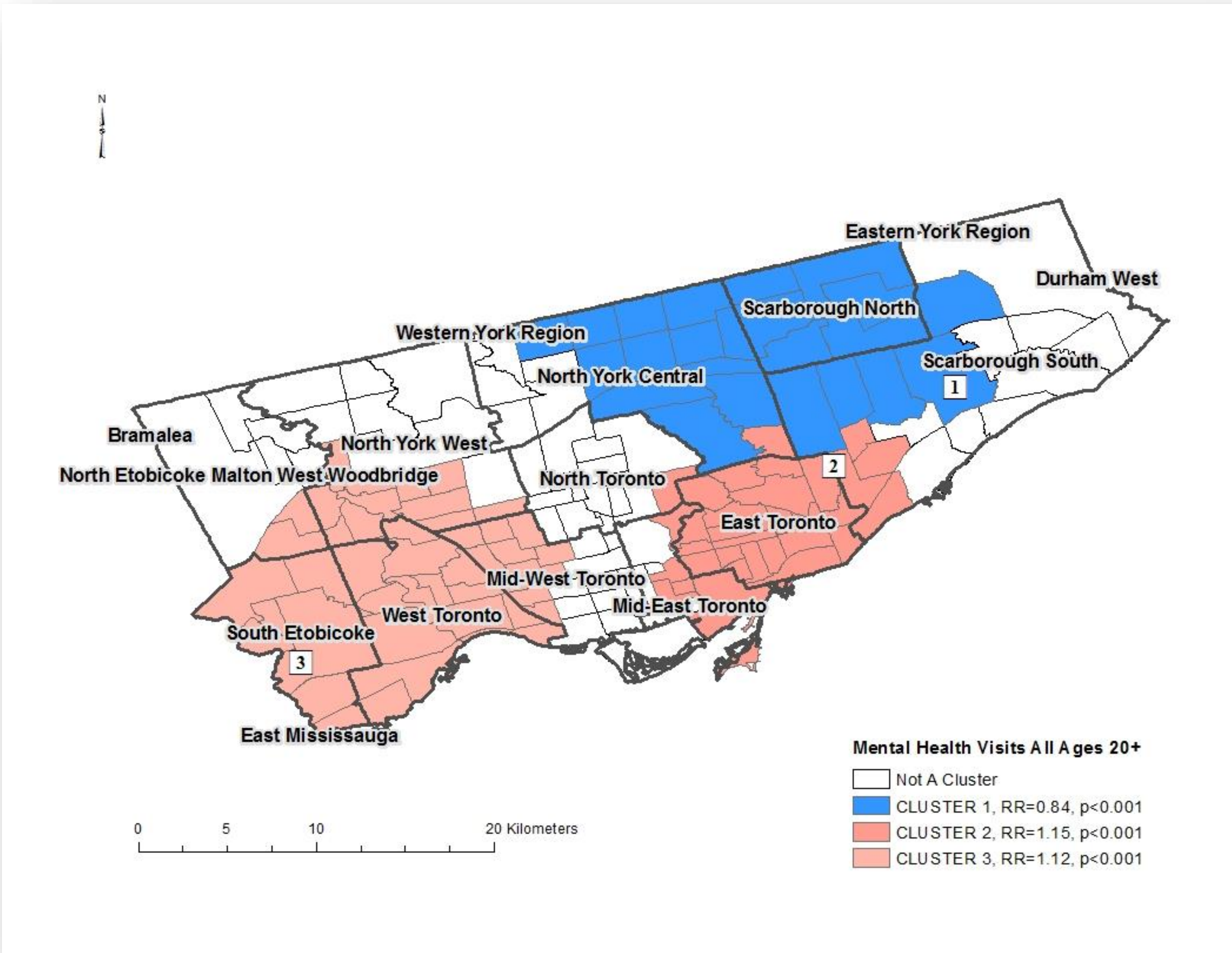

Figure 5.1.2 1 Map of clusters for mental health visits among population all ages 20+ in the City of Toronto by neighbourhood
Hot spots(red) are areas with high prevalence of mental health visits; cold spots (blue) are areas with low prevalence of mental health visits. Clusters and Health Sub-Region names were labeled.

The most likely cluster for all population age twenty and over is a cold spot, located in Scarborough North, North York Central, and west part of Scarborough South. Two hot spots were generally found in East Toronto, Mid-East Toronto, South Etobicoke, West Toronto, North York West (south), and Mid-West Toronto (west). The secondary cluster was primarily located in East Toronto sub-region with a relative risk of 1.15 ($p < 0.001$), indicating residents living within East Toronto sub-region were 15% more likely than people residing outside to have MHV. Even though 15% appears to be a relatively small size of risk, the translation of this risk to the entire sub-region can be considerably significant.

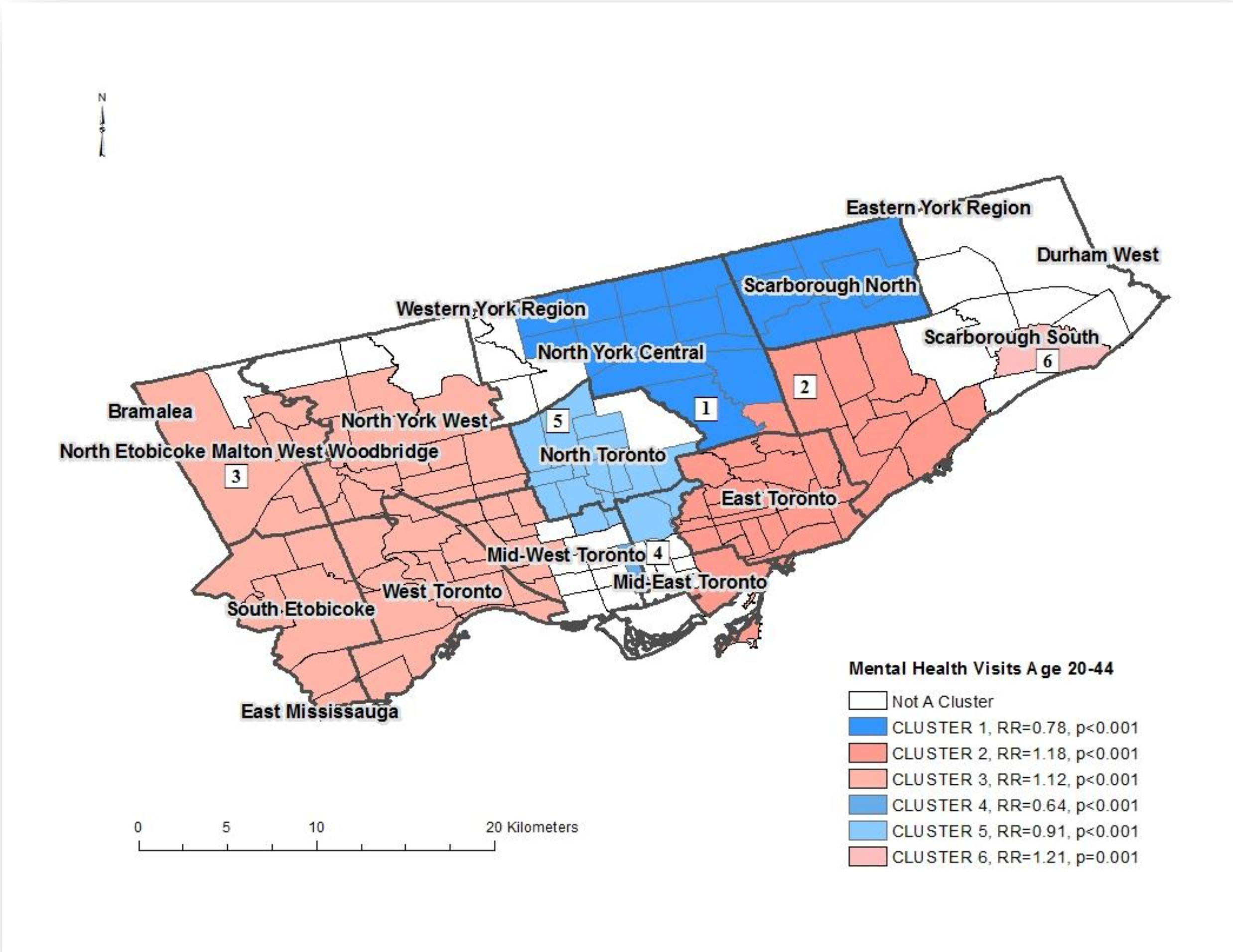

Figure 5.1.2 2 Map of clusters for mental health visits among population age 20-44 in the City of Toronto by neighbourhood
Hot spots(red) are areas with high prevalence of mental health visits; cold spots (blue) are areas with low prevalence of mental health visits. Clusters and Health Sub-Region names were labeled.

Three cold spots and three hot spots were detected for MHV in population age 20-44. Two large high-risk clusters covered wide areas in the southeast and west of the city, specifically, sub-regions including East Toronto, Scarborough South, West Toronto, South Etobicoke, North York West, and North Etobicoke Malton West Woodbridge. Low-risk clusters were mainly found in North York Central, Scarborough North, and North Toronto.

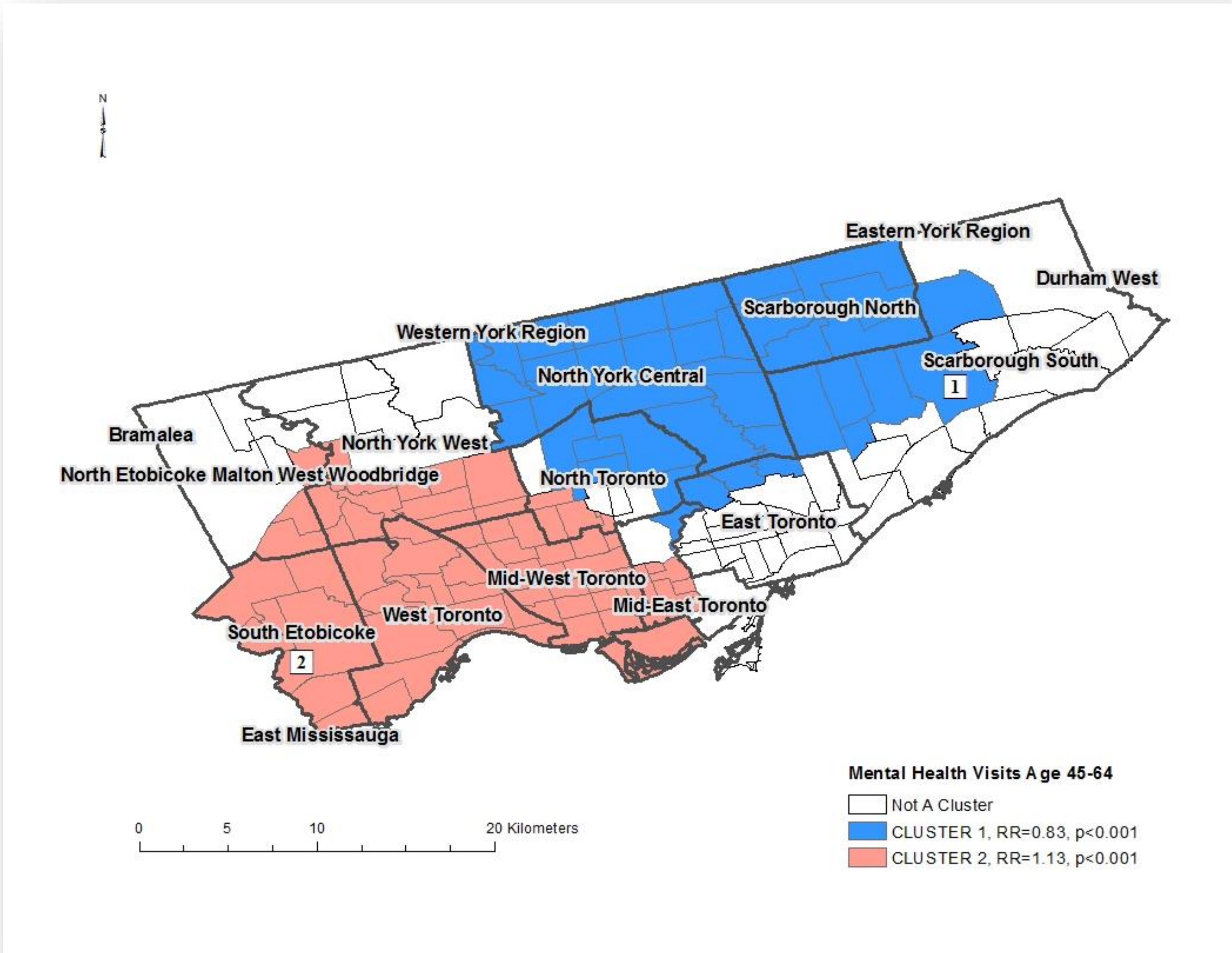

Figure 5.1.2 3 Map of clusters for mental health visits among population age 45-64 in the City of Toronto by neighbourhood
Hot spots(red) are areas with high prevalence of mental health visits; cold spots (blue) are areas with low prevalence of mental health visits. Clusters and Health Sub-Region names were labeled.

A low-risk cluster consisted of 37 neighbourhoods and a high-risk cluster consisted of 60 neighbourhoods were detected for MHV among people age 45-64. The large hot spot located in the west of the city covered the main areas of South Etobicoke, West Toronto, Mid-West Toronto, and North York West.

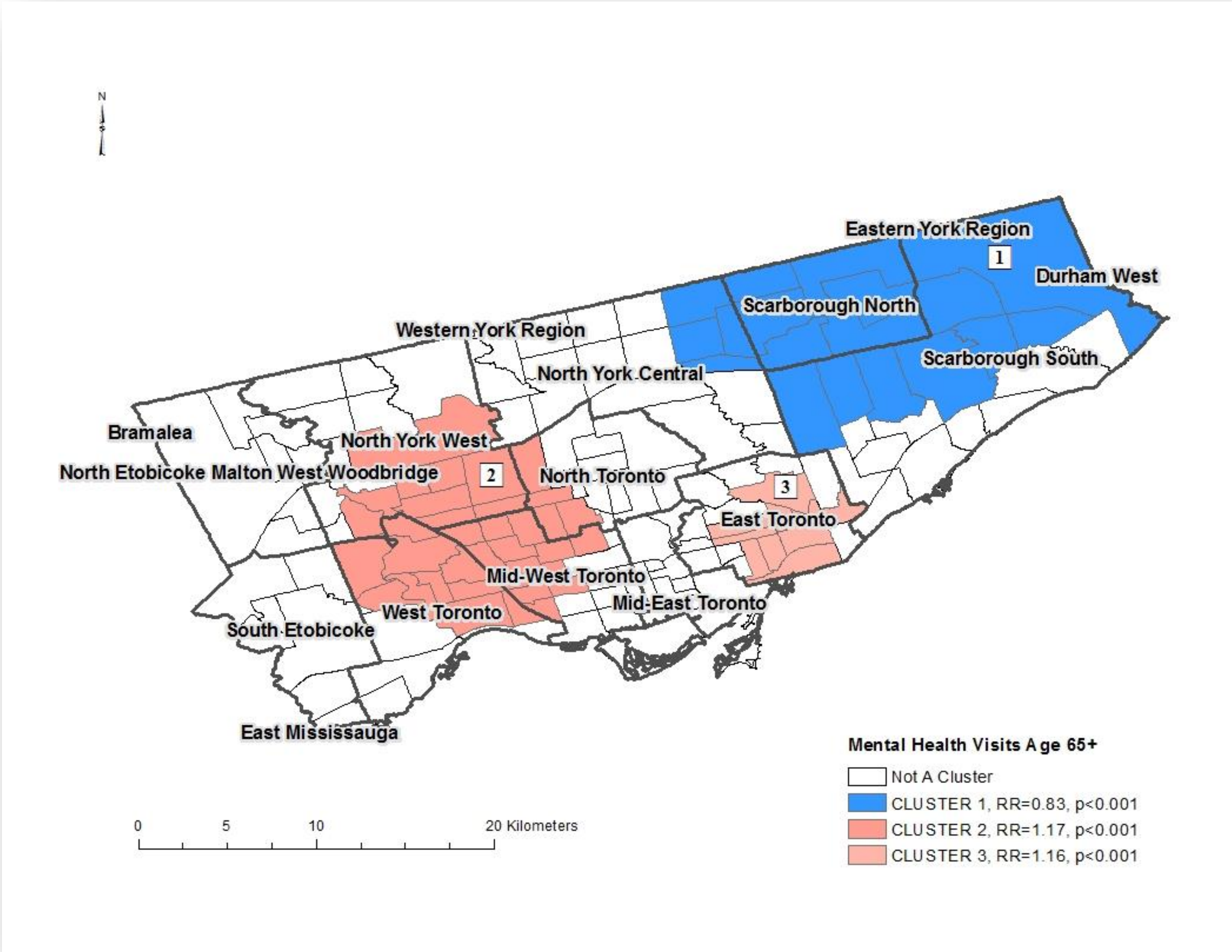

Figure 5.1.2 4 Map of clusters for mental health visits among population age 65+ in the City of Toronto by neighbourhood
Hot spots(red) are areas with high prevalence of mental health visits; cold spots (blue) are areas with low prevalence of mental health visits. Clusters and Health Sub-Region names were labeled.

For senior population, areas with high prevalence of MHV were clustered in North York West, West Toronto, Mid-West Toronto, North Toronto, and East Toronto. One cold spot was located in the far eastern region of the city, namely, Scarborough North and Scarborough South.

In a nutshell, cluster patterns did not appear to vary dramatically across age groups but did exhibit differences in distribution, whereby high risk clusters of MHV were more salient among younger adults who age 20-44 in terms of a relatively broader range and larger size of the hot spots. North York West, West Toronto, and Mid-West Toronto were consistently detected as hot spots across all the three age groups, suggesting there are disproportionately more adults had MHV in these areas than the city as a whole. Neighbourhoods within these sub-regions have the highest need for mental health prevention and intervention programs. Likewise, cold sports were consistently located in North York Central and Scarborough North. South Etobicoke was identified as a hot spot in population age 20-44 and 45-64, but not for older adults (age 65+). Similarly, cold spot was found in North Toronto in population age 20-44 and 45-64, but not in population age 65+.

5.2 Social Factors Associated with Mental Health Visits

Bivariate spatial regression analyses were carried out first for each of the explanatory variables to examine their independent relationships with MHV. The confounder median household income was accounted for throughout the process of bivariate regression analyses. The results for bivariate spatial regression analyses can be found in Appendix Ⅲ. Pairwise correlations between explanatory variables were also calculated and displayed in correlation matrices, which can be found in Appendix Ⅳ.

Social factors were first examined by subcategory, and those variables had a liberal $p < 0.2$ were included in one model to further select social variables for the final modelling process. Property crime was dropped since it was insignificant in bivariate analysis. Table 5.2.1, 5.2.2, 5.2.3 and 5.2.4 exhibit results of spatial regression analyses for subcategories including SES, demographic factors, social aid, and neighbourhood safety, respectively. Table 5.2.5 shows the results of spatial regression analyses for a total of nine social factors selected from each of the four subcategories.

5.2.1 Socioeconomic Status

Table 5.2.1 Spatial regression results for socioeconomic status

Socioeconomic Status				
Explanatory Variables	**Spatial Error Model**		**Spatial Lag Model**	
	Coef	***p***	***Coef***	***p***
Median Household Income	0.667	0.321	0.740	0.242
Income Inequality	5.917	0.006*	6.277	0.001*
Marginalization Index	0.027	0.838	0.021	0.869
Education	-0.018	0.026	-0.008	0.096*

Notes:
Coef = Regression Coefficient;
"*" denotes $p < 0.2$

5.2.2 Demographic Factors

Table 5.2.2 Spatial regression results for demographic factors

Demographic Factors				
Explanatory Variables	**Spatial Error Model**		**Spatial Lag Model**	
	Coef	***p***	***Coef***	***p***
Ethnic Diversity				
Median Household Income	-1.854	<0.001	-1.628	<0.001
Non-Visible Minorities	-0.001	0.944	0.011	0.381
South Asian	-0.018	0.345	0.003	0.808
East Asian	-0.033	0.062*	-0.010	0.471
Southeast Asian	-0.019	0.404	-0.003	0.875
Black	-0.003	0.888	-0.015	0.401
Population Mobility				
Median Household Income	-1.978	<0.001	-1.779	<0.001
Recent Movers	-0.017	0.055*	-0.010	0.060*
Recent Immigrants	-0.016	0.350	-0.028	0.014*

Notes:
Coef = Regression Coefficient;
"*" denotes $p < 0.2$

Table 5.2.2 Spatial regression results for demographic factors (Continued)

Demographic Factors				
Explanatory Variables	**Spatial Error Model**		**Spatial Lag Model**	
	Coef	*p*	*Coef*	*p*
Family Composition				
Median Household Income	-0.288	0.536	-0.141	0.722
Lone Parent Families	0.032	0.002*	0.029	0.001*
Population Living Alone	0.002	0.852	-0.0001	0.987
Language				
Median Household Income	-1.917	<0.001	-1.789	<0.001
Linguistic Diversity Index	-1.483	0.016*	-1.083	0.016*
No Knowledge of English or French	-0.001	0.938	-0.015	0.285

Notes:
Coef = Regression Coefficient;
"*" denotes $p < 0.2$

5.2.3 Social Aid

Table 5.2.3 Spatial regression results for social aid

Social Aid				
Explanatory Variables	**Spatial Error Model**		**Spatial Lag Model**	
	Coef	*p*	*Coef*	*p*
Median Household Income	-0.405	0.395	-0.329	0.367
Social Assistance Recipient	0.033	0.005*	0.031	0.001*

Notes:
Coef = Regression Coefficient;
"*" denotes $p < 0.2$

5.2.4 Neighbourhood Safety

Table 5.2.4 Spatial regression results for neighbourhood safety

Neighbourhood Safety				
Explanatory Variables	**Spatial Error Model**		**Spatial Lag Model**	
	Coef	*p*	*Coef*	*p*
Median Household Income	-0.969	0.011	-0.786	0.015
Property Crime	-0.003	0.149*	-0.003	0.162*
Violent Crime	-0.001	0.654	-0.001	0.619
Drug Arrests	0.008	0.005*	0.007	0.020

Notes:
Coef = Regression Coefficient;
"*" denotes $p < 0.2$

5.2.5 All Social Factors

For all social factors, the spatial error model and the spatial lag model consistently identified a significant positive association between income inequality and MHV ($p < 0.05$) as well as a significant negative association between the proportion of East Asian residents and MHV ($p < 0.05$). However, there is discrepancy in the results generated from the two spatial models, with the proportions of recent movers and social assistance recipients only significant in the spatial lag model ($p < 0.05$). The spatial lag model outperformed the spatial error model (BIC: 265.9 vs. 257.7).

Table 5.2.5 Spatial regression results for all social factors

Social Factors								
Explanatory Variables	**Spatial Error Model**				**Spatial Lag Model**			
	BIC = 265.9				**BIC** = 257.7			
	Coef	*p*	—— **95% CI** ——		*Coef*	*p*	—— **95% CI** ——	
Median Household Income	-0.107	0.877	-1.461	1.247	-0.475	0.446	-1.699	0.748
Income Inequality	4.773	0.039*	0.230	9.317	5.336	0.012*	1.149	9.522
Education	-0.008	0.419	-0.026	0.011	0.009	0.252	-0.006	0.023
East Asian	-0.024	<0.001*	-0.035	-0.013	-0.013	0.002*	-0.021	-0.005
Recent Movers	-0.018	0.059	-0.036	0.001	-0.019	0.015*	-0.035	-0.004
Recent Immigrants	-0.010	0.651	-0.053	0.033	-0.012	0.508	-0.049	0.024
Lone Parent Families	0.007	0.587	-0.019	0.033	0.002	0.842	-0.022	0.027
Linguistic Diversity Index	-0.799	0.224	-2.088	0.490	-0.779	0.143	-1.824	0.265
Social Assistance Recipients	0.023	0.204	-0.013	0.204	0.034	0.040*	0.001	0.067
Drug Arrests	0.001	0.654	-0.004	- 0.006	0.0001	0.964	-0.005	0.005

Notes:
Coef = Regression Coefficient; CI = Confidence Interval;
"*" denotes $p < 0.05$

5.3 Built Environment Factors

Similarly, three separate regression models were first built for neighbourhood physical surroundings, housing, and transportation (see Table 5.3.1, 5.3.2 and 5.3.3, respectively) whereby variables with a liberal p < 0.2 were put in one model to further decide what built environment factors should be included in the final model. Table 5.3.4 shows the results of spatial regression analysis for the four selected built environment factors.

5.3.1 Neighbourhood Physical Surroundings

Table 5.3.1 Spatial regression results for neighbourhood physical surroundings

Neighbourhood Physical Surroundings				
Explanatory Variables	**Spatial Error Model**		**Spatial Lag Model**	
	Coef	*p*	*Coef*	*p*
Median Household Income	-1.204	0.001	-0.998	<0.001
Community Places for Meeting	0.014	0.189	0.012	0.075*
Health Providers	-0.009	0.004*	-0.011	<0.001*
Sports Facilities	-0.006	0.456	-0.005	0.564
Walk Score	0.004	0.214	0.005	0.176*
Green Space	0.001	0.608	0.001	0.672

Notes:
Coef = Regression Coefficient;
"*" denotes $p < 0.2$

5.3.2 Housing

Table 5.3.2 Spatial regression results for housing

Housing				
Explanatory Variables	**Spatial Error Model**		**Spatial Lag Model**	
	Coef	***p***	***Coef***	***p***
Median Household Income	-0.420	0.443	-0.428	0.248
Rented Households	0.013	0.033*	0.006	0.152*
Household Needs Major Repair	0.052	0.005*	0.074	<0.001*
Population in Mid-Century Household	-0.013	0.007*	-0.007	0.049*

Notes:
Coef = Regression Coefficient;
"*" denotes $p < 0.2$

5.3.3 Transportation

Table 5.3.3 Spatial regression results for transportation

Transportation				
Explanatory Variables	**Spatial Error Model**		**Spatial Lag Model**	
	Coef	***p***	***Coef***	***p***
Median Household Income	-1.609	<0.001	-1.326	<0.001
Overcrowded Routes	-0.027	0.113*	-0.018	0.184*
TTC Stops	-0.097	0.140	-0.100	0.093*
Road Volume	$1.917e^{-5}$	0.385	$3.946e^{-6}$	0.861

Notes:
Coef = Regression Coefficient;
"*" denotes $p < 0.2$

5.3.4 All Built Environment Factors

Focusing on all built environment factors, households in need of major repairs and the number of health providers per 10,000 residents were statistically significant ($p < 0.05$), and were thus used to build the final model. Specifically, the proportion of households in need of major repairs was found to be a risk factor for MHV in both models. Health providers was statistically significant in the spatial lag model ($p = 0.003$), but was marginally insignificant ($p = 0.051$) in the spatial error model. The spatial lag model showed marked improvement in goodness-of-fit over the spatial error model with a △BIC greater than 16.

Table 5.3.4 Spatial regression results for all built environment factors

Built Environment Factors								
Explanatory Variables	**Spatial Error Model**				**Spatial Lag Model**			
	BIC = 275.8				**BIC** = 259.3			
	Coef	*p*	**95% CI**		*Coef*	*p*	**95% CI**	
Median Household Income	-1.121	0.007	-1.930	-0.313	-0.821	0.010	-1.433	-0.199
Health Providers	-0.006	0.051	-0.012	0.00002	-0.008	0.003*	-0.013	-0.003
Households Need Major Repairs	0.045	0.013*	0.009	0.081	0.065	0.0001*	0.032	0.098
Overcrowded Routes	-0.030	0.069	-0.063	0.002	-0.025	0.053	-0.051	0.0003
TTC Stops	-0.051	0.439	-0.182	0.079	-0.047	0.434	-0.164	0.070

Notes:
Coef = Regression Coefficient; CI = Confidence Interval;
"*" denotes $p < 0.05$

5.4 Combining Social and Built Environment Factors: Final Model

The final model combined four social factors and two built environment factors to identify explanatory variables that can best explain the variation in MHV data . Table 5.4 displays spatial regression results for the final model. Both of the spatial autoregressive terms, λ in the spatial error model and ρ in the spatial lag model were statistically significant ($p < 0.001$). We found a significant correlation between income inequality and MHV ($p < 0.001$) in both models, whereby higher level of income inequality was linked to increased MHV. Likewise, both the spatial error model and the spatial lag model showed the proportion of East Asians was negatively correlated with MHV ($p < 0.001$). The spatial lag model also identified the proportion of households in need of major repairs and the number of health providers per 10,000 residents as significant contributors to higher and lower levels of MHV ($p < 0.05$), respectively, whereas the relationships were insignificant in the spatial error model.

The spatial lag model consistently provided a better fit as determined by a lower BIC value of 241.9 compared with 253.5 from the spatial error model. In a nutshell, the regression results of the final model indicated the MHV data were better modeled through the spatial lag model, in which income inequality, the proportion of East Asians, the number of health providers per 10,000 residents, and the proportion of households in need of major repairs were found to be important factors that explain variation in MHV at the neighbourhood level.

Table 5.4 Spatial regression results for the final model

Explanatory Variables	Final Model							
	Spatial Error Model				Spatial Lag Model			
	BIC = 253.5				**BIC** = 241.9			
	Coef	***p***	**95% CI**		***Coef***	***p***	**95% CI**	
Median Household Income	0.190	0.758	-1.019	1.400	0.390	0.455	-0.633	1.413
Income Inequality	6.252	0.001*	2.423	10.081	6.895	<0.001*	3.371	10.418
East Asian	-0.026	<0.001*	-0.036	-0.015	-0.018	<0.001*	-0.025	-0.010
Recent Movers	-0.022	0.001*	-0.035	-0.009	-0.009	0.099	-0.019	0.002
Social Assistance	0.021	0.114	-0.005	0.047	-0.002	0.873	-0.021	0.018
Health Providers	-0.005	0.089	-0.010	0.001	-0.007	0.011*	-0.012	-0.002
Households Need Major Repairs	0.014	0.500	-0.026	0.053	0.043	0.012*	0.009	0.077

Notes:
Coef = Regression Coefficient; CI = Confidence Interval;
"*" denotes $p < 0.05$

5.5 All-Subset Selection Results

Table 5.5 A list of top five combinations of explanatory variables with lowest BIC values

BIC	Variables in Model
232.1	Median Household Income + Income Inequality* + East Asian* + Recent Immigrants + Health Providers* + Major Repair Needed*
234.2	Median Household Income + Income Inequality* + East Asian* + Recent Immigrants + Health Providers* + Major Repair Needed* + Overcrowded Routes
234.3	Median Household Income + Income Inequality *+ East Asian* + Linguistic Diversity + Health Providers* + Major Repair Needed*
234.3	Median Household Income + Income Inequality* + East Asian* + Health Providers* + Major Repair Needed* + Overcrowded Routes
234.5	Median Household Income + Income Inequality* + East Asian* + Recent Movers + Linguistic Diversity + Health Providers*

Notes:
Median household income was always kept at each combination as a confounder;
"*" indicates one of the four statistically significant variables in the "final model".

Table 5.5 displays top 5 "best candidate models" with the lowest BIC values constructed through the all-subset selection approach fitting the spatial lag model. Models 2 – 5 (row 2 to 5) are almost identical according to BIC. The model with the smallest BIC value of 232.1 may be taken as the "best model", but the strength against the other four models is weak (△BIC = 2.1). It's worth noting that the automated variable selection method has consistently selected the four variables, that are income inequality, East Asian, health providers and major repairs needed, which also reached statistically significance in the final spatial regression model in Table 5.4. The results of the all-subset selection have further confirmed their importance in terms of explaining MHV variations. Model 1 also contains the variable recent immigrants, which was excluded from the final model since it had a p-value > 0.05 (p = 0.5) in the initial variable screening process. The most likely explanation is that recent immigrants is highly correlated with other social factors in the model (e.g. pairwise correlation matrix showing a r value of 0.46 between recent immigrants and recent movers), leading to an insignificant p-value. Recent immigrants may be useful in improving goodness-of-fit, but not as much as the other four variables. Hence the automated variable selection process has confirmed the findings in Table 5.4, giving us assurance that income inequality, East Asian, the number of health providers per 10,000 residents, and households in need of major repairs play important roles in explaining the geographic variation in MHV.

5.6 Testing Regression Residuals with Moran's I

The Global Moran's I was computed on the residuals of the final models before the end of the analysis. This final step is to test if there is any spatial autocorrelation left in the residuals that has not been accounted for by applying spatial regression models. Residuals from the final spatial lag model exhibited a Moran's I value closed to zero that was insignificant ($I = -0.03$, $p = 0.32$), thus no evidence of spatial autocorrelation in the residuals. Likewise, there was no spatial autocorrelation observed in the residuals of the final spatial error model ($I = -0.03$, $p = 0.35$). For comparison, we also performed this residual diagnostic for the OLS model including the same set of variables, and the residuals demonstrated statistically significant positive spatial autocorrelation ($I = 0.32$, $p = 0.001$). The results indicate the necessity for applying spatial regression models to account for spatial effects.

Chapter 6 Discussion

In this section, results of geographic variation in MHV are briefly discussed, followed by an intensive discussion on factors associated with MHV, with emphasis on the four factors that have been identified as overall prominent factors influencing MHV: income inequality, East Asian, households in need of major repairs, and health providers. Lastly, limitations and strengths, public health implications, and future work directions are outlined.

6.1 Geographic Variation in Mental Health Visits

As an initial step of the spatial analysis, the Global Moran's I was calculated to quantify spatial autocorrelation of MHV data. The Global Moran's I value was 0.659 ($p = 0.001$), providing empirical evidence of spatial clustering. Kulldorff's Spatial Scan Statistic confirmed the existence of clusters while detecting both their locations and their corresponding statistical significance. To explore clustering patterns among different age groups, age-specific cluster maps were generated to show areas with higher-than-expected prevalence of MHV for three separate age groups. By comparing maps, mental health interventions can be tailored to specific subpopulation at the local context. For instance, South Etobicoke was identified as a hot spot of MHV for adults age 20-44 and 45-64, but not for those age 65+, therefore, workplaces might be a more appropriate setting for mental health education programs in this sub-region. Furthermore, neighbourhoods of North York West (especially neighbourhoods located in the southern part), West Toronto, Mid-West Toronto are high priority areas where mental health intervention programs and further studies are to be carried out.

6.2 Social and Built Environment Factors Associated with Mental Health Visits

The identified clusters may point to underlying social or built environment factors contributing to mental health variation, and this is where confirmatory spatial analysis comes to play. Both the spatial lag model and the spatial error model were applied, and these two models represent distinct specifications of spatial effects that are driven by different motivations. The spatial lag model, given by $y_i = \rho W_y + x_i\beta + \varepsilon_i$, is a *theory-driven* specification that has been built on the theoretical basis of a spatial reaction function (Anselin, 2002). Brueckner (2003) posited two types of theoretical frameworks for a spatial reaction function: the first type is referred to as the *spillover* model, in which the level of y of an individual i is directly affected by other individuals, say y_{i+1}; the second type of theoretical framework is called the *resource flow* model, where the individual's level of y is only indirectly affected by other individuals, and the indirect effect is a consequence of the distribution of a particular "resource" that shared in this area. An example fits in the spillover model is that individuals with similar levels of mental health affecting each other, namely a true contagion; an example falls into the resource flow model is that the levels of mental health not only depends on the neighbourhood itself, but also depends on the distribution of health resources (e.g., physician supply). The spatial error model, on the other hand, is a *data-driven* specification, or more specifically, data "problems" driven which include a conceptual mismatch between the "true" scale and the available scale (this often occurs when exploring environment or resource-related outcomes, say agricultural land market, at an administrative unit level such as census tract) and missing a key variable that are spatially dependent (e.g., natural topographical features such as presence of rivers and mountains) (Anselin, 2002; Brueckner, 2003).

We speculate that the spatial lag model fits the data better as compared to the spatial error model. There is indirect evidence in support of the spillover effect in mental health by which Fowler & Christakis (2008) followed a cohort over 20 years and found happiness were transferrable from one to another. The resource flow model is also plausible since there is a consensus that the distribution of medical resources has a profound impact on health. Duncan et al. (2013) in their study of built environment and depressive symptoms in Boston, the United States concluded that the spatial lag model is the most appropriate model compared to OLS and the spatial error model. Furthermore, there is no clear evidence of a scale mismatch or unmeasured inherently spatially correlated covariate pointing to the spatial error specification. However, the cross-sectional nature of the MHV data does not provide sufficient information to distinguish the two different frameworks that are observationally equivalent (Anselin, 2002). In fact, the spatial regression results generally support the theorization. According to BIC, the spatial lag model is deemed as a better final model with a lower BIC value than that of the spatial error model (△BIC = 11.6). When modelling social and built environment separately, the spatial lag model was consistently superior to the spatial error model, with a △BIC of 8.2 for the former and a △BIC of 16.5 for the latter.

There are other more complicated spatial models that incorporate more than one type of spatial interaction effect. For example, the spatial Durbin model, given by $y = \rho W_y + X\beta + W_x\theta + \varepsilon$, includes a spatially lagged dependent variable and spatially lagged independent variable(s), which can be simplified to the spatial lag model when θ = 0; the spatial Durbin error model, given by $y = X\beta + W_x\theta + u,\ u = \lambda W_u + \varepsilon$, includes spatially lagged independent variable(s) as well as a lagged error term (LeSage & Pace, 2009). Likewise, the spatial error model can be considered a special case of the spatial Durbin error model when $\theta = 0$. Another commonly used spatial model is referred to as the SARAR model, which has spatially lagged dependent variable and error term. We also fitted the final model using the spatial Durbin model, the spatial Durbin error model, and the SARAR model. However, it appeared that more complex spatial specifications did not improve the goodness-of-fit as none of these models had a BIC value lower than that of the spatial lag model. The remaining of this section provides a detailed discussion for the four variables that best explain MHV data according to the final spatial lag model.

Income inequality

Income inequality was found to be a prominent social factor associated with MHV in Toronto neighbourhoods. In a multi-level Welsh study, Fone et al. (2013) reported that income inequality, represented using Gini coefficient, was a relatively weak determinant of mental health at the local neighbourhood level, but was a significant risk factor for mental health at the larger unitary authority level. It's worth noting that in this study, the mean population size of neighbourhood and unitary authority was 1,500 and 150,000, respectively. Interestingly, the average population size of Toronto neighbourhood was approximately 19,000, which was more than twelve times larger than the neighbourhood in Fone's study, while nearly eight times smaller than that of unitary authority. The above comparison suggests the effect of income inequality on mental health seems to be unlikely to operate at a fine scale with a few thousands of people as the population size is too small to present the substantial social structure of the study population. Consequently, when comparing findings from studies on the same topic, one should be aware that income inequality is substantially an ecological-level measurement, thus caution should be taken in regards to variation in population size.

The mechanism how income inequality affects mental health is currently under debate. Multiple hypotheses have been put forward to explain this association. These hypotheses have been argued to operate at distinct ecological levels. At the individual level, psychological distress and social defeat play vital roles (Patel et al., 2018). When it comes to large scales like states and nations, the neo-materialist hypothesis posits that economic policies derived from income inequality, such as differential investment in housing, education, health services and other public infrastructure ultimately lead to unequal mental health (Layte, 2012; Patel et al., 2018)

Closely related to this study, at the small-area level, the social capital hypothesis is one of the most widely accepted mechanisms. Social capital is a community-level variable, as opposed to a person's social networks at the individual level, which is defined as the features of social organization that facilitate cooperative actions to achieve common benefits for individuals embedded in it (Kawachi et al., 1997; Layte, 2012). Income inequality has been argued to decrease interpersonal trust, leading to the erosion of social capital, which in turn affects mental health (Fone et al., 2013; Layte, 2012; Patel et al., 2018) .

The question then arises as to how social capital relates to mental health. According to Berkman and Kawachi (2014), neighbourhood's social capital exerts a contextual effect on residents' mental health through three plausible pathways: 1) health-related behaviours that can promote mental health tend to spread more quickly through a well-connected community. The simplest example is to seek for mental health support - a person who suffers from mental health problems might be encouraged to see a doctor by a friend, or even a friend's friend with similar experiences. 2) A tightly-knit neighbourhood can rely on its residents to intervene deleterious behaviours for mental health, namely informal social control. For instance, adults are more likely to speak out against drug abuse or discrimination towards mental illness. 3) Social capital is associated with "collective efficacy" manifesting as higher civic engagement. Residents' associations enable the inhabitants' voice to be heard, for example, protecting against budget cuts affecting mental health, which will benefit the whole community.

Although income inequality can affect the entire neighbourhood, individuals with low socio-economic status tend to be more vulnerable to the negative mental health consequences of residing in an unequal neighbourhood. Research showed that people with low wealth living in an economically disadvantaged neighbourhood reported the most depression symptoms (Wight, Ko, & Aneshensel, 2011). People at the bottom half of the income level often lack motivation to involve in mental health promotion programs, which has a tendency to widen the gap of mental health condition between the most and the least well-off residents. For neighbourhoods with high levels of income inequality, policy makers should ensure the fair inclusion and integration of voices and perspectives of economically disadvantaged subgroups in health policy decision-making processes.

East Asian

The *Employment Equity Act* defines visible minorities as "persons, other than Aboriginal peoples, who are non-Caucasian in race or non-white in colour" (Statistics Canada, 2013b).

Among visible minority groups including South Asian, East Asian, Southeast Asian, and Black, East Asian (i.e. Chinese, Korean, and Japanese) was the only ethnic group who had a significant association with MHV ($p < 0.05$). Table 6.2 lists top five neighbourhoods with the highest concentration of East Asian, four of which have more than half of population being East Asian ethnicity. The table below makes a first impression that neighbourhoods with high proportions of East Asians have considerably low prevalence of MHV.

Table 6.2 Five neighbourhoods with the highest concentration of East Asian and their prevalence of MHV

Neighbourhood ID	Neighbourhood Name	Proportion of East Asians	Prevalence of MHV Mean=8.1	Rank of MHV out of 140 neighbourhoods
116	Steeles	71.3%	5.7	1st lowest
130	Milliken	68.0%	5.7	1st lowest
129	Agincourt North	56.0%	5.9	2nd lowest
48	Hillcrest Village	50.6%	6.7	8th lowest
128	Agincourt South-Malvern West	48.9%	6	3rd lowest

Findings from prior studies have indicated that the negative association between East Asian and MHV may be predominantly due to the under use of mental health services. Research showed Chinese immigrates were less likely to use mental health services, not only compared with white people but also compared with other Asian immigrant groups such as South Asian and Southeast Asian (Tiwari & Wang, 2008). Similarly, a study in British Columbia reported a lower level of mental health professional consultation among Chinese Canadians than non-Chinese Canadians, irrespective of mental health status (Chen, Kazanjian, & Wong, 2009). Moreover, the CCHS data showed that Chinese respondents had the poorest self-rated mental health, lowest use of mental health services, highest level of unmet needs, and the weakest sense of belonging to local community when comparing with South Asian, black, and white respondents (Chiu et al., 2018). Most notably, a large population-based study of psychiatric patients in Ontario revealed that Chinese patients had higher odds of involuntary admission and severer illness symptoms than general patients, which directly pointed to a reluctance and delay in seeking help from family physicians and psychiatrists in the outpatient setting (Chiu et al., 2018).

Several studies have focused on discerning the underlying rationale behind East Asians' negative attitude towards consulting mental health services. Age, gender, education, family income, and immigration status were proven to be non-significant predictors of seeking professional help among Canadian East Asian immigrants (Chen et al., 2009; Fung & Wong, 2007; Tiwari & Wang, 2008), suggesting the infrequent utilization of mental health services is unlikely to be explained by common demographic factors. In fact, the whole story behind this pattern of help-seeking is likely to be complex and multifaceted (Anderson, McKenzie, & Kurdyak, 2017). Possible explanations are discussed from two aspects: patient driven and provider driven. While lack of English knowledge may be a barrier for some East Asians, evidence indicated cultural issues being more plausible explanations (Chen et al., 2009). Culturally informed recognition of nature, etiology and cures of mental illness has a profound impact on pathways that individuals followed when making help-seeking decisions (Leong & Lau, 2001). Additionally, higher levels of social stigma, lower levels of acculturation, and conflicts between traditional collectivistic value orientation of East Asians and individual-centralized Western treatment philosophy can all be deterrent to seeking help (Chen et al., 2009; Leong & Lau, 2001). Another major barrier to seeking mental health services reported by 1000 immigrant and refugee women in Toronto was less perceived access to culturally and linguistically appropriate services (Fung & Wong, 2007). From the perspective of health providers, culturally governed symptom expression and communication norms of East Asian patients can often be challenging. Physicians are likely to misdiagnose or underdiagnose mental disorders due to a failure to minimize biases stemming from cultural differences (Leong & Lau, 2001). For instance, physicians can mistakenly judge an individual's culturally sanctioned belief or behavior as hallucination due to their unfamiliarity to the patient's culture (Leong & Lau, 2001). Patients with negative prior experience in mental health services may develop resistance-to-care behaviours in the future, and East Asians are at great risk of encountering such situation.

The finding suggests a tendency of underutilization of mental health services among East Asians in Toronto neighbourhoods. Therefore, we have reason to believe, there is potentially a large group of people residing in neighbourhoods with high density of East Asians who are experiencing mental health problems without seeking any help. Prevention and intervention programs are needed to address barriers to mental health care for East Asians. Given the lower level of perceived access revealed in Fung & Wong's (2007) study, the focus turns to improving the level of perceived access rather than access alone in a region with the greatest supply of mental health services like the City of Toronto. Therefore, education programs regarding stigma reduction and available mental health and addictions services can be implemented in East Asian neighbourhoods. In addition, stakeholders should make efforts to improve mental health services through, for example, recruiting bicultural providers or delivering culturally tailored treatments, to provide ethnic-specific mental health care that adequately serving East Asian communities (Leong & Lau, 2001). Meta-analysis also showed that culturally tailored mental health interventions, especially to a specific cultural group, had enhanced treatment outcomes for Asian American patients (Huey & Tilley, 2018).

Major Repairs Needed

The proportion of dwellings in a poor condition with major repairs needed was positively correlated with neighbourhood MHV. According to the 2011 National Household Survey (NHS), dwelling owners were asked about the condition of their occupied private housing. A major repair, defined as problems that “compromised the dwelling structure or the major systems (heating, plumbing, and electrical)” such as “defective plumbing or electrical wiring” or “structural repairs to walls, floors or ceilings”, was considered an indicator of housing inadequacy by housing organization (Statistics Canada, 2013a). This inverse relationship between poor housing conditions and mental health has been confirmed in previous studies (Evans et al., 2001; Leclair & Innes, 1997; Pevalin et al., 2017). According to Evans et al. (2003) , housing quality can affect mental health through a psychosocial pathway with a variety of mediating processes including identity and self-esteem, insecurity stemming from concerns about safety and hygiene, and a sense of helplessness.

The federal government has also realized the pivotal role housing plays in mental health through a series of successfully implemented housing strategies. For example, a nationwide project “*At Home/Chez Soi*” funded by Health Canada through the MHCC took place in five cities:

Moncton, Montreal, Toronto, Winnipeg, and Vancouver (Stergiopoulos et al., 2014). Through providing people experiencing serious mental illness and homelessness with housing and service supports, the project achieved an average savings of $15.05 among high-need participants and $2.90 among moderate-need participants for every 10$ invested, as well as substantial reduction in mental health symptoms among participants in the Toronto site (Stergiopoulos et al., 2014). The significant effect of housing quality on mental health identified in this study, along with convergent evidence from prior research may suggest that housing quality is of equal importance to housing availability and stability, thus should be taken into account in housing projects for mental health promotion in the future.

Even though the finding of the current study demonstrated a consistent relationship between housing quality and mental health with previous findings, there are several limitations that need to be considered. First, it should be borne in mind that the dichotomous self-reported assessment of major housing problems had substantial under-reporting issues given the respondents were owners of the dwellings. Second, as a voluntary survey, the NHS was completed by approximately 16% of the Canadian population and was anticipated to have a slightly higher sampling error than that of from a mandatory long-form census (Statistics Canada, 2015). More importantly, the survey question on condition of dwelling was restricted to people owning private dwellings, thus excluding a large amount of population, particularly those with relatively lower economic status while at greater risk of having mental illness. This limitation is even more pronounced in our study region given the considerably low housing ownership rate in the City of Toronto. According to the 2011 NHS, there were as many as 44% rented households in the City of Toronto. The reporting bias and selection bias can affect both internal validity and external validity. Lastly, there is a concern that the correlation may be the product of reverse causality as individuals with mental disorders are more likely to live in poor conditions as a result of restricted economic opportunities (Pevalin et al., 2017). As already mentioned, it is unlikely people with severe mental disorders and illness were part of the survey question respondents because of their lower chances of owning a house. Therefore, reverse causality appeared to be a minor, or moderate problem. Future research can analyse housing quality data with better representation and lower reporting bias, or most ideally, researchers may conduct health surveys to collect data on housing quality and residents' perceived effects on mental health.

Health Providers

Health provider was identified as a salient factor for MHV, with neighbourhoods having a greater number of health providers per 10,000 residents exhibiting lower levels of MHV. It should be clear here that health providers were not limited to mental health care providers but were a collective of general medical facilities such as doctor offices, dentist offices, pharmacies, clinics and other health employers.

Assuming that the number of health providers had nothing to do with neighbourhood mental health status but solely acting as a contextual enabling factor of Anderson's Behavioural Model of Health Service Use (Andersen, 2008), we would expect a positive, but in no way a negative association between health providers and MHV since better supply often leads to increased health services utilization. The correlation direction somehow suggests that health providers may have a protective effect on neighbourhood mental health.

Adult mental health disorders are preventable: 25% to 60% of adult mental disorder cases had a diagnosable disorder in childhood thus could possibly be prevented by early intervention (Kim-Cohen et al., 2003). In general, family doctors and other primary care health providers practicing at doctor offices and clinics are naturally the first and most frequent contacts with patients. Therefore, having adequate primary healthcare resources may increase the chance of detecting mental health problems at an early stage. In addition to that, patients with mental health illness are facing poor physical health owing to a variety of comorbid physical conditions and side effects of psychotropic medication. Evidence showed people with mental health and substance use conditions used more services for both mental health and non-mental health purposes (Graham et al., 2017). And more notably, they are also more likely to experience unmet physical health needs. It was estimated that the non-treatment rate was 30% for diabetes, 62% for hypertension, and 88% for dyslipidemia among individuals with schizophrenia (Nasrallah et al., 2006). Moreover, two-thirds of emergency department visits made by patients with mental health and substance use conditions were strikingly for non-mental health reasons. Mental health and physical health are closely interconnected with a mutual influence and, in a word, there is no mental health without physical health. Poor physical health as a result of inadequate access to quality general health services can put mental health patients in high risk of experiencing relapse or recurrence of their mental illness. On the other hand, individuals with undiagnosed and undertreated physical conditions are at great risk of developing mental health disorders.

The relationship between access or supply of services and mental health outcomes has been intensively examined, but the emphasis of the literature on this topic has been almost exclusively placed on mental health specific services and providers. Providers in other health settings, though play essential roles in prevention, detection, treatment, and management of mental health illness and its corresponding complications, have often been overlooked. It should be recognized that the promotion of mental health requires a comprehensive integration of mental health and non-mental health-specific providers. Primary care services are both physically and financially more accessible, and have reduced stigma as they are not associated with any specific health conditions, thereby are generally better accepted by mental health patients (World Health Organization, 2003). Pharmacists have much to offer in terms of triage, health promotion, early detection, optimal treatment outcomes, education, helping to shape public policy, interprofessional collaborative practice, and research on mental health (International Pharmaceutical Federation, 2015). A collaborative practice model emphasizing specialized clinical pharmacy services was shown to significantly improve medication adherence and patient satisfaction, and reduce the patients' subsequent visits to primary care providers (Finley et al., 2002). Dentists offices also have a potential to play a key role in physical health promotion among people with mental health conditions considering the reality that severe mental illness, affective disorder, and eating disorders are positively correlated with oral diseases, and people with severe mental illness are 2.7 times more likely to lose all their teeth (Kisely, 2016; Ngamini Ngui & Vanasse, 2012).

To our knowledge, the present study for the first time, examined the association between the number of generic health providers and mental health. The result provided preliminary evidence supporting a protective role that general health providers may play towards mental health. While a high supply of health providers does not necessarily translate into a better service performance, supply of health facilities should be given a high priority ranking in health planning since lack of medical services and resources is a salient barrier to care. It might be necessary to increase the number of generic health providers, or extend the office hours of care services if elevated mental health concerns are presented in a neighbourhood. Medical facilities can also be used as important settings of mass media interventions, for instance, audiovisual message and health promotion poster in pharmacies and doctors' waiting room may help reduce stigma, ultimately improve mental health (Thomas et al., 2016). Study showed broadcasting an audiovisual message was associated with increased vaccination prescriptions (Eubelen et al., 2011). Meanwhile, additional research focusing on specific types of health providers is needed to gain a better understanding of the impact health facilities have on mental health.

Other Factors associated MHV

The results of the all-subset selection suggest recent immigrants was also a contributing factor of MHV. Neighbourhoods with a high concentration of recent immigrates were associated with a lower level of MHV. This protective effect, termed the "healthy migrant effect" was supported by Ali (2002), Menezes et al. (2011), and Salami et al. (2017). Possible explanations for this phenomenon include two aspects: the host country selection - the requirements for skills and educational attainment, and more importantly, health screening by immigration authorities; the immigrant self-selection by which the healthiest and the most well-off individuals are more likely to migrate (Kennedy, Kidd, McDonald, & Biddle, 2015). It is noticeable that all three supportive studies relied on self-reported mental health data from health surveys, which had a tendency to under-report mental illness. Our results supplement existing findings on the presence of "healthy migrant effect" phenomenon for mental health by analysing mental health data from administrative databases.

Green space has received much interest in past studies on built environment and mental health, however was not a significant contributor of MHV variations based on our findings. The benefits of green space for mental health were supported by solid evidences from a twin study (Cohen-Cline et al., 2015) as well as a panel study (Alcock et al., 2014). What interests us the most is a New Zealand-based study with similar study design and mental health data to ours, whereby the protective effect against anxiety/mood disorder was only significantly observed from green space within a 3 km buffer, but not a 300 m buffer (Nutsford et al., 2013). Further to that, in a multi-level study conducted in the Netherlands, the buffering effects of green space against self-reported stressful life events were found only for the green space within 3 km of residents' homes, but not for the 1 km radius (van den Berg et al., 2010). The green space data in the present study used a 1 km buffer, which provided a plausible explanation for the insignificant association. It was theorized that a 1 km radius was not wide enough to capture large-scale natural areas, whose restorative effects against stress may improve mental well-being (van den Berg et al., 2010). It is also possible that the failure to account for length of residence might affect study results. It has been found that benefits of urban green space were time-dependent, and it may take time to achieve green space benefits for mental health (Alcock et al., 2014).

6.3 Public Health Implications

The policy decision-making is often a complex process relying on a wide range of evidence drawn from disparate data sources with different study designs. The present study performed at the neighbourhood level covering the entire population of the City of Toronto can help guide mental health planning for the general population. Meanwhile, the nature of the spatial design makes it possible to tailor mental health services at the local context.

Social factors can deeply influence mental health, and our findings have confirmed their effects. There are certain socio-demographic groups who are exposed to elevated risk of developing mental health disorders (e.g., individuals residing in neighbourhoods with high levels of income inequality) or are facing more challenges in receiving appropriate mental health care (e.g., East Asians). After understanding the role of social context in mental health, clinicians and health planners should take these factors into account to minimize mental health inequalities.

East Asians were found to be associated with low levels of mental health service use. Based on qualitative evidence from previous studies (Chen et al., 2009; Fung & Wong, 2007; Leong & Lau, 2001), we recommend that health providers practicing at neighbourhoods with high proportions of East Asians (e.g. Steeles, Milliken, and Agincourt North etc.) provide culturally sensitive mental health services and education programs. For instance, *Journey to Promote Mental Health* is a culturally tailored training program developed by a collaboration between the Hong Fook Mental Health Association of Toronto and the Ontario Council of Agencies Serving Immigrants (OCASI) that helps newcomers to identify early signs and improve knowledge of mental health (Mental Health Commission of Canada, 2012). This project can be modified to benefit East Asian communities.

Not surprisingly, income inequality was identified as a standout risk factor for mental health. Although it is not realistic to eliminate income inequality, we need to assure equitable participation in health funding decision-making and program design for those living in highly unequal areas. The MHCC established a *Citizens Reference Panel*, whereby 36 panelists were selected representing all 36 million Canadians to work together like a jury to identify the highest priority mental health issues and actions in Canada. The opinions of the panelists were highly valued and were incorporated into the design and structure of the Mental Health Strategy framework (Mental Health Commission of Canada, 2016). When selecting members, the MHCC may give more weights to low income individuals living at highly unequal neighbourhoods as well as East Asians to acquire insightful knowledge about how to remove mental health inequalities in demographic groups with high risk. To sum up, the broad-based evidence drawn from ecological data may not be sufficient to initiate an independent mental health project, but it is useful in terms of narrowing or expanding existing mental health programs to target specific subgroups.

One novel finding from this study was that neighbourhoods with larger number of health providers per 10,000 residents, including doctor offices, dentist offices, pharmacies, etc. were associated with decreased prevalence of MHV. General health providers play an essential role both in secondary (early detection) and tertiary prevention (relapse and complication reduction) of mental illness. It could be a reminder to temporarily switch attention from mental health specific services to general medical care whereby health planners may consider increasing the number of primary health providers in neighbourhoods where mental health is a major concern. Furthermore, stakeholders can maximize the protective effect of general care settings through implementing mass media intervention, particularly in East Asian neighbourhoods whose residents are less likely to seek help, to reduce stigma, improve knowledge and early detection of mental health problems. On the other hand, the importance of housing quality was once again highlighted in this study. Therefore, it is feasible to incorporate quality with availability, affordability, and stability into housing projects such as MHCC's *At Home/Chez Soi* or *Turning the Key*.

Lastly, the current study generated MHV cluster maps using GIS techniques and spatial statistical methods. These cluster maps can be used as a useful planning tool to identify specific neighbourhoods for resource allocation, intervention implementation, and further exploration. Since neighbourhood is naturally a planning unit, initiatives can be directly implemented at the unit of analysis or at larger scales like sub-region and LHIN as they are closely linked to neighbourhood. Further to that, the cluster maps provided a clear direction as to where more focused qualitative research is to be carried out, which is logically a further step following a population-level investigation. Conducting a city-wide multilevel study requires a large sample of individuals covering every single unit of analysis. Normally, this can be really difficult for a refined geographic scale and may result in insufficient participants in some areas. Collecting data on a few selected neighbourhoods is much more feasible and cost-effective. A combination of ecological-level administrative data and individual-level qualitative data is instrumental in supporting evidence-based policies making for mental health care.

6.4 Limitations

Data Limitation

The primary limitation pertains to the MHV data. The prevalence of MHV is expected to be under-recording since Community Health Centre (CHC) visits, which account for nearly 7% of physician claims in Ontario, and non-OHIP claims were not included (Toronto Community Health Profiles, 2015). Additionally, MHV occurred out of the city and under-diagnosed cases were not counted. Misclassifications due to geocoding errors and out-of-date insurance addresses also limited the accuracy of the data. The MHV rates should be interpreted with great cautious. It should be noted that MHV is not a valid indicator of the prevalence of mental health conditions as it considerably underestimated the rates of mental health morbidity. It was estimated that less than 40% of patients sought help for their diagnosable mental disorders or substance dependence in Canada (Urbanoski, Rush, Wild, Bassani, & Castel, 2007). The patients whose mental health care needs have been met might be very much “the tip of the iceberg”. In addition, the age-standardized MHV rates partially account for innate individual traits with no adjustment for gender. Future research can look at specific age and sex groups to make more rigorous inferences.

It should be clear that clusters of high rates of MHV can either be due to more residents with mental health issues living in the neighbourhood, or a greater proportion of patients chose to seek treatment. Given that MHV is regarded as a rough indicator of mental health conditions and “expressed” service needs in this study, it is assumed that individuals have an equal opportunity to use mental health services. The predominant interest in this indicator derives from its relative magnitudes between neighbourhoods, which is an important first step toward removing neighbourhood mental health inequities.

The limitation of the explanatory variables should also be noted. Using data from various of original sources, some independent variables were not calculated for the year of 2012 when MHV data were collected. For example, the Marginalization Index was based on 2006 Census data, and that was the reason why it was not used to adjust for deprivation. Although dramatic changes in neighbourhood social and built environment are unlikely, it is important to bear in mind that the neighbourhood environment at the time when MHV was made might have been slightly different. Furthermore, little information is available in relation to the validity of neighbourhood environment measurement, such as those GIS-derived built environment covariates (e.g., neighbourhood physical surroundings), which may invalidate our findings.

MAUP

The Modifiable Areal Unit Problem (MAUP) is a universal issue affecting spatial analysis on aggregate data. The term “modifiable” is used due to the fact that all geographical boundaries are artificial with no intrinsic geographical meaning (Openshaw, 1984), making MAUP an unavoidable problem to all small-area spatial analysis. Consider that the information lost in aggregation is permanent, the way that the aggregation is performed will undoubtedly shape the resulting inference (Waller & Gotway, 2004).

The MAUP consists of two forms of problems termed the scale effect and the zoning effect. The scale effect is the inconsistent statistical results obtained when the same basic data are grouped into fewer or larger spatial units (Openshaw, 1984). An example of this is repeating the analysis with the same set of variables but using LHIN as the scale for analysis may yield distinct results. The zoning effect, also known as the boundary effect, refers to the impact of altering the locations of boundaries of the zones at a given number of areal units (Cromley & McLafferty, 2012; Patel et al., 2018). In the context of this study, all variables are available at the same geographic level with unchanged boundaries, hence MAUP is not considered a major concern.

Ecological Fallacy

Another issue that cannot be ignored is the well-known ecological fallacy, which arises when the estimate yielded from grouped data is used to make inference upon an individual-level relationship (Haining, 2003). For instance, it is erroneous to conclude that all individuals reside in a hot spot have a higher rate of MHV. Perhaps the key point regarding this problem, as Waller and Gotway suggested, is to always be clear about what types of inferences we want to make (Waller & Gotway, 2004). For the purpose of drawing causal inference, individual-level data are preferred, although they can be expensive and time-consuming to collect. In contrast, ecological findings contain valuable information for policy makers and city planners as they aim to make inference about groups of people. This study is not designed to assess mechanisms but a crude examination of neighbourhood-level variation in MHV as well as factors that may be associated with MHV.

6.5 Strengths

Despite those limitations, this study has several strengths. A large number of Canadian studies on mental health used data from the CCHS, in which a majority Ontarians reported a very good or excellent mental health status (Brien et al., 2015). However, there is a significant tendency of under-reporting mental health needs in health surveys – each year nearly two million Ontarians were recorded to have MHV to doctors with only approximately one million Ontarians reported being affected by mental health conditions in health surveys (Brien et al., 2015). The current study adopted a valid measure of MHV with a sensitivity of 81% and a specificity of 97% drawn from a health administrative dataset that covered the entire population of the City of Toronto, therefore avoiding reporting and selection biases that are common in health surveys (Steele, Glazier, Lin, & Evans, 2004). In addition, it is noteworthy that this study examined a wide variety of social and built environment factors, among which a few built environment factors have been infrequently (e.g. meeting places) or barely (e.g. general health providers) tested in previous literature on the same topic.

Methodologically, the current study adopted spatial regression models with two disparate specifications of spatial effects – the spatial error model and the spatial lag model. These models have significantly improved model fit compared with OLS by accounting for spatial dependency. Rather than making inferences based on levels of significance alone, which is the most common case in public health research, an all-subset selection using BIC as the selection criterion was performed as an additional guide in this study.

6.6 Future Direction

One promising future direction of this research is to collect residents' subjective assessments of the neighbourhood environment. There is a theoretical rationale to value human experience: neighbourhood context has been argued to affect mental health through a psychological pathway, therefore assessments of neighbourhood environment are supposed to derive from residents' subjective experience (as opposed to from objectively measured government data) (Hill & Maimon, 2013). Ecological study is an eligible study design, however, we must take into account personal characteristic when formulating policies in a real context. The identification of specific neighbourhoods with concerns in this study also greatly simplifies future qualitative examination. A multi-level modelling approach can also be carried out if individual-level data are available.

Moreover, age-specific cluster maps exhibited discrepancies of MHV distribution across different age groups. Future research may adopt spatial statistical techniques, such as a shared component spatial modelling approach to jointly analyse and compare geographic variation of MHV in several age groups. It is possible that residents' perceptions of neighbourhood environment and their impacts on population mental health are not constant across age subgroups. For these reasons, further investigation into relationships between social and built environment and MHV for a specific age group may help develop targeted mental health promotion initiatives. Also, the MHV data accounted for primary care visits to family doctors only. Future studies may focus on MHV to psychiatrists and other specialists to shed light on the existence of mental health care inequalities in other care settings.

It is also possible to use MHV data of multiple years to perform a longitudinal data analysis by which to obtain a firmer understanding of the relationship between neighbourhood environment and MHV. The present study with a cross-sectional study design cannot be used to draw casual conclusion, which may be overcome by a longitudinal design in future research.

Chapter 7 Conclusion

Using administrative data, this study quantified geographic variation and assessed associated factors of MHV in the City of Toronto at the neighbourhood level. The cluster detection analysis revealed that the prevalence of MHV does not distribute evenly across Toronto neighbourhoods, with hot and cold spots existing in certain areas. Considering the multifactorial nature of mental health, this study examined up to thirty independent variables. The investigation identified two social factors and two built environment factors that together best explain MHV variation across Toronto neighbourhoods. In line with previous evidence, neighbourhood income inequality and poor housing quality, as measured by the proportion of dwellings in need of major repairs, were found to have adverse effects on mental health. On the contrary, neighbourhoods with high concentration of East Asian ethnicities and more health providers per 10,000 population had lower levels of MHV. The results overall suggest that both the social and built environment can affect population mental health.

Methodologically, the current study distinguishes itself from most of the previous studies that ignore the spatial dimension of mental health problems by adopting a spatial analytical approach. The cluster maps obtained from spatial statistical methods and GIS mapping techniques help to visualize areas with priority mental health needs at the primary care setting. Through accounting for the spatially correlated pattern of the dependent variable, the spatial regression models showed a clear advantage of modelling the data over the standard regression model, suggesting space matters as a factor in explaining MHV variation among Toronto neighbourhoods. Further, the spatial lag model provided a superior fit, indicating the prevalence of MHV is not only subject to the neighbourhood itself, but also influenced by MHV of neighbourhoods at nearby locations.

The findings of the present study expanded upon prior work on relationships between contextual factors and population mental health by examining a wide range of social factors and built environment characteristics that are rarely assessed for their influence on mental health. Undertaking analysis at the level of neighbourhood enables LHINs and sub-regions directly plan and deliver relevant prevention and intervention initiatives targeting specific areas. Future research can build upon these findings to perform more detailed and focused qualitative research to inform evidence-based mental health policies.

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Appendix I

Table A 1 Service and Diagnostic Codes for Ontario Physicians' Billing Claims (92)

TABLE A1. Service and Diagnostic Codes for Ontario Physicians' Billing Claims	
Mental Health Service Codes	**Mental Health Diagnostic Codes**
K005 Primary mental health care	
K007 Psychotheraphy	**Psychotic Disorders**
K623 Assessment for involuntary admission	295 Schizophrenia
	296 Manic-depressive psychoses, involutional melancholia
General Service Codes	297 Other paranoid states
A001 Minor assessment	298 Other psychoses
A003 Major assessment	
A007 Intermediate assessment	**Non-Psychotic Disorders**
A004 General re-assessment	300 Anxiety neurosis, hysteria, neurasthenia, obsessive-compulsive neurosis, reactive depression
A888 Partial assessment	301 Personality disorders
A005 Consultation	302 Sexual deviations
A905 Limited consultation	306 Psychosomatic illness
A006 Repeat consultation	309 Adjustment reaction
A901 Housecall assessment	311 Depressive disorder
A008 Mini assessment	
	Substance Use Disorders
	303 Alcoholism
	304 Drug dependence
	Social Problems
	897 Economic problems
	898 Marital difficulties
	899 Problems with aged parents or in-laws
	901 Family disruption/divorce
	902 Education problems
	904 Social maladjustment
	905 Occupational problems
	906 Legal problems
	909 Other problems of social adjustment

Appendix II

Table A 2 Description of Measures and Data Sources of All Explanatory Variables

Variable Name	**Variable Description**	**Data Source**
Social Factors – SES		
Median Household Income After Tax	Median after tax household income in each neighbourhood	Data Provider: Toronto Open Data Original Source: 2011 National Household Survey, Statistics Canada
Income Inequality Gini Coefficient	An indicator of income inequality on a scale from 0 (perfect equality) to 1 (perfect inequality)	Data Provider: Toronto Open Data Original Source: City of Toronto, Social Policy Analysis & Research with Ryerson University. Based on Census 2006 (Taxfiler 2005) distributions of individual income.
Marginalization Index	An index developed by exploring four distinct dimensions of marginalization (incl. residential instability, material deprivation, dependency and ethnic concentration)	Data Provider: Toronto Community Health Profiles Original Source: 2006 Census, Ontario Marginalization Index
Percent of Post-Secondary Education	Numerator: Population aged 25-64 with post-secondary certificate, diploma or degree Denominator: Total population aged 25-64 years	Data Provider: Toronto Community Health Profiles Original Source: 2011 National Household Survey (NHS), Statistics Canada
Social Factors – Demographic Factors – Ethnic Diversity		
Percent of Not a Visible Minority	Percentage of non-visible minority population	Data Provider: Toronto Open Data Original Source： 2011 National Household Survey, Statistics Canada

Table A 2 (Continued)

Variable Name	Variable Description	Data Source
Social Factors – Demographic Factors – Ethnic Diversity		
Percent of Minority Groups	Visible minority refers to whether a person belongs to a visible minority group as defined by the *Employment Equity Act* and, if so, the visible minority group to which the person belongs. The *Employment Equity Act* defines visible minorities as "persons, other than Aboriginal peoples, who are non-Caucasian in race or non-white in colour." Percentage of population who identify themselves as East Asian (Chinese, Korean, and Japanese), South Asian (East Indian, Pakistani, Sri Lanka, etc.), Southeast Asian (Filipino, Vietnamese, Cambodian, Malaysian, Laotian, etc.), and Black	Data Provider: Toronto Open Data Original Source： 2011 National Household Survey, Statistics Canada
Social Factors – Demographic Factors – Population Mobility		
Percent of Recent Movers	Percent of persons who have moved from one residence to another in the past five years are referred to as recent movers. Movers include non-migrants and migrants. Non-migrants are persons who did move but remained in the same city, town, township, village or Indian reserve. Migrants include internal migrants who moved to a different city, town, township, village or Indian reserve within Canada. External migrants include persons who lived outside Canada at the earlier reference date.	Data Provider: Toronto Open Data Original Source： 2011 National Household Survey, Statistics Canada
Percent of Recent Immigrant Population	Percent of persons who have been granted the right to live in Canada permanently by immigration authorities prior to May 10, 2011.	Data Provider: Toronto Open Data Original Source： 2011 National Household Survey, Statistics Canada
Social Factors – Demographic – Ethnic Diversity		
Lone Parent Families	Numerator: Number of census families with children that are headed by a lone parent Denominator: Total number of census families	Data Provider: Toronto Community Health Profiles Original Source： Statistics Canada, 2011 Census of Canada

Table A 2 (Continued)

Variable Name	Variable Description	Data Source
Social Factors – Demographic Factors – Family Composition		
Percent of Population Living Alone	Numerator: Population in private households that are living alone Denominator: Neighbourhood population based on 2011 Census	Data Provider: Toronto Community Health Profiles Original Source： Statistics Canada, 2011 Census of Canada
Social Factors – Demographic Factors – Language		
Linguistic Diversity Index	The probability that any two randomly selected people have different mother tongues calculated using Greenberg's Linguistic Diversity Index. Higher values indicate greater linguistic diversity (more heterogeneity), and lower values indicate less linguistic diversity (more homogeneity).	Data Provider: Toronto Open Data Original Source: Statistics Canada, 2011 Census, language tables; calculations performed by City of Toronto, Social Policy Analysis & Research
Percent of Population with No Knowledge of English or French	Percentage of population who are unable to conduct a conversation in either English or French.	Data Provider: Toronto Community Health Profiles Original Source: Statistics Canada, 2011 Census of Canada
Social Factors – Social Aid		
Percent of Social Assistance Recipient	Percentage of population receiving social assistance (incl. Ontario Works, Ontario Disability Support Program, non-OW special assistance for medical items)	Data Provider: Toronto Community Health Profiles Original Source: Toronto Employment and Social Services, Data Mart, 2012
Social Factors – Neighbourhood Safety		
Property Crime Incidents per 10,000 residents	Numerator: Counts of breaks & enters, thefts, and vehicle thefts. Denominator: Neighbourhood population based on 2011 Census	Data Provider: Toronto Open Data Original Source: ECRIME Database, CIPS Database, 2011
Violent Crime Incidents per 10,000 residents	Numerator: Counts of assaults, murders, robberies, and sexual assaults. Denominator: Neighbourhood population based on 2011 Census	Data Provider: Toronto Open Data Original Source: ECRIME Database, CIPS Database, 2011

Table A 2 (Continued)

Variable Name	Variable Description	Data Source
Social Factors –Neighbourhood Safety		
Drug Arrests per 10,000 residents	Numerator: Counts of drug arrests Denominator: Neighbourhood population based on 2011 Census	Data Provider: Toronto Open Data Original Source: ECRIME Database, CIPS Database, 2011
Built Environment Factors – Neighbourhood Physical Surroundings		
Community Places for Meeting	The population-weighted average number of meeting places (incl. libraries, recreation facilities, and places of worship) within a 10-minute walking distance from each residential block in the neighbourhoods.	Data Provider: Toronto Community Health Profiles Original Source: DMTI Spatial CanMap Route Logistics Road network file, 2013, Toronto Open Data; 2011 Census of Canada, Statistics Canada
Health Providers per 10,000 residents	Numerator: Location counts of health related businesses such as doctor offices, dentist offices, pharmacies, clinics and other health employers, multiplied by 10,000. Denominator: Neighbourhood population based on 2011 Census.	Data Provider: Toronto Open Data Original Source: City of Toronto, City Planning, Toronto Employment Survey, 2012
Sports Facilities per 10,000 residents	Numerator: Location counts of gyms, fields, hockey rinks, ice pads, swimming pools, courts, baseball diamonds and other sports facilities, multiplied by 10,000. Denominator: Neighbourhood population based on 2006 Census.	Data Provider: Toronto Open Data Original Source: City of Toronto, Parks, Forestry & Recreation, 2006
Walk Score	A walkability score on a scale from 0 (not very walkable) to 100 (very walkable) based on walking routes to destinations such as grocery stores, schools, parks, restaurants, and retail.	Data Provider: Toronto Open Data Original Source: Walk Score® www.walkscore.com internally validated using the Toronto Utilitarian walkability Index, 2012 (TUWI) from Toronto Public Health created by Urban Design 4 Health Ltd.
Green Space	The population-weighted average amount of green space (incl. parks and public areas) per square kilometer in a 1 km buffer from each residential block in the neighbourhoods.	Data Provider: Toronto Community Health Profiles Original Source: Shapefile of parks and green space, Toronto Open Data

Table A 2 (Continued)

Variable Name	Variable Description	Data Source
Built Environment Factors – Housing		
Percent of Rented Households	Numerator: Total number of private households that no member of the household owns the dwelling. Denominator: Total number of private households	Data Provider: Toronto Open Data Original Source: 2011 National Household Survey, Statistics Canada
Percent of Household that Needs Major Repairs	Numerator: Total number of owner-occupied dwellings in need of major repair. The examples of major repair are intended to capture problems that compromised the dwelling structure or the major systems of the dwelling (e.g., defective plumbing or electrical wiring, structural repairs to walls, floors or ceilings) Denominator: Total number of households own their private dwelling	Data Provider: Toronto Open Data Original Source: 2011 National Household Survey, Statistics Canada
Percent of Population in Mid-Century Household	Numerator: Residents living in mid-century high-rises that are built between 1945 and 1988 with more than 5 stories. Denominator: Neighbourhood population based on 2011 Census	Data Provider: Toronto Open Data Original Source: Tower Renewal Program, City of Toronto, 2011
Built Environment Factors – Transportation		
Overcrowded Routes per kilometre of road	Numerator: Toronto Transit Commission (TTC) overcrowded route lines are converted into points (centroids). The numerator is the number of such points in each neighbourhood. Denominator: Total kilometre-lengths of all roads within neighbourhood.	Data Provider: Toronto Open Data Original Source: Toronto Transit Commission, 2008
TTC Stops per kilometre of road	Numerator: TTC stops including all bus, streetcar and non-subway stops counted by neighbourhood. Denominator: Total kilometre-lengths of all roads within neighbourhood.	Data Provider: Toronto Open Data Portal at www.toronto.ca/open Original Source: Toronto Transit Commission, 2011

Table A 2 (Continued)

Built Environment Factors – Transportation		
Variable Name	**Variable Description**	**Data Source**
Road Volume	Collector roads average 24-hour motor vehicle traffic in both directions per collector.	Data Provider: Toronto Open Data Original Source: Traffic Management Centre, City of Toronto, 2009-2011 combined data

Appendix Ⅲ

Table A 3.1.1 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – SES (Spatial Error Model)

	Model 1[a]	Model 1[b]	Model 1[c]	Model 1[d]
BIC	265.179	261.647	266.736	262.904
Confounder				
Median Household Income	0.667 0.321	0.069 0.912	-0.882 0.059	-0.772 0.064
SES Variables				
Income Inequality	5.917 0.006*	5.736 0.008*		
Marginalization Index	0.027 0.838		0.163 0.189*	
Education	-0.018 0.026*			-0.018 0.017*

Note: "*" denotes liberal p > 0.2

Table A 3.1.2 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – SES (Spatial Lag Model)

	Model 1[a]	Model 1[b]	Model 1[c]	Model 1[d]
BIC	268.811	263.035	270.465	268.792
Confounder				
Median Household Income	0.740 0.242	0.245 0.649	-0.835 0.040	-0.838 0.010
SES Variables				
Income Inequality	6.277 0.001*	5.664 0.004*		
Marginalization Index	0.021 0.869		0.097 0.410	
Education	-0.008 0.096*			-0.006 0.138*

Note: "*" denotes liberal p > 0.2

Table A 3.2.1 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – Ethnic Diversity (Spatial Error Model)

	Model 2[a]	Model 2[b]	Model 2[c]	Model 2[d]	Model 2[e]	Model 2[f]
BIC	262.14	255.493	265.489	252.312	268.19	268.436
Confounder						
Median Household Income	-1.854 <0.001	-2.083 <0.001	-1.464 <0.001	-1.319 <0.001	-1.343 0.001	-1.246 0.002
Ethnic Diversity Variables						
Non-Visible Minorities	-0.001 0.944	0.014 <0.001*				
South Asian	-0.018 0.345		-0.011 0.084*			
East Asian	-0.033 0.062*			-0.026 <0.001*		
Southeast Asian	-0.019 0.404				-0.008 0.612	
Black	-0.003 0.888					0.001 0.915

Note: "*" denotes liberal p > 0.2

Table A 3.2.2 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – Ethnic Diversity (Spatial Lag Model)

	Model 2[a]	Model 2[b]	Model 2[c]	Model 2[d]	Model 2[e]	Model 2[f]
BIC	261.087	257.442	268.958	248.332	271.093	270.551
Confounder						
Median Household Income	-1.628 <0.001	-1.689 <0.001	-1.196 <0.000	-1.233 <0.001	-1.109 <0.001	-0.981 0.002
Ethnic Diversity Variables						
Non-Visible Minorities	0.011 0.381	0.009 <0.001*				
South Asian	0.003 0.808		-0.007 0.142*			
East Asian	-0.010 0.471			-0.019 <0.001*		
Southeast Asian	-0.003 0.875				-0.003 0.821	
Black	-0.015 0.401					0.005 0.442

Note: "*" denotes liberal p > 0.2

Table A 3.3.1 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – Population Mobility (Spatial Error Model)

	Model 3[a]	Model 3[b]	Model 3[c]
BIC	262.819	258.737	261.503
Confounder			
Median Household Income	-1.978 <0.001	-1.830 <0.001	-1.898 <0.001
Population Mobility Variables			
Recent Movers	-0.017 0.055*	-0.022 0.002*	
Recent Immigrants	-0.016 0.350		-0.035 0.007*

Note: "*" denotes liberal p > 0.2

Table A 3.3.2 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – Population Mobility (Spatial Lag Model)

	Model 3[a]	Model 3[b]	Model 3[c]
BIC	262.865	263.618	261.486
Confounder			
Median Household Income	-1.779 <0.001	-1.421 <0.001	-1.648 <0.001
Population Mobility Variables			
Recent Movers	-0.010 0.060*	-0.014 0.008*	
Recent Immigrants	-0.028 0.014*		-0.035 0.002*

Note: "*" denotes liberal p > 0.2

Table A 3.4.1 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – Family Composition (Spatial Error Model)

	Model 4[a]	**Model 4[b]**	**Model 4[c]**
BIC	263.156	258.249	267.282
Confounder			
Median Household Income	-0.288 0.536	-0.293 0.528	-1.137 0.003
Family Composition Variables			
Lone Parent Families	0.032 0.002*	0.032 0.001*	
Population Living Alone	0.002 0.852		0.013 0.279

Note: "*" denotes liberal p > 0.2

Table A 3.4.2 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – Family Composition (Spatial Lag Model)

	Model 4[a]	**Model 4[b]**	**Model 4[c]**
BIC	265.163	260.222	270.761
Confounder			
Median Household Income	-0.141 0.722	-0.141 0.722	-1.044 <0.001
Family Composition Variables			
Lone Parent Families	0.029 0.001*	0.028 0.001*	
Population Living Alone	-0.0001 0.987		0.004 0.535

Note: "*" denotes liberal p > 0.2

Table A 3.5.1 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – Language (Spatial Error Model)

	Model 5[a]	Model 5[b]	Model 5[c]
BIC	265.791	260.856	266.515
Confounder			
Median Household Income	-1.917 <0.001	-1.919 <0.001	-1.399 <0.001
Language Variables			
Linguistic Diversity Index	-1.483 0.016*	-1.506 0.005*	
No Knowledge of English or French	-0.001 0.938		-0.023 0.158*

Note: "*" denotes liberal p > 0.2

Table A 3.5.2 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – Language (Spatial Lag Model)

	Model 5[a]	**Model 5[b]**	**Model 5[c]**
BIC	263.303	259.49	264.429
Confounder			
Median Household Income	-1.789 <0.001	-1.775 <0.001	-1.370 <0.001
Language Variables			
Linguistic Diversity Index	-1.083 0.016*	-1.312 0.001*	
No Knowledge of English or French	-0.015 0.285		-0.032 0.008*

Note: "*" denotes liberal p > 0.2

Table A 3.6.1 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – Social Aid (Spatial Error Model)

	Model 6
BIC	260.955
Confounder	
Median Household Income	-0.405 0.395
Social Aid Variable	
Social Assistance Recipient	0.033 0.005*

Note: "*" denotes liberal p > 0.2

Table A 3.6.2 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – Social Aid (Spatial Lag Model)

	Model 6
BIC	260.962
Confounder	
Median Household Income	-0.329 0.367
Social Aid Variable	
Social Assistance Recipient	0.031 0.001*

Note: "*" denotes liberal p > 0.2

Table A 3.7.1 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – Neighbourhood Safety (Spatial Error Model)

	Model 7[a]	Model 7[b]	Model 7[c]	Model 7[d]
BIC	268.843	267.678	267.973	261.825
Confounder				
Median Household Income	-0.969 0.011	-1.261 0.001	-1.180 0.002	-0.983 0.009
Neighbourhood Safety Variables				
Property Crime	-0.003 0.149*	-0.002 0.380		
Violent Crime	-0.001 0.654		0.001 0.490	
Drug Arrests	0.008 0.005*			0.007 0.009*

Note: "*" denotes liberal p > 0.2

Table A 3.7.2 Bivariate and Within-Subcategory Spatial Regression Results for Social Factors – Neighbourhood Safety (Spatial Lag Model)

	Model 7[a]	Model 7[b]	Model 7[c]	Model 7[d]
BIC	273.661	270.581	270.469	266.512
Confounder				
Median Household Income	-0.786 0.015	-1.068 0.000	-0.965 0.003	-0.827 0.007
Neighbourhood Safety Variables				
Property Crime	-0.003 0.162*	-0.002 0.452		
Violent Crime	-0.001 0.619		0.001 0.405	
Drug Arrests	0.007 0.020*			0.005 0.032*

Note: "*" denotes liberal p > 0.2

Table A 3.8.1 Bivariate and Within-Subcategory Spatial Regression Results for Built Environment Factors – Neighbourhood Physical Surroundings (Spatial Error Model)

	Model 8[a]	Model 8[b]	Model 8[d]	Model 8[e]	Model 8[f]	Model 8[g]
BIC	276.487	266.908	260.703	268.230	267.119	268.343
Confounder						
Median Household Income	-1.204 0.001	-1.130 0.003	-1.374 <0.001	-1.252 0.001	-1.261 0.001	-1.269 0.001
Neighbourhood Physical Surroundings Variables						
Community Places for Meeting	0.014 0.189*	0.013 0.213				
Health Providers	-0.009 0.004*		-0.008 0.004*			
Sports Facilities	-0.006 0.456			-0.004 0.641		
Walk Score	0.004 0.214				0.004 0.248	
Green Space	0.001 0.608					0.001 0.747

Note: "*" denotes liberal p > 0.2

Table A 3.8.2 Bivariate and Within-Subcategory Spatial Regression Results for Built Environment Factors – Neighbourhood Physical Surroundings (Spatial Lag Model)

	Model 8[a]	Model 8[b]	Model 8[c]	Model 8[d]	Model 8[e]	Model 8[f]
BIC	271.821	270.244	257.591	271.118	268.64	270.869
Confounder						
Median Household Income	-0.998 <0.001	-0.998 0.001	-1.166 <0.001	-1.082 <0.001	-1.063 <0.001	-1.082 <0.001
Neighbourhood Physical Surroundings Variables						
Community Places for Meeting	0.012 0.075*	0.006 0.343				
Health Providers	-0.011 <0.001*		-0.010 0.000*			
Sports Facilities	-0.005 0.564			0.001 0.874		
Walk Score	0.005 0.176*				0.006 0.112*	
Green Space	0.001 0.672					0.001 0.601

Note: "*" denotes liberal p > 0.2

Table A 3.9.1 Bivariate and Within-Subcategory Spatial Regression Results for Built Environment Factors – Housing (Spatial Error Model)

	Model 9[a]	Model 9[b]	Model 9[c]	Model 9[d]
BIC	264.957	267.629	262.388	267.347
Confounder				
Median Household Income	-0.420 0.443	-0.890 0.107	-0.772 0.062	-1.517 0.001
Housing Variables				
Rented Households	0.013 0.033*	0.004 0.365		
Household Needs Major Repairs	0.052 0.005*		0.046 0.012*	
Population in Mid-Century Household	-0.013 0.007*			-0.004 0.293

Note: "*" denotes liberal p > 0.2

Table A 3.9.2 Bivariate and Within-Subcategory Spatial Regression Results for Built Environment Factors – Housing (Spatial Lag Model)

	Model 9[a]	Model 9[b]	Model 9[c]	Model 9[d]
BIC	259.99	269.826	254.406	270.296
Confounder				
Median Household Income	-0.438 0.248	-0.792 0.037	-0.478 0.128	-1.228 <0.001
Housing Variables				
Rented Households	0.006 0.152*	0.004 0.250		
Household Needs Major Repairs	0.074 <0.001*		0.074 <0.001*	
Population in Mid-Century Household	-0.007 0.049*			-0.003 0.358

Note: "*" denotes liberal p > 0.2

Table A 3.10.1 Bivariate and Within-Subcategory Spatial Regression Results for Built Environment Factors – Transportation (Spatial Error Model)

	Model 10[a]	Model 10[b]	Model 10[c]	Model 10[d]
BIC	271.437	264.294	264.498	268.258
Confounder				
Median Household Income	-1.609 <0.001	-1.458 <0.001	-1.457 <0.001	-1.284 0.001
Transportation Variables				
Overcrowded Routes	-0.027 0.113*	-0.033 0.040*		
TTC Stops	-0.097 0.140*		-0.125 0.045*	
Road Volume	$1.971e^{-5}$ 0.385			$9.999e^{-6}$ 0.664

Note: "*" denotes liberal p > 0.2

Table A 3.10.2 Bivariate and Within-Subcategory Spatial Regression Results for Built Environment Factors – Transportation (Spatial Lag Model)

	Model 10[a]	Model 10[b]	Model 10[c]	Model 10[d]
BIC	276.001	268.911	267.883	271.129
Confounder				
Median Household Income	-1.326 <0.001	-1.177 <0.001	-1.248 <0.001	-1.076 <0.001
Transportation Variables				
Overcrowded Routes	-0.018 0.184*	-0.020 0.137*		
TTC Stops	-0.100 0.093*		-0.109 0.069*	
Road Volume	$3.946e^{-6}$ 0.861			$-2.719e^{-6}$ 0.904

Note: "*" denotes liberal p > 0.2

Appendix Ⅳ

Table A 4.1 Pairwise Correlation Matrix for Social Factors – SES

	Confounder (MHI)	Income Inequality	Marginalization Index	Education
Confounder (MHI)	1.00			
Income Inequality	-0.86	1.00		
Marginalization Index	-0.72	0.58	1.00	
Education	0.50	-0.38	-0.65	1.00

Table A 4.2 Pairwise Correlation Matrix for Social Factors – Population Mobility

	Confounder (MHI)	Recent Movers	Recent Immigrants
Confounder (MHI)	1.00		
Recent Movers	-0.39	1.00	
Recent Immigrants	-0.49	0.46	1.00

Table A 4.3 Pairwise Correlation Matrix for Social Factors – Family Composition

	Confounder (MHI)	Lone Parent Families	Population Living Alone
Confounder (MHI)	1.00		
Lone Parent Families	-0.72	1.00	
Population Living Alone	-0.21	0.29	1.00

Table A 4.4 Pairwise Correlation Matrix for Social Factors – Language

	Confounder (MHI)	Linguistic Diversity Index	No Knowledge of English or French
Confounder (MHI)	1.00		
Linguistic Diversity Index	-0.53	1.00	
No Knowledge of English or French	-0.32	0.60	1.00

Table A 4.5 Pairwise Correlation Matrix for Social Factors – Social Aid

	Confounder (MHI)	Social Assistance Recipient
Confounder (MHI)	1.00	
Social Assistance Recipient	-0.65	1.00

Table A 4.6 Pairwise Correlation Matrix for Social Factors – Neighbourhood Safety

	Confounder (MHI)	Property Crime	Violent Crime	Drug Arrests
Confounder (MHI)	1.00			
Property Crime	0.04	1.00		
Violent Crime	-0.46	0.35	1.00	
Drug Arrests	-0.40	0.29	0.74	1.00

Table A 4.7 Pairwise Correlation Matrix for Built Environment Factors – Neighbourhood Physical Surroundings

	Confounder (MHI)	Community Places for Meeting	Health Providers	Sports Facilities	Walk Score	Green Space
Confounder (MHI)	1.00					
Community Places for Meeting	-0.31	1.00				
Health Providers	-0.04	0.17	1.00			
Sports Facilities	0.05	-0.04	-0.19	1.00		
Walk Score	-0.04	0.08	-0.07	0.04	1.00	
Green Space	0.02	-0.42	-0.27	0.03	-0.10	1.00

Table A 4.8 Pairwise Correlation Matrix for Built Environment Factors – Housing

	Confounder (MHI)	Rented Households	Household Needs Major Repairs	Population in Mid-Century Household
Confounder (MHI)	1.00			
Rented Households	-0.67	1.00		
Household Needs Major Repairs	-0.49	0.45	1.00	
Population in Mid-Century Household	-0.48	0.66	0.30	1.00

Table A 4.9 Pairwise Correlation Matrix for Built Environment Factors – Transportation

	Confounder (MHI)	Overcrowded Routes	TTC Stops	Road Volume
Confounder (MHI)	1.00			
Overcrowded Routes	-0.23	1.00		
TTC Stops	-0.33	0.18	1.00	
Road Volume	0.09	0.15	-0.004	1.00

Table A 4.10 Pairwise Correlation Matrix for All Social Factors

	Confounder (MHI)	Income Inequality	Education	East Asian	Recent Movers	Recent Immigrants	Lone Parent	Linguistic Diversity	Social Assistance	Drug Arrest
Confounder (MHI)	1.00									
Income Inequality	-0.86	1.00								
Education	0.50	-0.38	1.00							
East Asian	0.01	-0.004	0.15	1.00						
Recent Movers	-0.39	0.39	0.31	0.11	1.00					
Recent Immigrants	-0.49	0.31	-0.20	0.19	0.46	1.00				
Lone Parent	-0.72	0.74	-0.59	-0.21	0.28	0.16	1.00			
Linguistic Diversity	-0.53	0.38	-0.50	0.37	0.12	0.69	0.26	1.00		
Social Assistance	-0.65	0.59	-0.75	-0.27	0.11	0.44	0.77	0.43	1.00	
Drug Arrest	-0.40	0.58	-0.25	-0.08	0.31	0.02	0.59	0.06	0.47	1.00

Table A 4.11 Pairwise Correlation Matrix for All Built Environment Factors

	Confounder (MHI)	Health Providers	Household Needs Major Repairs	Overcrowded Routes	TTC Stops
Confounder (MHI)	1.00				
Health Providers	-0.04	1.00			
Household Needs Major Repair	-0.49	-0.18	1.00		
Overcrowded Routes	-0.23	-0.11	0.11	1.00	
TTC Stops	-0.33	0.31	0.22	0.18	1.00

Table A 4.12 Pairwise Correlation Matrix for the Final Model

	Confounder (MHI)	Income Inequality	East Asian	Recent Movers	Social Assistance	Health Providers	Household Needs Major Repairs
Confounder (MHI)	1.00						
Income Inequality	-0.86	1.00					
East Asian	0.01	-0.004	1.00				
Recent Movers	-0.39	0.39	0.11	1.00			
Social Assistance	-0.65	0.59	-0.27	0.11	1.00		
Health Providers	-0.04	0.05	0.22	0.40	-0.27	1.00	
Household Needs Major Repairs	-0.49	0.49	-0.29	0.01	0.60	-0.18	1.00