NEIGHBOURHOOD CHARACTERISTICS AND DEPRESSION IN COMMUNITY-DWELLERS WITH AND WITHOUT A CHRONIC CONDITION

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Table of Content

Abstract

***Background*:** Depression is a serious public-health problem and the leading cause of disability worldwide. Studies have shown neighbourhood characteristics to be associated with depression, but it is not clear which neighbourhood features matter most for depression, for whom this effect is most relevant and what pathways explain this association. Individuals with a chronic disease, such as diabetes, rely on their local area for resources and support, and might be particularly vulnerable in this context.

***Objectives*:** To assess the association of neighbourhood characteristics on risk of depression in adults with and without a chronic condition (objective 1); to examine potential moderators and mediators of this association (objective 2); and to explore the relationship between neighbourhood characteristics and changes in depression over time (objective 3).

***Design and methods*:** Secondary data analyses were conducted using two cohort studies combined with census, geospatial, satellite imagery and survey data. In a first step, I adopted a wide perspective to examine neighbourhood effects in the general population with and without a chronic condition, using 10 years of data from the National Population Health Survey (NPHS; 2000/01-2010/11; n=17,276 at baseline). In a second step, I focused specifically on people with type 2 diabetes, using 5 years of data from the Diabetes Health Study (DHS; 2008-2013; n=2003 at baseline). The two surveys were analyzed separately. Depression was measured using screening tools. For objective 1, I conducted survival analyses to examine the associations of neighbourhood factors and incident depression, in those with and without a chronic condition. For objective 2, I included interaction terms in the models and stratified analyses to investigate potential moderators. I performed a novel mediation analysis using the additive hazard model to

examine potential mediators. For objective 3, I used latent class growth modelling to examine the associations of time-varying neighbourhood factors on trajectories of depression over time.

Project 1 - Neighbourhoods and risk of depression in people with and without a chronic condition (NPHS data). Neighbourhood characteristics were not significantly associated with risk of depression in the general sample and in subsamples with a chronic condition. However, moderator analysis revealed that living in proximity to a park was associated with lower risk of depression for people living in crowded households.

Project 2 - Neighbourhoods and risk of depression in people with diabetes (DHS data). A greater number of physical activity facilities, cultural services and level of greenness in the neighbourhood were associated with lower risk of depression. Material deprivation was associated with increased risk of depression, particularly in adults with diabetes who were older or retired. Reduction in diabetes complications and disability were significant mediators in the pathway between neighbourhood fitness facilities and depression.

Project 3 - Neighbourhoods and trajectories of depression over time (NPHS data). Latent class growth modelling uncovered three distinct trajectories of major depression prevalence: low; moderate decreasing; and high persistent. The presence of neighbourhood parks and cultural services was associated with a significant shift in the trajectory of high persistent depression towards lower probability of major depression.

Conclusions: Aspects of the neighbourhood environment were significantly related to risk of depression, particularly in vulnerable subgroups, such as those with diabetes, those living in crowded households and those with persistent major depression symptoms. Future intervention research is needed for health policy recommendations.

Abrégé

Contexte: La dépression est un problème de santé publique majeur et la cause mondiale principale d'invalidité. Des études montrent des associations entre certaines caractéristiques du voisinage et la dépression. Ces recherches sont par contre limitées. Nous ne savons toujours pas quels aspects du voisinage ont le plus grand impact sur la dépression, quelles personnes sont les plus affectées et par quel mécanisme existe cette association. Les personnes ayant une maladie chronique, comme le diabète, dépendent du soutien et des ressources de leur voisinage, et donc pourraient être particulièrement vulnérables par leurs contextes environnementaux.

Objectifs: Évaluer l'association entre les caractéristiques du voisinage et le risque de dépression chez des adultes avec et sans maladie chronique (objectif 1); examiner les modérateurs et les médiateurs qui contribuent à cette association (objectif 2); et étudier la relation entre les caractéristiques de voisinage et les changements de la dépression à travers le temps (objectif 3).

Conception et méthodes: Cette thèse est une l'analyse de données secondaires tirées de deux récentes enquêtes canadiennes, combinées avec des données provenant de recensements canadiens, de bases de données géospatiales, d'imagerie satellite, et de sondages. De premier lieu, j'ai adopté une perspective globale des effets de voisinage dans la population générale (avec et sans maladie chronique), en me servant de 10 ans de données de l'Enquête nationale sur la santé de la population (ENSP 2000/01-2010/11, n = 17,276 au départ). De deuxièmement lieu, je me suis porté plus spécifiquement sur les personnes atteintes de diabète de type 2, en me servant de 5 ans de données de l'Étude sur la santé du diabète (ESD; 2008-2013; n = 2003 au départ). Les analyses des deux enquêtes ont été faites séparément. La dépression a été mesurée à l'aide d'outils de dépistage. Pour l'objectif 1, j'ai effectué des analyses de survie pour examiner les

associations entre les caractéristiques du voisinage et le risque de dépression chez les gens avec et sans maladie chronique. Pour l'objectif 2, j'ai testé des modérateurs potentiels en incluant des termes d'interaction dans les modèles et en stratifiant les analyses. J'ai testé des médiateurs potentiels à l'aide du modèle de risques additifs. Pour l'objectif 3, j'ai utilisé une analyse de croissance de classe latente afin d'examiner l'effet des caractéristiques des voisinages sur les trajectoires de la dépression à travers le temps.

Projet 1 - Voisinages et le risque de dépression chez les personnes avec et sans maladie chronique (des données de l'ENSP). Les caractéristiques des voisinages n'étaient pas associées de façon significative à un risque de dépression dans l'échantillon général, ni dans les sous-échantillons de personnes ayant une maladie chronique. Cependant, l'analyse des modérateurs a révélé qu'habiter près d'un parc était associé à un risque de dépression moindre pour les personnes vivant dans des logements surpeuplés.

Projet 2 - Voisinages et le risque de dépression chez les personnes atteintes de diabète (données de l'ESD). Un plus grand nombre d'installations d'activité physique, de services culturels, et un taux plus élevé verdure dans le voisinage étaient associés à un risque moindre de dépression, même après avoir ajusté pour les facteurs confondants. La privation matérielle était associée à un risque accru de dépression, en particulier chez les personnes avec le diabète qui étaient plus âgés ou à la retraite. La réduction des complications du diabète et de l'invalidité était des médiateurs importants expliquant le lien entre les installations d'activité physique dans le voisinage et un risque moindre de dépression chez les personnes diabétiques.

Projet 3 - Voisinages et trajectoires de dépression au cours du temps (données de l'ENSP). La modélisation de croissance de classe latente a révélé trois trajectoires longitudinales de

prévalence de dépression majeure: faible prévalence, prévalence modéré diminuant à travers le temps, et prévalence élevée chronique. La présence de parcs et de services culturels dans le voisinage était associée de façon significative à un changement dans la trajectoire de dépression élevée chronique vers une probabilité moindre de dépression majeure.

Conclusions: Les caractéristiques du voisinage sont associées à un risque de dépression, en particulier pour certains sous-groupes vulnérables, comme les personnes diabétiques, les personnes vivant dans des logements surpeuplés et les personnes avec des symptômes de dépression chroniques. Des études d'intervention sont nécessaires pour émettre des recommandations en matière de politique de santé.

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Contribution of Authors

Manuscript I: Neighbourhood characteristics and 10-year risk of depression in Canadian adults with and without a chronic illness

Authors: Genevieve Gariepy, Alexandra Blair, Yan Kestens, Norbert Schmitz

This manuscript is published in the journal *Health and Place* (2014), 30, 279–286.

Genevieve Gariepy was involved in the conception and design of the study, in the acquisition of data, in the analysis of data and interpretation of findings, and in writing the first draft. *Norbert Schmitz* was involved in the conception and design of the study, in the interpretation of findings, and in the critical revision of the article for intellectual content. *Yan Kestens* was involved in the acquisition of data, in interpretation of findings and critical revision of the article for intellectual content. *Alexandra Blair* provided critical revision of the article for intellectual content.

Manuscript II: Diabetes distress and neighbourhood characteristics in people with type 2 diabetes

Authors: Genevieve Gariepy, Kimberley J. Smith, Norbert Schmitz

This manuscript is published in *Journal of Psychosomatic Research* (2013), 75(2), 147-152.

Genevieve Gariepy was involved in the conception and design of the study, in the acquisition of data, in the analysis of data and interpretation of findings, and in writing the first draft. *Norbert Schmitz* was involved in the conception and design of the study, in the acquisition of data, in the analysis of data, in the interpretation of findings, and in the critical revision of the article for intellectual content. *Kimberley J. Smith* provided critical revision of the article for intellectual content.

Manuscript III: Place and health in diabetes: the neighbourhood environment and risk of depression in adults with type 2 diabetes

Authors: Genevieve Gariepy, Jay S. Kaufman, Alexandra Blair, Yan Kestens, Norbert Schmitz

This manuscript is accepted for publication in the journal *Diabetic Medicine*

Genevieve Gariepy was involved in the conception and design of the study, in the acquisition of data, in the analysis of data and interpretation of findings, and in writing the first draft. *Norbert Schmitz* was involved the conception and design of the study, the acquisition of data, the interpretation of findings, and in the critical revision of the article for intellectual content. *Yan Kestens* was involved in the acquisition of data, interpretation of findings and critical revision of the article for intellectual content. *Jay S. Kaufman* was involved in interpretation of findings and critical revision of the article for intellectual content. *Alexandra Blair* provided critical revision of the article for intellectual content.

Manuscript IV: The neighbourhood built environment and trajectories of major depression in adults: a latent class growth analysis

Authors: Genevieve Gariepy, Brett D. Thombs, Yan Kestens, Jay S. Kaufman, Alexandra Blair, Norbert Schmitz

This manuscript is submitted and under review for Plos One.

Genevieve Gariepy was involved in the conception and design of the study, in the acquisition of data, in the analysis of data and interpretation of findings, and in writing the first draft. *Norbert Schmitz* was involved in the conception and design of the study, in the acquisition of data, in the interpretation of findings, and in the critical revision of the article for intellectual content. *Yan Kestens* was involved in the acquisition of data, and critical revision of the article for intellectual content. *Brett D. Thombs, Jay S. Kaufman* and *Alexandra Blair* provided critical revision of the article for intellectual content.

Statement of Originality

The four manuscripts presented in this thesis make an original contribution to the literature on neighbourhood environment and mental health. Manuscripts I and III combined census, geospatial and satellite imagery data with survey data to investigate the association of a wide range of neighbourhood characteristics with the risk of depression and the moderators and mediators in this relationship, in people with and without diabetes and other types of chronic conditions. These studies are the first to use geospatial and satellite imagery data to examine the effect of density of services, land-use diversity and level of greenness on the risk of depression. They are also the first to investigate whether local cultural services has a potential protective factor for depression and the first to report on the impact of neighbourhood greenness on depression in people with a chronic illness. Manuscript III is the first cohort study to investigate the associations of a wide range of neighbourhood characteristics on the risk of depression in a representative sample of people with type 2 diabetes. Manuscript II is the first study to investigate the association between neighbourhood characteristics and diabetes distress, an emerging and important new outcome in people with diabetes. Results showed that the neighbourhood environment was an important correlate of diabetes distress. Manuscript IV investigated the effect of changes in the neighbourhood environment on trajectories of depression in a sample of the general population. This study is the first to take into account the dynamic nature of both depression and neighbourhood environment, an important next step in neighbourhood research. While I have received guidance and feedback from my supervisor, co-authors and doctoral committee members on methodology, statistics and substantive knowledge, the studies presented in this thesis represent my original work.

Statement of Support

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Research Ethics

For NPHS data, ethical approval for data collection was completed by Statistics Canada (Government of Canada). Written informed consent was obtained from all participants. Access to NPHS data was obtained through the Statistics Canada Research Data Centers following a rigorous screening process and approval of the research proposal. I further obtained approval to use NPHS data for my thesis project from the Research Ethics Board at the Douglas Mental Health University Institute, a health care facility within the McGill Affiliated Health Network. All data were anonymized to ensure the confidentiality and privacy of the patients involved.

For DHS data, DHS study protocols were approved by the Research Ethics Board of the Douglas Mental Health University Institute. All subjects participated voluntarily and provided verbal informed consent. Approval for use of DHS data specifically for my thesis project was again obtained from the Research Ethics Board at the Douglas Mental Health University Institute. All data were anonymized to ensure the confidentiality and privacy of the patients involved.

List of Abbreviations

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BMI	Body-Mass Index
CI	Confidence Interval
CIDI-SFMD	Composite International Diagnostic Interview-Short Form for Major Depression
CLOG-LOG	Complementary Log-Log
DHS	Diabetes Health Study
DMTI	Desktop Mapping Technologies, Inc
DSM-IV	Diagnostic and Statistical Manual of Mental Disorders, 4h Edition
GIS	Geographic Information System
HD	Hazard Difference
HR	Hazard Ratio
IP	Inverse Probability
IPC	Inverse Probability of Censoring
IPW	Inverse Probability Weighting
LCGM	Latent Class Growth Modelling
MI	Multiple Imputation
MICE	Multivariate Imputation with Chains Equations
MSM	Marginal Structural Modelling
NDVI	Normalised Differential Vegetation Index
NPHS	National Population Health Survey
PHQ-9	Patient Health Questionnaire
SES	Socioeconomic Status
SIC	Standard Industrial Classification

List of Tables

List of Figures

All figures in the thesis are original work from the author or reproduced with permission and cited.

List of Appendices

1 | Introduction

Depression is a serious public-health problem and one of the main contributors to the global burden of disease. According to the World Health Organization, depression is currently the leading cause of disability worldwide.[1] Depression is commonly described as an overwhelming sense of sadness, which is excessive and persistent, often accompanied by low energy and loss of enjoyment in activities that were once normally enjoyed.[2] Up to an estimated 1 in 3 individuals will experience high depressive symptoms at some point in their lives.[3-5] Currently, about 5% of the population is estimated to have depression in Canada and other Western countries.[3,4] While considerable research has been carried in the etiology of depression, an emerging area for research is the role of the neighbourhood environment on depression. **The overarching aim of this thesis is to examine the relationship between neighbourhood characteristics and depression in people with and without a chronic condition, particularly diabetes.** Depression is a general term that can refer to clinical depression, a disorder diagnosed from a clinical interview, or to high depressive symptoms, measured from screening scales and based on cut-offs, and which are usually used in epidemiological research. In this thesis, the term depression refers to the latter definition.

Individuals with a chronic condition such as diabetes are a growing subpopulation and are a particularly vulnerable subgroup to depression. In Canada, the prevalence of diabetes is about 7%, an increase of 70% over the previous decade, and steadily climbing.[6,7] The prevalence of cardiovascular diseases is about 5% in the general population, but 23% in those age 75 years and older.[8] The prevalence of asthma is about 8%, and chronic obstructive pulmonary condition about 4%.[9,10] The incidence and prevalence of depression is higher among those with a chronic condition.[11-14] For instance, the prevalence of depression is estimated to be between 10 to 30% in

populations with diabetes, about twice as much as the general population.[15,16] In people with a heart condition, prevalence of depression is between 10 to 20%, with prevalence estimated to reach 60% in those with a chronic heart failure.[17,18] In people with a chronic obstructive pulmonary disease, prevalence of depression is between 8-80%.[18]

For individuals with a chronic condition, depression can substantially complicate their adjustment, disease course and health outcomes. Depression is associated with poorer prognosis, disease complications, functional disability and early mortality.[19,20] For example, depression in diabetes is associated with micro- and macro-vascular complications[21,22], functional disability[20,23] and mortality[24,25]. Depression further worsens symptoms and impairs self-care. Depressed patients have been shown to be less physically active, less likely to engage in a healthy diet and less likely to adhere to medication.[26,27] In depressed patients, "the enthusiasm, the hope, the resiliency needed to [battle symptoms] are all eroded by depression".[28] An understanding of the risk factors contributing to depression in people with a chronic condition therefore has important clinical and public health implications with respect to management and prevention strategies.

Multiple factors are known to contribute to the development of depression in the general population and in those with a chronic condition, including physiological, social, economic, clinical and lifestyle-related factors.[29,30] The neighbourhood where people live is thought to relate to depression above and beyond the characteristics of individuals.[31-35] Interest in neighbourhood effects on health and wellness, including mental health, has been growing in recent years. Research in disease etiology has commonly focused downstream on the individual patients and their lifestyle. This has led to a focus on individual behaviour change and/or pharmacological treatment. Some argue that this approach may not have improved mental health

to the extent that is needed. Over the last decades, the prevalence of common mental disorders (e.g. mood and anxiety disorders) and other serious mental disorders has either remained stable or seemed to have increased in some populations.[36,37] This suggests that a new approach to mental health promotion may be warranted.[38] Addressing upstream social and contextual determinants of health - what Geoffrey Rose[39] called "causes of causes" – might be needed to promote healthy living. Figure 1.1 illustrates the distal upstream factors that affect the proximal downstream factors which cumulate into a health outcome (adapted from Kaplan, 2004[40]). In other words, better neighbourhoods could improve the living conditions of people, their social interactions and their health behaviours, which in turn might impact their physical and mental health.[38] Furthermore, the residential environment is a modifiable contributor to disease, whereas some individual-level risk factors, such as genetics, are fixed. Modifiable pathways are important as they indicate areas for potential public health intervention.

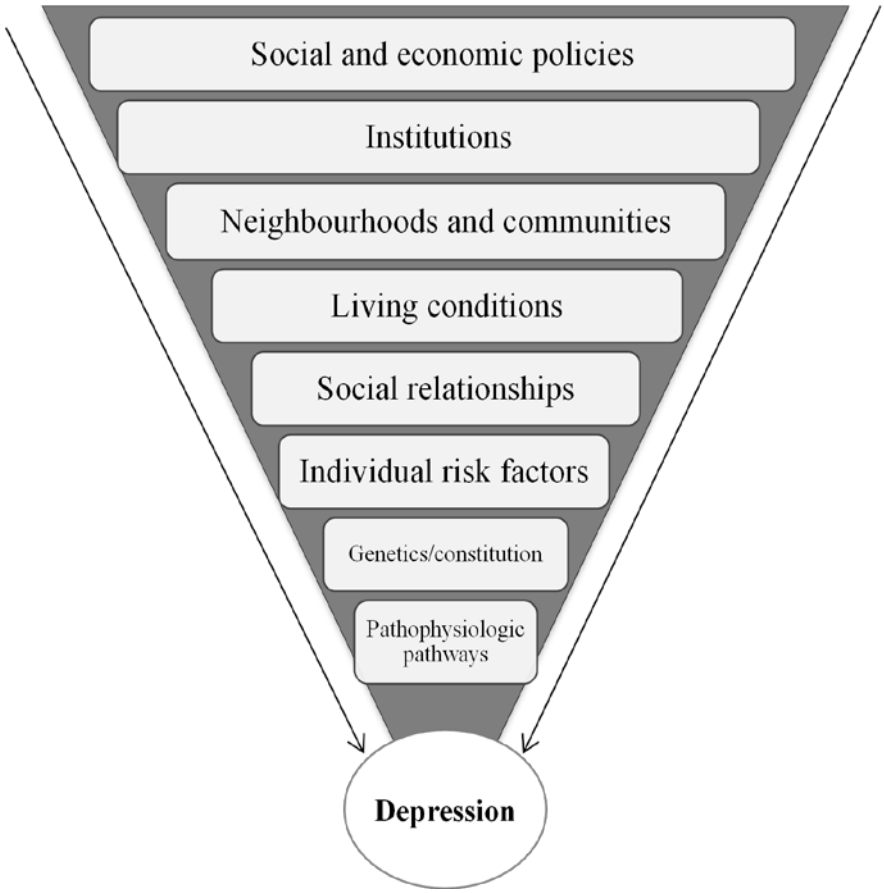


FIGURE 1.1 POTENTIAL DOWNSTREAM AND UPSTREAM RISK FACTORS OF DEPRESSION

Neighbourhoods can be broadly defined as specific geographic areas or social communities created by geographic proximity in which people live on a day-to-day basis. This environment, either deliberately or consequentially, has been planned, formed, and utilized to its best potential to meet human needs. Neighbourhoods include aspects of both the physical environment, such as noise, local amenities and street connectivity, and the social environment, such as neighbourly reciprocity, safety and social support. There are many theoretical reasons why neighbourhood environments may be particularly relevant to mental health. In Chapter 2, I present a detailed review of the potential mechanisms that are described in the literature. Briefly, the social and physical neighbourhood environment is hypothesized to affect depressive symptoms mainly by acting as a stressor or by affecting social connections. For example, disorder, violence and high crime rates can be chronic sources of stress leading to depression.[41,42] Conversely, green spaces might offer restoration from stress and protect mental health.[43] Other aspects of the neighbourhood may act as buffers to protect the mental health of individuals. For example, parks and recreation centers may promote social connections and social support, which in turn may protect against depression.[44] Furthermore, community norms may influence individual health beliefs, including mental health.[45] Several studies have reported a significant association between at least one measure of neighbourhood characteristics (e.g., neighbourhood SES) and depression, even after adjusting for individual-level factors.[31-34]

In this context, the neighbourhood environment is particularly important for people with a chronic condition. Individuals with a chronic condition may rely more on their local area for resources and support. Patients are often advised to self-manage their chronic illness through healthy lifestyle changes, such as diet and exercise. Yet, neighbourhood factors, such as lack of healthy food stores or places to exercise, may represent important barriers to managing a chronic

disease, and be a source of stress.[46] Local resources to cope with a chronic illness - or lack thereof - are also important. Limited resources, such as limited access to care or poor social support, may impact a person's ability to function with their disease, and result in depression. In our own work, we found that neighbourhood deprivation was associated with disability in adults with diabetes.[47] Additionally, because of limited mobility, people with a chronic illness may have increased exposure to neighbourhood hazards, such a noise and traffic, increasing their risk for adverse mental health outcomes.

OVERVIEW OF RESEARCH OBJECTIVES

Theories and evidence suggests that neighbourhood characteristics are important to mental health, but important knowledge gaps still exist.

- There is a need for more evidence concerning the possible neighbourhood effects on mental health, particularly among people with chronic conditions.[48] The first objective of this project is to investigate the association between neighbourhood characteristics and risk of depression across a range of chronic conditions and specifically in diabetes.
- There is sparse evidence for how and why (mediators) and for whom or under what circumstances (moderators) the neighbourhood environment affects depression. The second objective of this project is to test potential mediators and moderators in the neighbourhood-depression association, the majority of which have not yet been tested in the literature.
- Depression is a dynamic process, but the association between neighbourhood characteristics and depression over time has not been studied. The third objective is to

assess the associations between neighbourhood characteristics and changes in depression over time.

In this thesis, I present work from two large population-based samples and study a wide range of neighbourhood characteristics that could be risk factors for depression. In a first step, I adopted a wide perspective to examine neighbourhood effects in a general population sample and in general subsamples with a common chronic condition. In a second step, I focused specifically on people with diabetes. I examined both social factors (e.g. social cohesion) and physical features (e.g. number of parks) of neighbourhoods. Neighbourhood research is a relatively new field. Findings linking neighbourhood environment to mental health are still emerging, and methods and technologies to study neighbourhood effects are evolving. For this project, I used state-of-the-art geocoding methods to map the neighbourhood area around each individual (from postal code), instead of approximating neighbourhoods using administrative data. I linked several large datasets (census, geospatial, satellite imagery and survey data) to characterize neighbourhoods and investigated a broad range of neighbourhood characteristics. I used advanced statistical methods, such as discrete-time survival analysis, additive hazards method for mediation effects and several sensitivity analyses to carefully analyze the data.

ORGANIZATION OF THE THESIS

This thesis is made up of four core chapters that include four manuscripts. Chapter 2 provides a review of the literature and presents the conceptual framework of the thesis. Chapter 3 describes the research objectives and hypotheses and a general overview of methods. Chapters 4 to 7 are the core chapters and address the research objectives. Chapter 4 addresses objective 1 and part of objective 2 (moderator analysis) from a wide perspective using data from the nationwide

Canadian National Population Health Survey (NPHS). This chapter includes Manuscript I ("Neighbourhood Characteristics and 10-year Risk of Depression in Canadian Adults with and without a Chronic Illness"). Chapter 5 addresses objective 1 and part of objective 2 (moderator analysis) from a more focused perspective on type 2 diabetes using data from the Diabetes Health and Wellbeing Study (DHS). Chapter 5 includes Manuscripts II ("Diabetes distress and neighbourhood characteristics in people with type 2 diabetes") and III ("Place and health in diabetes: the neighbourhood environment and risk of depression in adults with type 2 diabetes"). Chapter 6 focuses on objective 2 (mediation analysis) using DHS data. Chapter 7 covers objective 3 using NPHS data and includes Manuscript IV ("The neighbourhood built environment and trajectories of major depression in adults: a latent class growth analysis"). Additional details on methods and supplementary results beyond the submitted manuscripts are presented in the core chapters. Chapter 8 presents a final summary of the studies and discusses research and health policy implications of the findings.

2 | Literature Review

PREVIOUS REVIEWS

Four systematic reviews have been published on the association between the neighbourhood environment and depression since 2008.[31-34] In a systematic review from 2008, Mair et al. found that 37 of the 45 selected studies reported associations of at least one neighbourhood characteristic with depression or depressive symptoms, even after controlling for individual-level characteristics.[31] At that time, authors report that the most frequently studied aspect of the neighbourhood was neighbourhood socioeconomic status (SES) based on census data. The bulk of the evidence was cross-sectional, with only 10 papers conducting some type of prospective analysis. In that same year, Kim also published a similar systematic review of 28 studies and found similar results.[32]

In 2010, Paczkowski et al. conducted a review that focused on more recent studies (2009-2010) specifically investigating neighbourhood sociodemographic characteristics.[33] They found 8 relevant studies, all of which reported an association between neighbourhood sociodemographic factors and depression. The most studied neighbourhood feature was neighbourhood SES (5/8 studies), followed by ethnic composition (3/8 studies) and residential instability (2/8 studies). Of the 8 identified studies, 4 had a longitudinal design.

In the most recent review from 2012, Julien et al. focused on the association between neighbourhood factors and depression in older adults (>65 years old).[34] They identified 19 relevant studies in the literature, the majority of which were cross-sectional (16/19 studies). Evidence overall suggested a significant association between neighbourhood variables and depressive mood (22/38 tested neighbourhood variables) in the elderly population.

UPDATE TO LITERATURE REVIEWS

In addition to the studies found in these reviews, I conducted a systematic literature review in PubMed and ISI Web of Science for studies published between August 2007 (last date of systematic review by Mair et al[31]) and April 2014. Search terms can be found in Appendix A. I included studies that examined the association between aspects of the neighbourhood and depression or depressive symptoms. Specifically, papers were included if they were original publications based on individual data that provided quantitative measures of association. All papers were downloaded into End-Note (version X7) and duplicates were removed. I excluded studies that were based on children (<18 years of age) and the perinatal period. I only reviewed papers that were written in French or English. A flow diagram of the study selection is presented in appendix B. For the final study selection, I extracted basic study information (publication date, authors, country, type of study), population characteristics (number of participants, specific characteristics), methods (neighbourhood definition, measure of neighbourhood, measure of depression, analytical technique), and results (estimates of measure of association (OR, RR, etc. and their confidence intervals). In my final selection, I included 40 studies, 22 of which were new or had not been cited in previous reviews.

From my systematic review and those of others, I identified 80 studies that have investigated neighbourhood characteristics and depression or depressive symptoms in various samples of the adult population. Summary information on these studies is presented in Table 2.1.

TABLE 2.1 SUMMARY OF PREVIOUS STUDIES ON NEIGHBOURHOOD AND DEPRESSION OR DEPRESSIVE SYMPTOMS

Author, year	Study design	Study sample	Definition of neighbourhood	Neighbourhood measure	Depression measure	Analytical technique	Results (significant results for least one neighbourhood factor?)
Tweed et al, 1990	Cross-sectional	3,481 adults aged 18+ from the eastern third of the city of Baltimore	Census tract	Racial congruence: % of the residential area population that is the same racial/ethnic group as individuals	Depressed mood (criterion A of DSM-III), major depressive episode (based on DSM-III diagnosis)	Tests of significance comparing prevalence rates of depression	Yes. An inverse relationship exists between racial congruity and depressed mood
La Gory and Fitzpatrick, 1992	Cross-sectional	725 adults aged 55+ from four metropolitan counties in Alabama	Census tract and respondent-perceived neighbourhood	Racial congruence, % of aged 55+, availability of automobile transport, perceived environment, social support	CES-D score	Linear regression	Yes. Being environmentally dissatisfied, having limited social supports, and living in neighbourhoods with transportation problems were associated with increased levels of depressive symptoms.
Reijneveld and Schene, 1998	Cross-sectional	5,121 residents of Amsterdam	Borough	Area deprivation, assessed through registered income, household income below minimum, and unemployment rate	GHQ score	Multilevel linear analysis	No. No significant association between deprivation and depressive symptoms after adjusting for age and sex.
Wilson et al, 1999	Cross-sectional and longitudinal	3,298 participants aged 65+ (1,886 participants at follow-up)	Postal district	Neighbourhood SES	Depression using GMS-AGECAT	Logistic regression	Yes. Higher neighbourhood socioeconomic disadvantage increased risks of being depressed or becoming depressed 2 years later.
Yen and Kaplan, 1999	Longitudinal	1,737 participants in the Alameda County study who responded in follow-up	Census tract	Poverty	Score from response to 18 questions; similar to CES-D	Logistic regression	No. Living in a poverty area was not associated with increased risk of depressive symptoms after adjustment for confounders (OR 1.21 (0.76 to 1.93)).
Ross, 2000	Cross-sectional	2,482 Illinois residents from the community, crime and health data set	Census tract and respondent-perceived neighbourhood	Perceived neighbourhood disorder scale (participant reported), neighbourhood disadvantage (from census)	CES-D score	Multilevel linear regression	Yes. Neighbourhood disadvantage is associated with depression (b=0.228).
Ross et al, 2000	Cross-sectional	2,482 Illinois residents from the community, crime and health data set	Census tract and respondent-perceived neighbourhood	Neighbourhood stability, poverty, and their interaction (from census); informal social ties with neighbors, fear, and sense of	Modified CES-D score	Multilevel linear regression	Yes. Neighbourhood stability is associated with depressive score, but only in economically advantaged neighbourhoods; it has a slight negative effect in poor neighbourhoods

				personal powerlessness (participant reported)			
Steptoe et al, 2001	Cross-sectional	658 respondents living in the London area	U.K. postal sector and respondent-perceived neighbourhood	Neighbourhood problems, social cohesion, informal social control, neighbourhood SES)	GHQ score	Logistic regression	Yes. Highest quartile of neighbourhood problems had higher distress levels (OR=2.65(1.47–4.47)), adjusted for social cohesion and control.
Weich et al, 2001	Cross-sectional	5,511 participants in a representative sample of individuals in private households in the UK	Standard region	Gini coefficient (income inequality)	GHQ score	Linear regression	No. No significant association between Gini coefficient and depression (0R 0.99 (0.87 to 1.13)
Hill and Herman-Stahl, 2002	Cross-sectional	103 mothers of kindergarten children from a semiurban US city	Respondent-perceived and interviewer-observed neighbourhood	Perceived neighbourhood safety	CES-D score	Multilevel linear regression	Yes. Significant association of depressive symptoms with respondent-perceived ($b = -0.38$, $p < 0.00$) and assessor-rated neighbourhood safety ($b = -0.25$, $p < 0.01$).
Silver et al, 2002	Cross-sectional	11,686 residents from five areas of the USA, in the epidemiological catchment area	Census tract	Neighbourhood disadvantage and neighbourhood residential mobility	Depression from diagnostic interview schedule using DSM-III diagnoses	Logistic regression	Yes. Depression more prevalent in residentially mobile (OR 1.14 (1.03 to 1.27)) and disadvantaged neighbourhoods (OR 1.14 (1.01 to 1.31)), after controlling for individual risk factors
Weich et al, 2002	Cross-sectional	1,887 people from two wards in London, UK	Housing area: area with homogenous housing type and form	Built environment site survey checklist (carried out by an urban design postgraduate who did not live in the area)	Depression based on CES-D	Logistic regression	Yes. Association between depression and characteristics of the built environment, after adjusting for individual SES and internal characteristics of dwellings (OR for properties with deck access 1.28 (1.03 to 1.58); OR for recent construction 1.43 (1.06 to 1.91).
Christie-Mizell et al, 2003	Longitudinal	2,204 women with at least one child from NLSY	Respondent-perceived neighbourhood and census tract	Perceived neighbourhood disorder (participant reported)	Score on seven-item version of CES-D	Linear regression	Yes. Across all racial groups, neighbourhood perceptions influence maternal distress (b (SE) 0.17 (0.02)).

Leventhal and Brooks-Gunn, 2003	Randomized trial	550 persons in public housing in high-poverty census tracts from the Moving To Opportunity study at the New York City site	Census tract	Section 8 housing voucher and special assistance to move to low-poverty (<10%) neighbourhood	Depressive Mood Inventory score	Linear regression	Yes. Significant effect on intervention on depressive score (Intent-to-treat analysis : b = -0.19, p < 0.10)
Latkin et al, 2003	Longitudinal	818 participants in high drug use areas in Baltimore, Maryland	Respondent-perceived neighbourhood	Social support, social integration, perception of neighbourhood characteristics	CES-D score	Linear regression	Yes. Association between negative perceived neighbourhood characteristics and subsequent depressive symptoms, after adjusting for baseline depression (b=0.28, p<0.01).
Muramatsu, 2003	Cross-sectional	6,640 non-institutionalized participants aged 70+	County unit	Neighbourhood income inequality and mean income	CES-D score	Multilevel linear regression	Yes. Higher county-level income inequity was related to more depressive symptoms (b = 2.64, SE = 0.81)
Ostir et al, 2003	Cross-sectional	2,710 non-institutionalized Mexican-Americans aged 65 years or older, from five southwest states	Census tract	Percentage of Mexican-Americans in census tract, neighbourhood SES	CES-D score	Multilevel analysis and single-level linear regression	Yes. Each 10% increase in neighbourhood poverty was associated with a 0.76 (95% CI 0.06 to 1.47) increase in CES-D score, after adjustment for individual characteristics.
Weich et al, 2003	Cross-sectional	8,978 respondents from the BHPS in Britain, Scotland, and Wales	Electoral ward, grouped into 14 principal groups	Carstairs index of socioeconomic deprivation	Depression based on GHQ	Multilevel logistic and linear regression	No. No association between socioeconomic deprivation and depression.
Fauth et al., 2004	Quasi-experimental study	315 African Americans and Latinos living in public housing in New York	Census tract	Selection to move to low-poverty neighbourhoods	Depression subscale of Symptom-Driven Diagnostic System for Primary Care screen	Linear regression	No. No significant different between movers and non-movers (b = -0.28, p > 0.10)
Gee et al., 2004	Cross-sectional	1,503 Chinese Americans aged 18–65 in Los Angeles, California	Census tract and respondent-perceived neighbourhood	Neighbourhood % below poverty line; perceived neighbourhood physical conditions and crime; % taking public transportation	Score from the depression subscale of Revised Symptom Checklist 90	Multilevel linear regression	Yes. Significant association with neighbourhood % below poverty line (b > 0, p < 0.10) but not with perceived neighbourhood conditions (p > 0.05) and neighbourhood vehicular burden (p > 0.05).

Greiner et al, 2004	Cross-sectional	4,601 subjects from the Kansas Behavioral Risk Factors Surveillance System	County and respondent-perceived neighbourhood	Overall community ratings (neighbourhood-level trust) and social participation (participant reported)	Depression based on optional depressive symptom questions from the survey	Multilevel logistic regression	Yes. Community rating was associated with depression (OR 0.65 (0.57 to 0.75)), but community involvement was not (OR 0.99 (0.71 to 1.36)), after adjustment
Hahn, 2004	Cross-sectional	863 participants aged 65-74 in Taiwan	Respondent-perceived neighbourhood	Perceived neighbourhood social capital (greeting, mutual concern, mutual help, etc.)	Depression based on Taiwanese Depression Questionnaire	Logistic regression	Yes. Living in neighbourhood with high social capital decreases the risks of being depressed (OR: 0.91 (0.87-0.94)).
Schieman et al, 2004	Cross-sectional	1,167 men and women aged 65+ in Washington DC and two adjoining counties	Respondent-perceived neighbourhood	Neighbourhood problems	Seven items about depressive symptoms in the past week	Linear regression	Yes. Neighbourhood problems were associated positively with depression in men (b (SE) 0.095 (0.094)) and women (0.087 (0.082)).
Wainwright and Surtees, 2004	Cross-sectional	19,687 participants in the EPIC-Norfolk study	Electoral ward	Overall index of multiple deprivation	Depression based on DSM-IV criteria	Logistic regression	Yes. Significant association between area deprivation and current mood disorders, after adjusting for individual-level risk factors (OR for top vs bottom quartile of deprivation 1.29 (1.1 to 1.5)).
Walters et al., 2004	Cross-sectional	13,349 persons aged 75+ in the United Kingdom	Enumeration district	Neighbourhood SES (Carstairs deprivation score, based on district unemployment, overcrowding, non-car ownership, social class)	Depression based on Geriatric Depression Scale	Logistic regression	No. Not significant association between depression and low neighbourhood SES (vs. high neighbourhood SES) (OR = 1.10, 95% CI: 0.81, 1.50).
Cutrona et al, 2005	Cross-sectional and longitudinal	720 women from a large-scale study of African-American families who live outside metropolitan inner cities in the USA	Census block group	Economic disadvantage index (from census), neighbourhood-level social disorder	Depression based on UM-CIDI	Multilevel logistic analysis	Yes. Neighbourhood disadvantage/social disorder was associated with recent onset of depression, after controlling for individual-level risk factors (OR 1.92, 1.04 to 3.52). However, neighbourhood disadvantage and disorder did not predict onset of depression at a later date
Galea et al, 2005	Cross-sectional	1,355 residents of New York City	Census tract	Characteristics of the internal built environment and the external built environment	Depression based on National women's study depression module, consistent with DSM-IV criteria	Multilevel analysis	Yes. Characteristics of the built environment were associated with depression.

Henderson et al, 2005	Cross-sectional	3,437 adults aged 18–30 from the Coronary Artery Risk Development in Young Adults study	Census block group	Neighbourhood socioeconomic (from census variables reflecting wealth/income, education, and occupation); ethnic density	Depression based on CES-D	Multilevel logistic analysis	No. Neighbourhood socioeconomic characteristics and ethnic density were not associated with depression after controlling for individual-level characteristics
Kubzansky et al, 2005	Cross-sectional	2,109 non-institutionalized people 65 and older in New Haven, Connecticut	Census tract	Neighbourhood socioeconomic disadvantage and advantage, racial/ethnic heterogeneity, residential stability, age structure (from census), service density (constructed from phonebook listings)	CES-D score	Multilevel linear analysis	Yes. Low neighbourhood SES (b=6.51 (1.02, to 12.00)) and presence of older people (b=-13.55 (-24.76 to -2.34)) were associated with depressive symptoms in older people after controlling for individual characteristics.
Mulvaney and Kendrick, 2005	Cross-sectional	846 mothers of young children living in deprived areas (Townsend deprivation scores >0) in the UK	Enumeration district and respondent-perceived neighbourhood	Social capital, stress, perceived social support, neighbourhood deprivation (participant-reported)	Depression based on CES-D	Multilevel logistic regression	Yes. Neighbourhood deprivation (OR for highest vs lowest fifth 2.4 (1.28 to 4.48)), lack of social support (OR 2.51 (1.75 to 3.61)), and self-reported stress (OR 10.42 (6.29 to 17.28)) were all associated with depressive symptoms in the adjusted model.
Veenstra, 2005	Cross-sectional	1,435 persons in 25 communities in British Columbia, Canada	Census tract	Median household income, number of public spaces, voluntary organizations per capita; average levels of community trust and political trust	Score from 11-item depression scale	Multilevel linear regression	Yes. Significant associations of higher levels of depressive symptoms with number of public spaces per capita (b = 0.001, p = 0.02)/ No significant associations for other community social capital variables and community SES.
Weich et al, 2005	Longitudinal	7,659 participants in the British Household Panel Survey aged 16–74	Electoral ward	Carstairs index of socioeconomic deprivation	Depression based on GHQ	Multilevel logistic regression	No. Ward level socioeconomic deprivation does not influence the onset and maintenance of depression.
Hybels et al, 2006	Cross-sectional	2,998 adults 65+ years old in North Carolina	Census tract	Neighbourhood SES, racial/ethnic heterogeneity, residential stability, and neighbourhood age structure (from census)	CES-D score	Multilevel linear analysis	No. None of the neighbourhood characteristics were significantly associated with depressive symptoms.
Matheson et al, 2006	Cross-sectional	56,428 adults aged 18–74 living in metropolitan areas in Canada	Census tract	Residential instability, material deprivation, dependency, ethnic diversity (from census)	Depression based on CIDI-SF MD	Multilevel logistic analysis	Yes. Residential instability (OR 1.04, $p<0.05$) and material deprivation (OR 1.05, $p<0.01$) were associated with depression after adjusting for individual characteristics.

Yen et al, 2006	Cross-sectional	435 adults with asthma in northern California	Respondent-perceived neighbourhood	Neighbourhood problems (too much traffic, excessive noise, trash and litter, smells, smoke) (participant reported)	Depression based on CES-D	Single-level linear regression	Yes. subjects in the top quartile of neighbourhood problems were more likely have depressive symptoms than the bottom quartile, after adjustment (OR 4.8 (2.4 to 9.5)
Anehensel et al, 2007	Cross-sectional	3442 individuals aged 70+ years living in urban areas in the USA	Census tract	Socioeconomic disadvantage, affluence, racial/ethnic composition, residential stability, proportion of persons >65 years (from census)	Score on CES-D short form	Multilevel linear analysis	Yes. Depressive symptoms were associated with residential stability (b (SE) 0.72 (0.27)) after controlling for individual-level characteristics, but not with any of the other neighbourhood characteristics
Berke et al, 2007	Cross-sectional	740 adults aged 65 + from King County, Washington	Buffer zone of 100, 500, and 1000m around each subject's home	Neighbourhood walkability	Depression based on CES-D	Logistic regression	Yes. There was an association between neighbourhood walkability and depressive symptoms for men (OR for the interquartile range of walkability score=0.31–0.33 for the buffer radii, p=0.02) after adjustment for key individual-level factors, but not in women (p>0.68).
Dupéré and Perkins, 2007	Cross-sectional	412 residents from 50 neighbourhoods in a large city in the Mid-Atlantic region of the USA	Respondent-perceived neighbourhood	Neighbourhood disorder, fear of crime, formal participation, informal ties with neighbors (participant-reported)	Depression based on 6-item depression factor of the CES-D scale	Multilevel logistic analysis	No. The community-level stressors and resources had no impact on mental health over and above individual and block socioeconomic characteristics
Galea et al, 2007	Longitudinal	1,120 adult residents of New York City	Community district	Neighbourhood SES (from census)	Depression based on modified version of SCID	Multilevel logistic analysis	Yes. Significant odds ratio of incident depression for participants living in low versus high SES neighbourhoods (OR = 2.19 (95% CI 1.04 to 4.59))
Gary et al, 2007	Cross-sectional	1,408 African-American and white adult residents of Baltimore, Maryland	Respondent-perceived neighbourhood	Perceptions of potential neighbourhood problems, availability of a community leader, community cohesion, resources within the community	Depression based on PHQ-9	Logistic regression	Yes. Perception of severe community problems was associated with depression (OR 2.2 (White), 1.9 (African-American), p<0.05 (both)). Community cohesion was only associated with lower levels of depression in whites (OR 0.5, p<0.05).
Kruger et al., 2007	Cross-sectional	801 persons aged 18-100 living in Flint and Genesee County, Michigan	Buffer zone of 0.25 miles around a respondent's home	Environmental block assessment of neighbourhood residential and commercial building deterioration; Respondent-perceived neighbourhood social capital, fear of crime	Score on the Brief Symptom Inventory-18 depression subscale	Structural equation modeling	Yes. Building deterioration determined lower neighbourhood social capital/higher fear of crime, in turn predicting higher individual depressive symptoms; adding direct effect of building deterioration on depressive symptoms did not improve fit.

Lofors and Sundquist, 2007	Longitudinal	2,287,349 men and 2,229,438 women in Sweden, aged 25-64 years	Small Area Market Statistics area	Neighbourhood SES (% of low education, unemployed, elderly living alone, children aged <5 years, single parents, moving in past year, and foreign birth); mean participation in local governmental elections	First hospitalization with diagnosis of selected affective disorders including depression	Logistic regression	Yes. Significant association between neighbourhood SES (low vs. high) and depression in men (OR = 1.20, 95% CI: 1.11, 1.30) and women (OR = 1.33, 95% CI: 1.24, 1.43) as well as neighbourhood voting participation (low vs. high) in men (OR = 1.16, 95% CI: 1.09, 1.23) and women (OR = 1.11, 95% CI: 1.06, 1.17)
Schootman et al., 2007	Longitudinal	998 African Americans aged 50–64 living in low-SES inner-city area and suburban area of St. Louis, Missouri	Census tract	Deprivation index (poverty, education, housing, etc.); interviewer rating of block of residence of respondent; respondent-perceived neighbourhood conditions	Depression based on 11-item modified CES-D	Multilevel logistic regression	No. No significant effect of neighbourhood deprivation (low vs. mean) on incident depression (OR = 1.58, 95% CI: 0.50, 4.99), of interviewer-rated neighbourhood conditions (4–5 conditions rated as fair/poor vs. 0–1 conditions rated as fair/poor) (OR = 0.54, 95% CI: 0.24, 1.23) or of respondent-perceived neighbourhood conditions (worst condition vs. mean condition) (OR = 1.42, 95% CI: 0.70, 2.86)
Stockdale et al., 2007	Cross-sectional	12,716 adults living in 60 American communities	Census tract	Neighbourhood SES: median family income, % of owner-occupied units; neighbourhood alcohol outlet density; density of alcohol, drug, and mental-health facilities; neighbourhood violent crime arrest rate	Depression based on CIDI-SF	Multilevel logistic regression	Yes. Significant association for probable depression/anxiety disorder with neighbourhood median family income (OR = 1.00, $p < 0.05$), but not neighbourhood % of owner-occupied units (OR = 1.00, $p > 0.05$), neighbourhood alcohol outlet density (OR = 1.00, $p > 0.05$), neighbourhood density of alcohol, drug, and mental-health facilities (OR = 0.998, $p > 0.05$).
Echeverria et al., 2008	Cross-sectional	5,943 persons aged 45-84 years living in six American communities	Respondent-perceived neighbourhood	Neighbourhood problems (e.g., lack of parks, lack of access to adequate food shopping, violence); neighbourhood social cohesion	CES-D score	Multilevel linear regression	Yes. Significant association of depressive symptoms with respondent-perceived neighbourhood problems (low vs. high) ($b = -0.34$, $p < 0.05$), other respondent-derived neighbourhood problems (low vs. high) ($b = -0.21$, $p < 0.05$), respondent-perceived neighbourhood social cohesion (low vs. high) ($b = 0.13$, $p < 0.05$), but not with other respondent-derived neighbourhood social cohesion (low vs. high) ($b = 0.05$, $p > 0.05$).

Tonorezos et al., 2008	Cross-sectional	150 caregivers Baltimore Indoor Environment Study of Asthma in Kids	Respondent-perceived neighbourhood	Fear of neighbourhood violence	Depression based on CES-D	Multilevel logistic model	Yes. Fear of neighbourhood violence increased the odds of depression by 6.7.
Trupin et al., 2008	Cross-sectional	957 patients with confirmed SLE diagnoses	Census block group	Neighbourhood SES	Depression based on CES-D (score > or = 19)	Logistic regression	Yes. neighbourhood SES remained significant, after adjustment for individual SES, demographic, and health-related covariates
Yen et al., 2008	Longitudinal	340 adults with asthma in northern California	Respondent-perceived neighbourhood	Neighbourhood problems (too much traffic, excessive noise, trash and litter, smells, smoke)	Depression based on CES-D (score > or = 16)	Linear regression	Yes. High neighbourhood problems predicted over two-fold odds of depression at follow-up (OR=2.34; 95% confidence interval: 1.09-5.00)
Yen et al., 2008	Cross-sectional	301 participants 65-74 years old from Taiwan	Township delimitation	Neighbourhood poverty, elderly concentration, density of physician population, disposable money, home ownership, welfare expenditure, self-reported neighbourhood quality	Depression, based on Taiwanese Depression Questionnaire	Multilevel logistic regression	No. None of the variables were related to depressive symptoms.
Beard, 2009	Longitudinal	808 New York City residents aged 50 years or older	Census tract	Compositional characteristics of the respondents' neighbourhoods based on factor analysis (socioeconomic influences, residential stability, racial composition)	PHQ-9 score	Multilevel linear regression	Yes. Socioeconomic influences was significantly associated with depressive symptoms (b= -0.48, CI -0.83, -0.12), but not residential stability and racial composition, in fully adjusted model.
Bierman, 2009	Longitudinal	836 individuals aged 65+ from the USA	Respondent-perceived neighbourhood	Neighbourhood problems (noise, vandalism, etc.)	Score from 4 items of the Hopkins Symptoms Checklist	Linear regression	Yes. More neighbourhood problems predicted more depressive symptoms in the future (b = 0.15, SE = 0.06).
Ellaway et al, 2009	Cross-sectional	1,637 adults living across a range of neighbourhoods throughout Scotland	Respondent-perceived neighbourhood	Neighbourhood incivilities (e.g. litter, graffiti); large-scale infrastructural incivilities (e.g. telephone masts); and the absence of environmental goods (e.g. safe play areas for children)	Frequency of feeling of sadness or depression in past year (1 item)	Logistic regression	Yes. Respondents with the highest levels of perceived street-level incivilities (OR=1.53, CI 1.04, 2.27) and the highest levels of perceived absence of environmental goods (OR=1.94, CI 1.31, 2.76) reported more frequent feelings of depression, after adjusting for age, sex and social class.

Lee , 2009	Cross-sectional	400 Hispanic-Americans from Chicago	Neighbourhood cluster based on cluster analysis of census tracts	Residential segregation	Depressive symptoms based on DSM-V criteria	Multilevel linear regression	Yes. Neighbourhood segregation was strongly associated with the mental health of Mexican Americans even after controlling for other covariates, but not in Puerto Ricans.
Mair et al., 2009	Cross-sectional and Longitudinal	2,619 healthy adults aged 45-84 years	Buffer zone of 1 mile around participants' home	Perceived neighbourhood cohesion and stressors (by informants)	Score and depression based on CES-D	Marginal maximum likelihood estimation	Yes, in cross-sectional data. Lower levels of social cohesion and aesthetic quality and higher levels of violence were associated with higher CES-D scores in men (-1.01 (95% CI: -1.85, -0.17)) and women (1.08 (-1.88, -0.28)). No associations with incident depression for women (OR of incident depression 0.89 (0.63, 1.26)) or men (OR=0.96 (0.74, 1.25)).
Pikhartova et al, 2009	Cross-sectional	7,616 adults aged 45-69 years in a Czech study	Census tract	% of university educated persons and % of unemployed	Depression based on CES-D	Multilevel logistic regression	No. No significant association
van Praag et al., 2009	Cross-sectional	21,367 respondents in the Belgian Health Interview Survey	Municipality	Neighbourhood SES (unemployment rate, density, median area income)	Score on the subscale of the Symptoms Checklist 90-Revised	Multilevel linear regression	Yes. Living in an area with high unemployment was significantly associated depression in women, but not men.
Wight et al., 2009	Longitudinal	1871 participants aged 70+ years from USA who responded in five-year follow up	Census tract	Neighbourhood SES (education, poverty, etc.); affluence; racial composition; residential stability; % elderly	CES-D score	Multilevel linear regression	No. No significant association with any neighbourhood-level variables when adjusting for individual-level characteristics.
Wilbur et al, 2009	Longitudinal	278 African-American woman participating in an RCT walking intervention	Respondent-perceived neighbourhood and 1-mile radius buffer	Neighbourhood deterioration and crime (objective and perceived)	CES-D score	Linear regression	Yes. Objective neighbourhood deterioration was significantly associated with lower depressive symptoms, whereas perceived neighbourhood deterioration was associated with higher symptoms at follow-up.
Glymour et al., 2010	Longitudinal	4,000 enrollees aged 55-65 years in the national Health and Retirement Study	Census tract	Neighbourhood disadvantage based on 6 socioeconomic status indicators	Depression based on CES-D	Logistic regression	No. neighbourhood disadvantage did not predict new cases of depression (OR, 0.97; 0.81-1.16)

Mair et al., 2010	Cross-sectional	3105 adults from the Chicago Community Adult Health Study	Respondent-perceived neighbourhood	Neighbourhood stressors (perceived violence and disorder, physical decay and disorder)	CES-D short-form score	Multilevel linear regression	Yes. Neighbourhood stressors were associated with higher levels of depressive symptoms in women (b= 0.04, CI 0.00, 0.08) and in men (b= 0.04, CI 0.00, 0.09), even after adjusting for neighbourhood- and individual-level covariates
Mair et al., 2010	Cross-sectional	5667 adults aged 45-84 from the Multi-Ethnic Study of Atherosclerosis	Census tract	% of residents of the same racial/ethnic background	CES-D score	Multilevel linear regression	Yes. Living in a neighbourhood with a higher percentage of residents of the same ethnicity was associated with increased CES-D scores in African American men.
Menec et al., 2010	Cross-sectional	77,930 participants, aged 65+ from Canada	Census tract	Neighbourhood income areas (in quintiles); residential stability; elderly (65+) concentration	Depression based on ICD-9-CM	Multilevel linear regression	Yes. Living in the lowest neighbourhood income quintile increased risks of depression vs highest quintile (OR = 1.19, $p<0.05$), higher proportion of 65+ years in the neighbourhood increased depressive mood (b = 0.02, SE = 0.01)
Ahern and Galea, 2011	Cross-sectional	4,000 participants from New York Social Environment Study	Community district	Neighbourhood collective efficacy	Depression based on PHQ-9	Multilevel marginal modeling	Yes. In older adults (65+), living in low collective efficacy neighbourhood increased risks of depression (difference in depression prevalence rates: 6.2%; 95% CI: 0.1, 17.5). Not significant association in young adult.
Gary-Webb et al., 2011	Cross-sectional	1,010 trial participants in the Action for Health in Diabetes	Census tract	% living below poverty	Beck Depression Inventory score	Linear regression	No. No significant association between neighbourhood poverty and depression score (b = 0.68, -0.12, 1.48).
Gerst, 2011	Cross-sectional	1,875 Mexican American age 75+ years	Census tract	% of Mexican-American living in neighbourhood (adjusted for % living in poverty)	CES-D score	Multilevel linear regression	Yes. Higher racial composition was related to less depressive symptoms in men (b = –0.07, SE = 0.03), but not in women.
Haines et al, 2011	Cross-sectional	497 residents of 32 neighbourhoods in an American city	Census tract	Neighbourhood disadvantage from summary measure from a census data	CES-D score	Multilevel linear regression	Yes. Significant beta (0.154, $p<0.05$) for neighbourhood disadvantage, even after adjusting for individual-level covariates.
Johnson et al. 2011	Cross-sectional	1,091 individuals aged 70 years old in Scotland	Geographic data zone in Scotland	Neighbourhood quality (income, employment, health, education, etc)	HADS score	Multilevel linear regression	No. Neighbourhood environment quality was not related to depressive symptoms.

Roh et al, 2011	Cross-sectional	420 Korean American older adults, residents of the New York City metropolitan area	Respondent-perceived neighbourhood	Perceived neighbourhood environment (e.g., perceived ethnic density, safety, social cohesion, and satisfaction)	CES-D score	Multilevel linear regression	Yes. Significant association between perceived neighbourhood safety (b= -0.10, p<0.05) and neighbourhood satisfaction (b=-0.14, p<0.01) and depressive symptoms, adjusted for confounders.
Saarloos et al., 2011	Cross-sectional	5,218 men aged 65-79 years from Australia	Census tract	Neighbourhood SES, age composition, walkability, street connectivity, residential density, land-use mix, land-use availability	Depression based on Geriatric Depression Scale	Logistic regression	Yes. Living in neighbourhoods with greater land-use diversity increased risks of being depressed (for 2nd tertile, OR = 1.54, 95% CI: 1.10, 2.16; for 3rd tertile, OR = 1.52, 95% CI: 1.08, 2.14), and presence of retails in the neighbourhood increased risks of being depressed (OR = 1.40, 95% CI: 1.04, 1.90).
Stafford et al, 2011	Longitudinal	7,500 participants of the English Longitudinal Study of Ageing	Respondent-perceived neighbourhood	Neighbourhood social cohesion and perceived safety	CES-D score	Structural equation modeling	Yes. Neighbourhood social cohesion was associated with reporting fewer depressive symptoms independent of demographic and socioeconomic factors and baseline depressive symptoms.
Valle et al, 2011	Cross-sectional	3023 Parisians	Respondent-perceived neighbourhood and census tract	Neighbourhood deprivation	Depression based on Mini-international neuropsychiatric interview	Logistic regression	Yes. Respondents who had given a negative assessment of their neighbourhood were more likely to be depressed (OR = 1.57; 95% CI = 1.24–1.99
Vega et al., 2011	Cross-sectional	1,468 urban Latino adult respondents in Los Angeles County	Respondent-perceived neighbourhood and census tract	Neighbourhood socioeconomic index, perceived neighbourhood collective efficacy, proportion of linguistically isolated households	Self-reported physician-diagnosed depression	Multilevel logistic regression	Yes. Neighbourhood deprivation, neighbourhood collective efficacy and neighbourhood % of linguistic isolation were significantly associated with depression.
Buu et al., 2011	Longitudinal	273 females in their 30s and 40s	Census tract	Neighbourhood residential instability and neighbourhood socioeconomic disadvantage	Score on the Hamilton Rating Scale for Depression	Multilevel linear regression	Yes. Neighbourhood residential instability was associated with higher depression, controlling for individual and familial influences. Neighbourhood socioeconomic disadvantage was not associated.
Chung et al., 2011	Cross-sectional	127 urban, African American young adults	Respondent-perceived neighbourhood	Neighbourhood disorder, neighbourhood trust and cooperation	Depressive symptoms from the Adult Self-Report Inventory	Structural equation modeling	Yes. Higher levels of neighbourhood disorder were related to higher rates of depressive symptoms in communities with low levels (b=0.25, P<.05) and high levels (b=0.17, P<.05) of trust and cooperation.

Miles et al., 2012	Cross-sectional	2,000 community-residents in Miami, Florida	Census tract	Housing unit density; acres of green space, land-use diversity; auto commuter density; economic deprivation, residential stability	CES-D score	Linear regression	Yes. Significant association between the depressive symptoms and economic deprivation, residential stability and housing density. Land-use diversity was not significant. Acreage of green space was not significant across all categories.
Cromley et al., 2012	Cross-sectional	5,688 people aged 50-74, living in New Jersey	Census tract	Neighbourhood poverty, residential stability and crime	CES-D score	Spatial auto-correlation and geo-graphically weighted regression	Yes. Parameters of the poverty variable were positive and significant almost everywhere in the state. Parameters for residential stability and crime varied in their association with depressive symptoms in different regions of the state. Places where people with high levels of depressive symptoms lived were often proximate to other places where people with high levels of depressive symptoms lived.
Wight et al., 2013	Longitudinal	2,184 middle-aged adults aged 51–61 years living in the USA	Census tract	Neighbourhood unemployment history: average % unemployed in 1990 -2000 and change in % unemployed 1990 -2000	CES-D score	Multilevel linear regression	Yes. Higher depressive symptoms in people residing in neighbourhoods characterized by high historical average unemployment beginning in 1990 and increasing unemployment between 1990 and 2000
Wilson-Genderson and Pruchno, 2013	Cross-sectional	5,688 persons aged 50-74 living in New Jersey	Census tract	Neighbourhood violent crime (quartiles) and perception of neighbourhood safety	CES-D score	Multilevel structural equation analysis	Yes. Higher levels of neighbourhood violent crime and poorer perceptions of neighbourhood safety were significantly associated with higher levels of depressive symptoms
Bassett and Moore, 2013	Cross-sectional	2,707 adults from Montreal Metropolitan Area	Census tract	Trust in neighbors and neighbourhood social cohesion	Depression based on CES-D	Multilevel logistic regression	Yes. Trust in neighbors, and perceptions of neighbourhood cohesion reduced the likelihood of depression
Shell et al, 2013	Cross-sectional	1,238 Mexican-descent adults living in Texas City, Texas.	Census tract	Hispanic neighbourhood composition	CES-D score	Multilevel linear regression	Yes. Higher percent Hispanic is associated with lower depressive symptoms in a monotonic trend; but only the highest percent Hispanic level (>45%) compared with the lowest level (<16%) is significantly associated (beta -0.30, $p<0.05$)

b: beta coefficient; CES-D: Center for Epidemiologic Studies; CIDI-SF MD: Composite Diagnostic Interview Schedule Short Form for major depression; DSM-IV: Diagnostic and Statistical Manual of Mental Disorders; GHQ: General Health Questionnaire; GMS-AGECAT: Geriatric Mental State using the Automated Geriatric Examination for Computer Assisted Taxonomy; PHQ-9: Patient Health Questionnaire; SCID: Structured Clinical Interview for Diagnostic and Statistical Manual of Mental Disorders; SES: socioeconomic status; SF-36: Mental health index of the Short Form Health Survey 36; SMDI: Multiscore Depression Index, short form; OR: odds ratio; UM-CIDI: University of Michigan Composite International Diagnostic Instrument.

PREVIOUS STUDIES IN ADULT SAMPLES

The most studied neighbourhood characteristics were neighbourhood socioeconomic characteristics derived from census data (e.g., proportion of residents living below the poverty line, proportion of university-educated residents), which were often combined into a neighbourhood deprivation index (46/80 studies). Studies on perception of neighbourhood problems (e.g., perception of neighbourhood safety) were also prevalent (22/80 studies), as were studies that examined social aspects of the neighbourhood environment (e.g., social participation, social support) (18/80 studies) and neighbourhood demographic characteristics (e.g., ethnic composition, age structure) (17/80 studies). Only 9 previous studies examined the association of the built environment with depressive symptoms, all of them using cross-sectional data. Among these, only 2 studies investigated land-use mix[49,50] and 1 examined green spaces[50]. The density of business and services was rarely studied. One cross-sectional study assessed neighbourhood density of services (desirable and undesirable services) in a sample of older adults[51], while another cross-sectional study focused specifically on neighbourhood alcohol density outlet and density of alcohol, drug, and mental-health facilities.[52]

A total of 20 publications had a longitudinal design, of which 12 reported a significant association between a neighbourhood factor and depression or depressive symptoms at follow-up. Only 7 longitudinal studies specifically assessed incidence of depression, 4 of which were based on older samples. Neighbourhood factors were significantly associated with risk of depression in less than half of the longitudinal studies (3/7 studies).

Previous Studies Specific to Adults with a Chronic Condition

The association between neighbourhood and depressive symptoms in people with a chronic condition has been examined in 4 study samples.[53-57] Except for one study[55], all analyses were cross-sectional. One cross-sectional study in adults with arthritis reported a significant association between perceived neighbourhood characteristics and prevalent depressive symptoms.[53] Those who reported living in neighbourhoods that were less safe or less socially cohesive had significantly higher odds of depressive symptoms. A cross-sectional study among individuals with systemic lupus found a significant association between area poverty and high depressive symptoms, after adjusting for confounders.[56] In a cohort of adults with asthma, researchers found cross-sectional and longitudinal associations between perceived neighbourhood problems (such as too much traffic and noise) and high depressive symptoms, after controlling for asthma severity and demographic factors.[54,55] Finally, a cross-sectional study investigated the association between neighbourhood poverty and depressive symptoms in a sample of overweight volunteers with type 2 diabetes.[57] Results suggested a weak and non-significant association, after adjusting for individual-level factors.

Knowledge Gaps in the Literature

Based on my review and those of others[31-34,58], there are several knowledge gaps that still exist in the literature:

- The majority of previous studies used census-based aggregate data to characterize neighbourhoods. The physical environment and access to services might be important additional factors to consider.
- The majority of studies are cross-sectional. Longitudinal studies are needed to identify the independent association of neighbourhood and incidence of depression, in addition to individual-level risk factors.
- Previous studies have mainly used administrative geographic units (e.g., census tracts) as a crude proxy to define neighbourhoods. Non-census based neighbourhood definitions (e.g., person-centered neighbourhood) are hypothesized to more accurately capture the specific neighbourhood characteristics involved in the development of depression[59], but these have been rarely used in depression research.
- There is little information regarding which variables mediate the pathway between neighbourhood factors and depression (mediators) (e.g. health behaviours) and which variables modify the association between neighbourhood factors and depression (moderators) (e.g. social support).
- A limited number of studies have examined the association between neighbourhood characteristics and depression in those with a chronic condition. No previous study has examined the mediating pathways and moderators of the relationship in a chronically ill population.
- The majority of studies were conducted in the United States and the United Kingdom where neighbourhoods might be different than those from Canada. There is a need to study neighbourhood and mental health in the Canadian context.

In sum, there have been few studies that focused on understanding the longitudinal relationship between neighbourhood factors, depression, and chronic conditions in ways that would assist in sorting out causality and allow us to make research and intervention recommendations to improve outcomes, particularly in the Canadian context.

Conceptual Framework

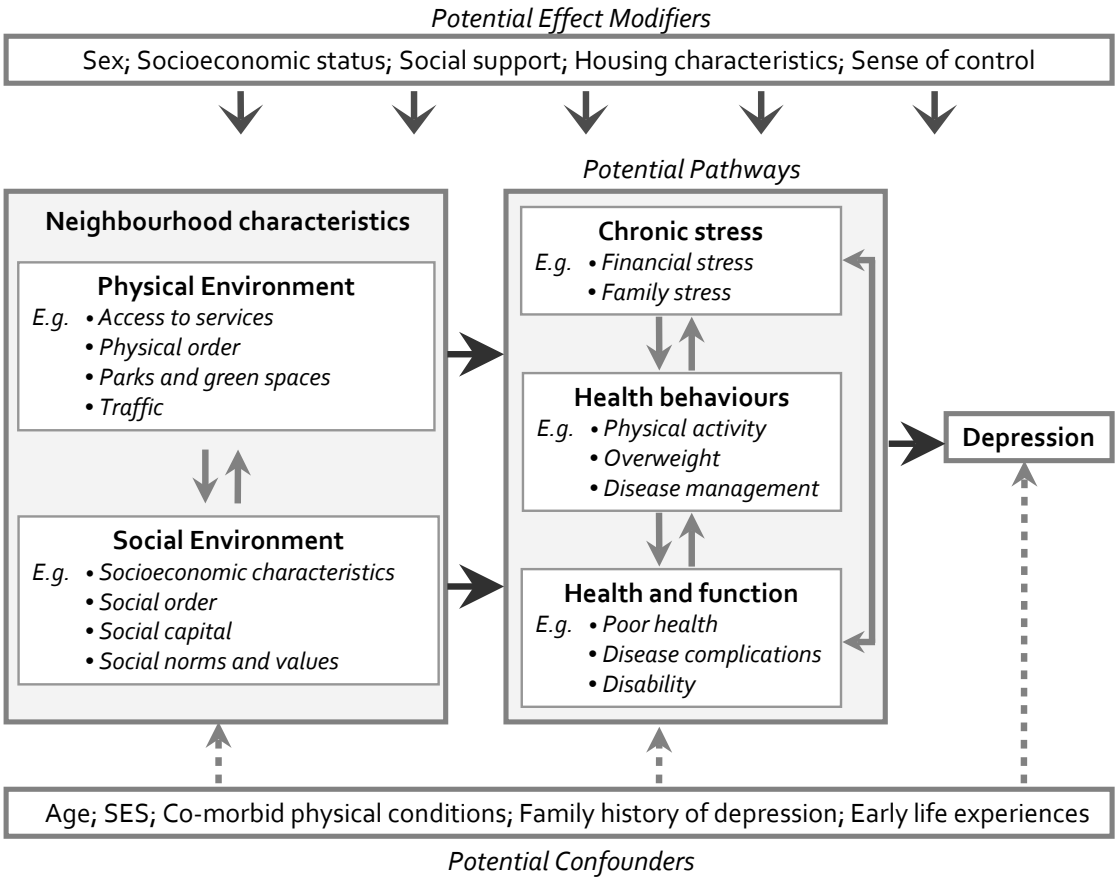
Mediating Pathways from Neighbourhoods to Depression

In the General Adult Population

There are numerous hypotheses for why the neighbourhood environment matters to depression in the general population.[31-33,35,60] The social stress model suggests that the stress of living in a socially disorganized area increases the risk of depression.[61] Characteristics, such as socioeconomic disparities and high crime rates, may function as chronic stressors and affect mood.[41,62,63] These factors might also indirectly affect depression by altering social processes.[64,65] For example, high crime rates may lead to fear of others and social isolation, and affect mental health.[62,66] Another model, the concentrated disadvantage model, suggests that depression is the result of the cumulative effect of deleterious elements in the neighbourhood environment.[67] In other words, it is the concentrated disadvantage of a neighbourhood that is overwhelmingly impoverished that causes depression.[67] An alternative model is the social cognitive model. This model posits that social factors are determinants of health: strong self-efficacy, healthy goals and outcomes will be less effective in reaching good physical and mental health if social processes impede it.[68] Evidence supports that community norms influence individual

health beliefs.[45] Other mechanisms may also exist. For instance, physical activity, which is plausibly shaped by the built environment[69], has been shown to buffer stress and reduce the risk of depression.[70,71]

FIGURE 2.1 CONCEPTUAL FRAMEWORK OF THE RELATIONSHIP BETWEEN NEIGHBOURHOODS AND DEPRESSION



Using a realist review approach, we synthesized what neighbourhood researchers posit are the causal pathways linking neighbourhoods to depression.[35] We included a total of 14 longitudinal studies that investigated the association between neighbourhood and depression, out of which 11 reported a significant relationship for at least one of the following neighbourhood variables: neighbourhood deprivation, disorder, instability, and

social ties. Researchers proposed that these neighbourhood characteristics have an impact on depression mainly through 1) the stress that they place on individuals; 2) the effect that they have on social support; 3) the effect that they have on level of resiliency; 4) the way individuals perceive their neighbourhood; 5) and the sense of control individuals feel that they have in their context.

In spite of numerous hypotheses, I am aware of only 5 studies that formally tested potential mediators, including 4 cross-sectional studies and 1 prospective study. Ross found that perceived neighbourhood disorder mediated the association between neighbourhood disadvantage and depressive score.[72] Kruger et al. found that perceived fear of crime and social capital mediated the association between building deterioration and depressive symptoms.[73] Haines et al. reported that social network was a mediator between neighbourhood disadvantage and depression score.[74] Shell et al. found that social support, discrimination and stress were significantly related to depression and removed part of the significance of neighbourhood Hispanic composition on depressive symptoms in a sample of Mexican-American.[75] Finally, Stafford et al. used structural equation modelling and longitudinal data from 7,500 English adults. They found that both friendship quality and sense of control were significant mediators between neighbourhood social cohesion and depressive symptoms.[76]

IN THE POPULATION WITH A CHRONIC CONDITION

The pathways relating neighbourhood factors and depression might differ for those with diabetes or other chronic conditions. Inadequate local resources, such as poor access to

health care, healthy foods and physical activity facilities, may be barriers in the management of a chronic condition[46] and an important source of stress for chronically ill individuals. For example, people with type 2 diabetes are encouraged to exercise to manage their diabetes, but living in an area with few places to exercise may make it difficult to maintain an active lifestyle[77], which could increase the risk of complications and poor health outcomes, resulting in depression. Evidence shows that the negative effects of disadvantaged neighbourhoods on physical health are amplified in those with a chronic condition.[46] A decline in health in people who are already chronically ill may have important psychological repercussions. Barriers in the neighbourhood environment, such as social stress (e.g., high crime rates) or physical barriers (e.g., very steep hills), may interact with physical limitations to further limit a person's capacity to function.[78,79] In a previous study, we found that neighbourhood deprivation was associated with significant disability in individuals with diabetes.[47] The effect of the neighbourhood environment on the quality of life in people with a chronic illness may lead to depression.[80] This project is the first to test specific pathways linking neighbourhood characteristics to depression in people with a chronic condition.

Moderators of the Association between Neighbourhoods and Depression

The effect of neighbourhood context on depression may vary between sub-groups. Studies report different associations by sex[60,63,71,81,82], age group[42], racial/ethnic group[83], SES[81,84,85], and social support[66]. Sex differences may exist because of different societal roles. Women are typically the family caregivers and are more likely to be affected by

neighbourhood factors that disrupt this role and negatively impact their family, such as lack of safe play areas for children.[81,86] Social support could also moderate the neighbourhood effect on mental wellbeing.[66,75,87] Social support is thought to buffer the effects of psychosocial adversity by enhancing individuals' coping abilities.[87,88] A sense of control over life can also protect against the deleterious effects of stress, such as environmental stress.[89,90] There is also evidence that poor housing conditions, such as noise and disrepair, are linked to psychological distress and may amplify the effects of neighbourhood deprivation.[65,91] Finally, neighbourhood characteristics may interact with one another to affect depression. For example, Ross et al. found that neighbourhood stability was associated with depressive symptoms, but only in poor neighbourhoods.[72] This project is one of the first to investigate some of these moderators and the first to study these moderators in people with a chronic condition. The conceptual framework for my project is illustrated in Figure 2.1.

3 | Objectives and Overview of Methods

RESEARCH OBJECTIVES

The overarching goal of the thesis was to investigate the association between neighbourhood physical and social characteristics and risk of depression in adults with and without a chronic condition (using health survey data from a general population sample) and specifically in adults with diabetes (using survey data from a sample with diabetes). As described in Chapter 2, the neighbourhood environment is thought to impact the risk of depression, but evidence in people with a chronic condition is lacking; it is not clear how or why this effect exists; and for whom or under what conditions it is most relevant. This project answers the call of scholars to advance neighbourhood and mental health research by clarifying the knowledge gaps in the literature and overcoming some of the methodological limitations of previous studies. [31-34,48]

Objective 1 (primary objective): To assess the associations of neighbourhood social and physical characteristics and risk of depression among adult community dwellers with and without a chronic condition, after adjusting for important confounding factors including individual demographic and socioeconomic characteristics.

Hypothesis: I expected that both social and physical neighbourhood characteristics would be associated with depression, above and beyond individual-level characteristics, and that the association would be stronger in people with a chronic condition.

Objective 2: To investigate specific moderators and mediators of the association between neighbourhood characteristics and risk of depression in adults with and without a chronic condition.

Hypothesis: I expected that chronic stress, health behaviours and health status would mediate the relationship, and that socioeconomic resources, sex, social support and housing characteristics would modify the association. Health behaviours and health status would be particularly relevant to those with a chronic condition.

Objective 3: To explore the relationship between neighbourhood characteristics and changes in depression over time in adults with and without a chronic condition.

Hypothesis: I expected that changes in social and physical neighbourhood factors would affect trajectories of depression over time.

Overview of Methods

The doctoral project was a secondary data analysis using longitudinal data from two cohort studies: the National Population Health Survey (NPHS) and the Diabetes Health and Wellbeing Study (DHS). In order to study various aspects of the neighbourhood, I obtained information on neighbourhood characteristics from 4 additional data sources. I used 1) Canadian census data to assess the demographic and socioeconomic characteristics of neighbourhoods; 2) geospatial databases to assess the density of services, resources and land use (e.g., the number of fruits and vegetable stores in an area); and 3) satellite imagery to map the density of green spaces, combined within a

geographic information system (GIS). I also conducted 4) a supplementary telephone survey with a sub-cohort of DHS participants to assess the perceived social and physical neighbourhood environment. The timeline of data collection is illustrated in Table 3.1.

TABLE 3.1 TIMELINE OF DATA COLLECTION

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Participant data														
NPHS	x		x		x		x		x		x			
DHS									x	x	x	x	x	x
Neighbourhood data														
Census data		x					x					x		
Geospatial data			x				x				x			
Satellite data	x	x	x			x	x	x		x	x	x		
Survey data from DHS sub-study												x	x	x

Neighbourhood data were not available for every survey because timing was either fixed (census data collected every 5 years) or limited by availability (geospatial and satellite data). Therefore, I used the neighbourhood data that were closest in time to a survey to approximate the neighbourhood characteristics of that survey. I collaborated with Dr Yan Kestens and his team at the Montreal Epidemiological and Geographical Analysis of Population Health Outcomes and Neighbourhood Effects (MEGAPHONE) group[92] to extract and analyze geospatial data. MEGAPHONE is a spatial data infrastructure developed at the University of Montreal to support research for documenting, analyzing and understanding environmental influences on population health. The geographic dataset

built for this thesis project will be made available for future studies in neighbourhood research.

Data from the two cohort studies were analyzed separately. The NPHS is a large nationwide health survey with 14 years of follow-up data. I used NPHS data from a wide perspective in order to study the associations of neighbourhood and risk of depression across a broad range of chronic conditions, such as diabetes, in a nationally representative sample. Although the NPHS has several strengths, such as a large sample size and long follow-up time, it has some shortcomings. Interview items do not cover topics related to perceived neighbourhood environment. Participants' perceptions of their neighbourhood may capture important neighbourhood features that are not measured by census or geospatial data (e.g., social cohesion). NPHS assessments were biennial. A shorter follow-up time would more accurately measure changes in depression status. Also, although the NPHS data provide information for people with and without a chronic condition, it does not offer a detailed assessment of diabetes and diabetes management.

To overcome these limitations, I used data from a second study, the DHS. The DHS is a community-based survey of adults with diabetes from Quebec. DHS participants were followed annually from 2008 to 2013. DHS data allowed me to conduct a detailed investigation of the associations of neighbourhood characteristics and risk of depression in people with diabetes living in the same province. The DHS also provided the opportunity to conduct a supplementary sub-study with a sample of DHS participants to measure perceived social and physical neighbourhood characteristics.

Secondary data analysis using NPHS data was funded by a CIHR grant (Grant SEC-117118), of which I was a co-investigator. The proposal was developed as a joint collaboration with Dr Kestens and Dr Schmitz. I provided substantial intellectual input in developing the research questions and methods and was therefore invited as a co-investigator. The DHS was funded by a CIHR grant (Grants MOP-84574) and by a grant from the Canadian Diabetes Association (Project OG-3-10-3099-NS). I have been involved with the DHS for several years as a research coordinator and as a researcher on different research projects.

As described in Chapter 2, previous evidence for neighbourhood effects on depression has been limited by measurement of the neighbourhood environment. The breadth of neighbourhood characteristics measured within the same population sample has been limited and most studies have relied on census-based aggregate data to measure neighbourhood attributes. The studies in this thesis make a significant contribution to the literature by being the first to use a rich dataset of both social and physical neighbourhood characteristics by combining 4 sources of data together: census data, geospatial data, satellite imagery data and survey data. Prior studies have also typically defined neighbourhoods using administrative geographic units. In this thesis, state-of-the-art geographic information system was used to map out a unique neighbourhood for each individual using the postal code of survey participants. This allowed for more precision in characterizing the surrounding environment of people, thereby reducing potential measurement error found in previous work. Studies from this thesis also contribute to

neighbourhood and depression research by being one of the few to use high-quality longitudinal data and to consider the time-varying nature of neighbourhood characteristics. The thesis further adds to knowledge by investigating several potential moderators and mediators in the relationship between neighbourhood characteristics an depression, many of which have yet to be examined.

4 | Associations between Neighbourhood Characteristics and Risk of Depression in People with and without a Chronic Condition from the General Population (Manuscript I)

Previous reviews and results from my own systematic review in Chapter 2 suggest important knowledge gaps in the current literature, including limitations in neighbourhood measurement, lack of longitudinal studies and limited research in the Canadian context. The study from this chapter attempts to overcome these limitations. In this chapter, I adopt a wide general population perspective in the study of neighbourhood characteristics and depression. In later chapters (Chapters 5 and 6), I focus my research specifically on people with the chronic condition of diabetes.

This chapter outlines the detailed methods of my first manuscript (Manuscript I). In this manuscript, I examined the association between neighbourhood factors and the risk of depression in Canadian adults and in subgroups with a chronic condition, using data from the NPHS. I also investigated potential moderators of the association. I chose NPHS data as a first step in this research because it is a longitudinal Canadian community sample with a large sample size, which is important when investigating neighbourhood effects that are known to be small. The NPHS also provided 10 years of follow-up data for this project, which is a time period that is reasonably long enough for the neighbourhood environment to impact mental health. The NPHS offered regular follow-up data, important to take into account time-varying variables, such as marital status. The study also had information on participant's postal code, which was needed to link individuals with neighbourhood data.

This first manuscript makes several important contributions to research. It is the first study to use longitudinal data to examine the association of a wide range of neighbourhood characteristics on risk of depression, including the built environment, in the general Canadian adult population and the first study to examine this association across several types of chronic conditions. It is the first to provide evidence of moderation by household and neighbourhood characteristics. It is also one of the few studies in the field to use advanced statistical methods and conduct extensive sensitivity analyses to check for robustness of results. Findings from this study provide direction for future research and intervention studies. Manuscript I is published in the journal *Health and Place*.

Detailed Methods

Study Sample

The NPHS is a 16-year (1994/95-2010/11) cohort study that was conducted by Statistics Canada. The NPHS is one of the largest longitudinal health surveys in Canada. The objective of the NPHS was to provide data related to health and health determinants from a representative sample of Canadians. For this project, I used the data to examine the associations of neighbourhood on risk of depression in the general adult population and in adults with a common chronic condition (including asthma, diabetes, chronic bronchitis, heart disease, arthritis, cancer, back pain, high blood pressure, migraines, stomach/intestinal ulcers, bowel disorder, thyroid condition). The baseline sample included 17,276 persons from all ages living in the 10 Canadian provinces. The sample

was selected from a random stratified two-stage sample design. The same persons were re-interviewed every 2 years using computer-assisted interview systems. Trained interviewers conducted computer-assisted telephone interview. Full details of the collection procedures and response profile of the NPHS are described more extensively elsewhere.[93] For this project, I included only participants between the ages of 18 and 80 at baseline (n= 13,618) because my focus was on adults. Because neighbourhood data were only available starting in 2000, I included interview cycles 4 to 9 (2000/01 to 2010/11; response rates 85%, 81%, 78%, 77%, 71% and 70%, for cycles 4 to 9, respectively), representing 10 years of follow-up.

DATA COLLECTION

MEASUREMENT OF DEPRESSION

The main outcome of interest was depression, defined as symptoms of either minor or major depressive disorder. This definition was selected because it captures the larger spectrum of depressive disorders that are thought to be important to health outcomes[94-97] and because it afforded greater study power. Additional analyses using major depression only as the outcome were also conducted. In the NPHS, past-year depressive symptoms were assessed using the Composite International Diagnostic Interview-Short Form for Major Depression (CIDI-SFMD), a screening instrument for depression.[98] The CIDI-SFMD is a validated measure that captures symptoms of depression consistent with the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV) criteria. To meet criteria for depression, a person must have two or four depressive symptoms

(minor depression) or five or more depressive symptoms (major depression), present for more than half of the days, for at least 2 weeks, with at least one of these symptoms being either depressed mood or loss of interest. The CIDI-SFMD diagnosis has good validity compared with the full CIDI (75%-90% positive predictive values).[98,99] Although the CIDI-SFMD is validated, it is not a clinical interview and therefore does not assess clinical depressive disorders per say, but determines depression based on cut-offs. Namely, the CIDI-SFMD does not apply all of the exclusion criteria that are present in DSM-IV, such as sadness episodes due to the death of a loved one or due to organic conditions such as medications. Because of this, the CIDI-SFMD may slightly overestimate prevalence of depression.[100] However, this effect appears to be modest[101] and incidence estimates from the CIDI-SFMD[102] are in line with those from a systematic review of high quality studies[5]. Participants from the NPHS were also asked if they had been prescribed antidepressant medications during the last year preceding the interview. People who responded positively to treatment with antidepressants may not exhibit depressive symptoms, and may be misclassified as not depressed using CIDI-SFMD. I therefore conducted a sensitivity analysis where subjects without depressive symptoms but with antidepressant medication were classified as meeting the criteria for depression.

Measurement of Neighbourhood Characteristics

Neighbourhood Definition

The definition of neighbourhood may affect the strength of association between area characteristics and health[103] and the accuracy of neighbourhood exposure

measurement[104,105]. The majority of previous studies defined neighbourhoods according to geographic administrative units, such as census tracts.[31] This approach is useful with census data, but may lead to misclassification of exposure if administrative areas do not represent the actual resident perceptions of neighbourhood boundaries. I therefore used a person-centered definition of neighbourhood, which is thought to more accurately reflect neighbourhoods.[106,107] Neighbourhood data were geocoded and a radius buffer was created around the center of each individual's postal code to measure neighbourhood characteristics within that zone (e.g., number of healthy food stores within a 1 km radius). The radius buffer accounts for road network and geographic obstacles (e.g., rivers). Figure 4.1 illustrates an example of a radius buffer.[108] A 1 km radius is generally used as a proxy for neighbourhood area because it represents the acceptable distance that adults can travel by foot to reach a

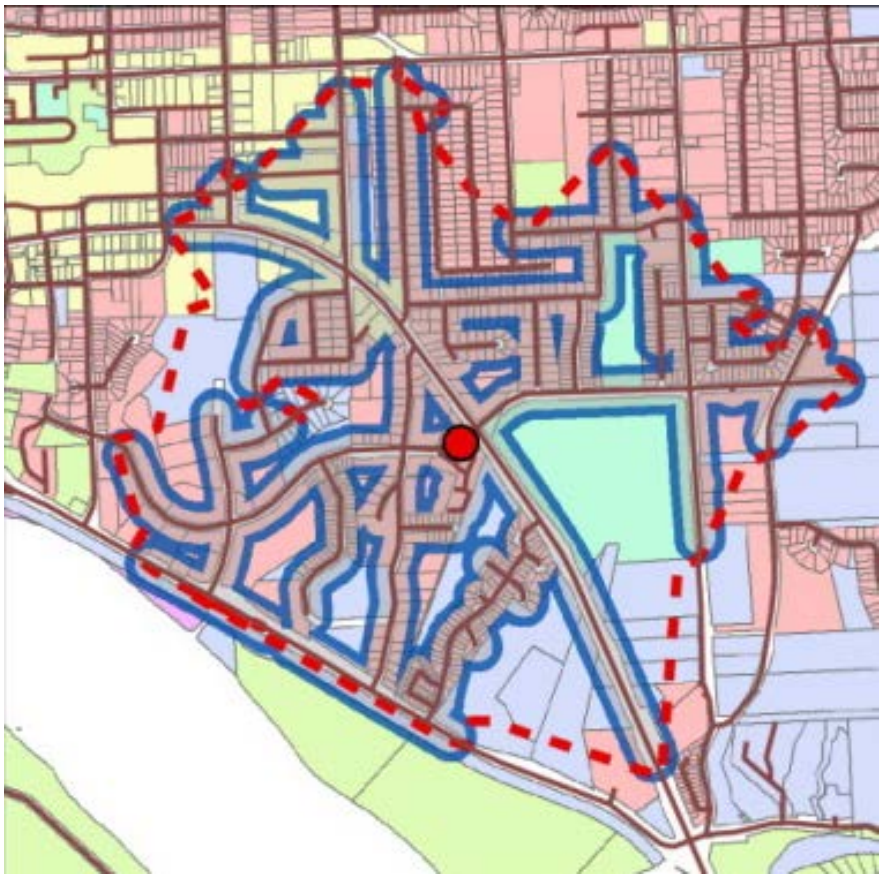


FIGURE 4.1 EXAMPLE OF RADIUS BUFFER ZONE AROUND CENTER OF POSTAL CODE (DASHED RED LINE). THE RADIUS BUFFER ACCOUNTS FOR GEOGRAPHIC OBSTACLES, SUCH AS RIVERS.

destination[109] , but because there is no consensus on the neighbourhood scale that is more important to depression, I conducted sensitivity analyses using 250m, 500m, 1000m and 1500m buffer radius sizes to check on which spatial scale associations were strongest.

Neighbourhood Physical and Social Deprivation

Neighbourhood physical and social deprivation were assessed separately using the Pampalon Deprivation Index[110], a measure of area socioeconomic position based on census data. The index was available for 2001 and 2006, corresponding to the Canadian census years. The Pampalon Index is calculated based on the smallest census unit (dissemination area, covering 750 people, on average) that is homogeneous from a socio-economic standpoint. It was constructed through a principal component analysis integrating six census variables into two components: material deprivation and social deprivation. Each of the two components accounted for slightly more than one-third of the variations in the six indicators considered for a total of 73%. Material deprivation is based on education (proportion of people aged 15 years and older with no high school diploma), employment (employment/population ratio of people aged 15 years and older), and income (average income of people aged 15 years and older), whereas social deprivation is based on parenting status (proportion of single-parent families), marital status (proportion of individuals aged 15 years and older who are separated, divorced or widowed), and living arrangement (proportion of individuals aged 15 years and older living alone). The items in the Pampalon index have good content validity.[110] The Pampalon index has been successfully used in several studies[111], including our own[47].

The two indexes were linked with the survey data by postal code. An algorithm based on the coverage of the buffer radius over different dissemination areas was used to estimate person-centered neighbourhood characteristics. For each dimension, I grouped factors into quintiles, where the first quintile represented the most privileged fifth of the Canadian population and the last quintile the most deprived (disadvantaged) fifth, to stay consistent with previous literature.[112]

PARKS AND LAND USE

Geospatial data provided information on parks and recreation and land-use mix. Data were from Desktop Mapping Technologies, Inc (DMTI)[113] and were available for 2002, 2005 and 2010. Density of parks and recreation was modelled as the percentage of the neighbourhood used for parks and sports tracks. Figure 4.2 is an example of a map

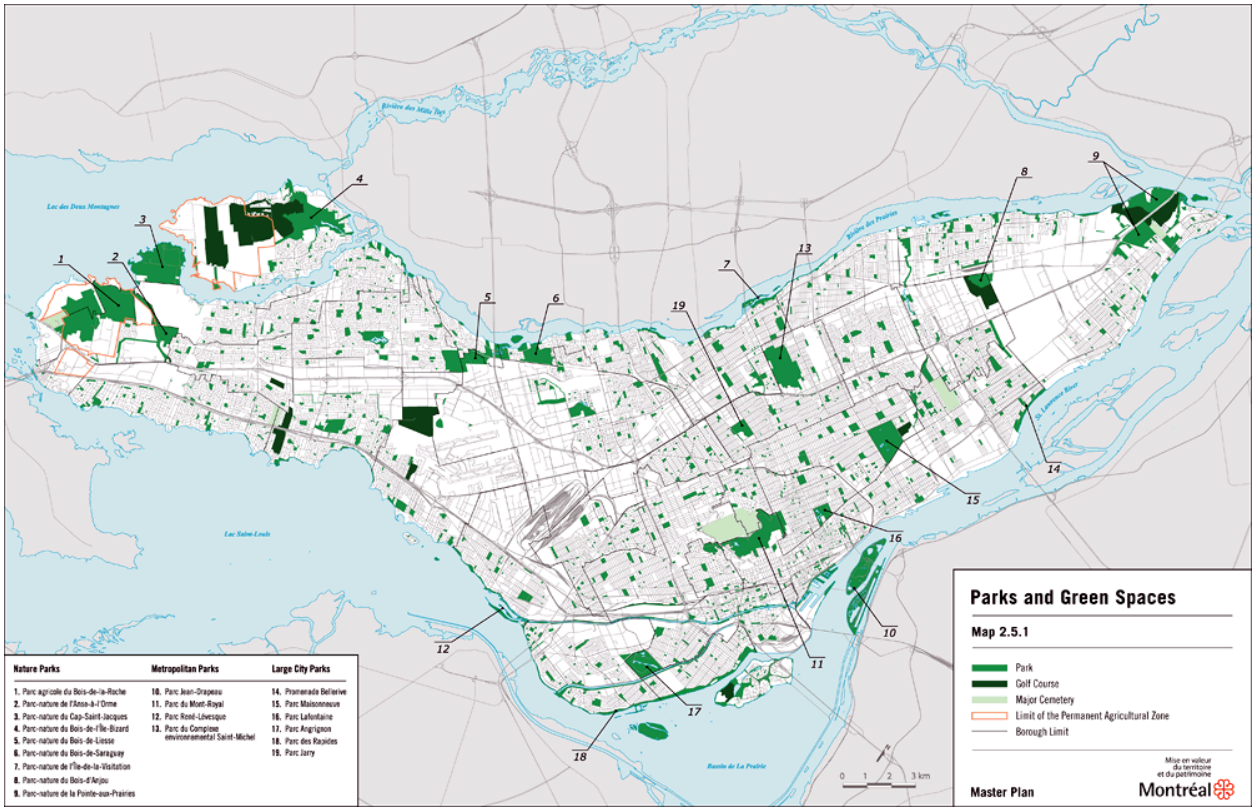


FIGURE 4.2 EXAMPLE OF MAP: PARKS ON MONTREAL ISLAND

illustrating number of parks in an area.[114] Land-use mix patterns were used as a proxy for availability of commercial or public destinations in the neighbourhood. This measure has been shown to be associated with walking and other physical activity behaviours.[115,116] An area with diverse land uses typically offers more non-residential destinations for walking journeys, and may thus facilitate transport-related physical activity by residents. Land-use pattern was measured using the land-use mix index, which varies between 0 and 1, where a higher score represents a higher mix of residential, commercial, government and institutional, industrial, open area, and parks.[117] Land-use mix has been shown to be associated with walking and other physical activity behaviours.[77]

Density of Businesses and Services

DMTI also provided data on operating businesses across Canada. In collaboration with MEGAPHONE, we developed specific algorithms using Standard Industrial Classification (SIC) codes in the DMTI databases to identify the number of fast-food restaurants, healthy food stores, healthcare services, physical activity facilities and cultural services in the neighbourhood. Healthy food stores included stores that offer a selection of fruits and vegetables, meats, fish and/or seafood. Healthcare services include those covered by the Canada Health Act, which largely includes care delivered in hospitals and by physicians. Cultural services were establishments that contributed to the local culture, including libraries, museums and botanical gardens. Cultural service is a neighbourhood characteristic that has yet to be studied in the depression literature. These services have been hypothesized to foster neighbourhood cohesion, trust and contact, as

well as community empowerment and social cohesion.[118] Keywords were searched for anywhere in the "name" field of the DMTI database. Unequivocal keyword terms or chain names were searched regardless of SIC code to maximize coverage. Potentially equivocal keyword terms were searched only under relevant SIC codes, to avoid false positives. Although seemingly relevant SIC classification exist in the database (e.g., SIC for health services), some did not meet our needs (e.g., too many missing or unwanted entities), and were therefore not included in their entirety.

FIGURE 4.3 EXAMPLE OF SATELLITE IMAGE: MONTREAL AND SURROUNDING AREA

LEVEL OF GREENNESS

Satellite imagery data cover Canada's landmass during the periods of 2000-02, 2004-06 and 2009-11. Figure 4.2 provides an example of a satellite image.[119] I used these data to estimate the level of greenness and vegetation density of the local area. Data were from Geobase, Natural Resources Canada.[120] Using available Landsat and SPOT satellite images[121], the Normalised Differential Vegetation Index (NDVI) was computed. Such an index, combining the red and near infrared spectral bands, provides a measure of vegetation density. The NDVI has been validated as a measure of neighbourhood

greenness.[122] Previous research has shown associations between local NDVI and depression among young mothers in Quebec.[123]

Data Analysis

Risk Analysis

The first objective for this study (objective 1) was to assess the association of neighbourhood characteristics and risk of depression among adults with and without a chronic condition. In order to identify new occurrences of depression, I excluded participants with depression at baseline. I conducted proportional hazards regressions to estimate hazard ratios (HRs) of incident depression by neighbourhood characteristics. I used a generalized linear model using the complementary log-log (clog-log) link function[124], equivalent to a discrete-time Cox proportional hazards model. The discrete clog-log hazard model is the appropriate method for analyzing NPHS data because it takes into account different lengths of follow-ups and correctly handles data collected at discrete time points. The Cox model assumes exact times of events are known, but with interval-censored data, such as NPHS data, event times are grouped at discrete time points (i.e., every follow-up), creating a large number of tied events. Although methods to manage ties exist within the Cox model (e.g. exact, Efron, Breslow), these assume that tied events actually occurred simultaneously, which may bias estimates.[125] The discrete clog-log hazard model estimates the same underlying coefficients as the Cox model while correctly assuming that depressive events occurred in the interval of time between two assessment points. For each interval, it models the probability of an event given that no

event occurred prior to that point. It then pools these units of time over all individuals. The model also allows for time-varying covariates, which is important because neighbourhood characteristics may change over time (e.g., neighbourhood SES may improve) and some confounders may also vary (e.g., marital status). Additionally, the clog-log model can easily accommodate study weights. One potential shortcoming of the clog-log model is that, in contrast to the Cox model, the baseline hazards function needs to be specified. However, clog-log estimates are relatively robust to baseline function misspecification.[126] In this study, I used a non-parametric specification for time (dummy variables) to allow full flexibility in the baseline hazard function. Individuals with missing information on depression at one time point were right censored because a hiatus $\geq$ 2 years might contain a depression event which would be missed. The objective of the study was to assess incidence of depression. If I had continued to follow non-responders after they missed a follow-up survey, the assumption would have been that they did not have depression during this time. This approach could lead to estimates being biased towards the null. I therefore used right-censorship to avoid this problem. The clog-log model assumes non-informative censoring, proportionality of hazards and linearity. I tested for potential non-informative censoring using weights (see Assessing Selection Bias described below) and I checked the proportionality assumption by examining the pattern of estimates for the interaction of covariates with time terms (time represented as dummy variables for each survey wave).[124] Neighbourhood factors were examined one at a time in the regression.

Because several neighbourhood factors were tested in the study, I considered the possibility of type I error due to multiple testing by calculating Bonferroni-adjusted and False-Discovery-Rate-adjusted p-values for significant results. Additionally, I reported uncorrected p-values, in part because I did not want to miss neighbourhood characteristics that have a weak but relevant effect on depression, and also because selection of neighbourhood factors was based on a priori hypotheses.

I used study weights and bootstrapping (500 replications) provided by Statistics Canada to adjust for non-response and lost to follow-up, and to account for the complex survey design. I coded neighbourhood factors at the individual-level using radial buffers around the postal code of participants. Although multilevel regression analysis is often used in neighbourhood research (to account for correlations between people from the same neighbourhood), this type of analysis is not appropriate for this project because neighbourhoods were person-centered resulting in a unique neighbourhood for each individual.

MODERATOR ANALYSIS

The second objective for this study (objective 2) was to investigate specific moderators and mediators of the association between neighbourhood characteristics and risk of depression in adults with and without a chronic condition. A moderator is a variable that alters the direction or strength of the relation between a predictor and an outcome.[127] I investigated potential moderators by introducing interaction terms in the discrete-time hazard regression model. I entered interaction terms one at a time in the model to increase

power. For significant interaction terms, I conducted stratified analyses to better understand the direction of association.

Mediation analysis was not undertaken using the NPHS data since none of the neighbourhood characteristics were significantly associated with risk of depression in the general sample and in subsamples with a chronic illness.

Sensitivity Analyses

Assessing missing values

Analyses revealed that 27.3% of study participants had missing information on family history of depression, 16.0% on income adequacy and 17.4% on work status at baseline. Other covariates had between 0 and 6% missing values. The use of complete case analysis could therefore substantially reduce the power of the analyses and potentially introduce bias. To test the impact of missing values, I conducted sensitivity analyses using multiple imputations (MI) to deal with missing data. MI assumes that the data are missing at random, i.e. missing data points are correlated with other data points that are available in the dataset. I included data from baseline and current survey in the imputation models. I also included depression score. It is recommended to include the dependent variable in the model: the strength of the relationship between the independent and dependent variables may otherwise be artificially reduced.[128] I performed imputations in STATA (version 12.1) using multivariate imputation with chains equations (MICE) with the mi function. The MICE is an iterative process where each iteration estimates the imputation model using both the observed data and the imputed

data from the previous iteration. I created 10 imputations for each missing value. I re-ran analysis on the 10 imputed datasets and combined results.

Assessing selection bias

Survival analysis assumes that censoring is non-informative. I addressed this potential problem using the sampling weights provided by Statistics Canada in the analyses. The weights are computed to represent the inverse probability of selection and are adjusted for non-response. People with a low probability of responding were therefore given a higher weight in the analysis to represent the non-respondents with similar characteristics.

Because the outcome of interest was new incidence of depression, the study excluded 2422 participants (18% of the baseline sample) with depression at baseline. The exclusion of these individuals from the analysis could however result in selection bias because this may have eliminated a subgroup in which neighbourhood characteristics were most linked to depression.[129] I therefore 1) compared characteristics between those depressed and not depressed at baseline, 2) conducted sensitivity analysis that included those who were depressed at baseline, but adjusted for baseline depression in the regression model.

Assessing information bias

To check for potential information bias in the outcome measure, I examined 1) incidence of major depression only. The CIDI-SFMD is a screening scale that has been validated mainly for major depression. Major depression also has important clinical relevance

separate from minor depression. In addition, I examined 2) incidence of depression that included those that were using antidepressant. People taking antidepressants may not exhibit depressive symptoms at the time of the interview and be misclassified as not depressed.

SUB-GROUP ANALYSES

In addition to the main analyses, I decided *a priori* to conduct stratified analyses by chronic conditions, by sex and by rural vs non-rural dwellers (determined from postal codes). I grouped participants by type of chronic condition into the following categories: cardiovascular diseases (heart disease, high blood pressure) (n=1849), respiratory diseases (asthma, bronchitis or emphysema) (n=1071), musculoskeletal problems (arthritis, back problems) (n=3612), migraines (n=1048), diabetes (n=451), gastro-intestinal problems (intestinal or stomach ulcers, bowel problems) (n=683), thyroid problems (n= 524) based on whether the participant reported the chronic condition during the first 4 cycles of the NPHS (1994/95 – 2000/2001). Categories were not mutually exclusive. I also conducted analysis on participants with any chronic condition (n=5407). I conducted stratified analyse by sex because sex differences in risk profile are known to exist.[130,131] Rural dwellers may have different life situations than urban dwellers (e.g., different access to healthcare) and data from rural areas are more difficult to accurately obtain.

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Neighbourhood characteristics and 10-year risk of depression in Canadian adults with and without a chronic illness

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ABSTRACT

The neighbourhood environment could play a role in the risk of depression in adults and those with a chronic illness. We investigated the effects of a range of neighbourhood characteristics on the 10-year risk of depression in a representative sample of 9026 Canadian adults and subsamples with a chronic condition. Characteristics of neighbourhoods were not significantly related to the risk of depression in the general sample and subsamples with a chronic condition. However, residing near a park was significantly associated with a lower risk of depression for people living in crowded households, and having a local health service nearby was protective for those living in materially deprived neighbourhoods. Living in a neighbourhood that was both socially advantaged and offered cultural services was also associated with lower risk of depression. Additional research is needed for smaller effect size detection. Future intervention research is warranted for health policy recommendations.

1. Introduction

Depression is an important public health concern and the leading cause of disability worldwide (World Health Organization, 2012). The prevalence of depression is about 5% in Canadians 15 years and older, with evidence suggesting that up to 1 in 3 individuals will experience high depressive symptoms during their lifetime (Public Health Agency of Canada, 2013). While considerable research has been carried in the etiology of depression, a growing area for research is the role of the neighbourhood environment. Evidence suggests an association between aspects of the neighbourhood and depressive symptoms (Julien et al., 2012; Mair et al., 2008). However, research has mainly focused on neighbourhood deprivation and poverty from census data. Little is known about the role of physical features of neighbourhoods. Neighbourhood green spaces could offer reprieve from stress and support mental health (Lee and Maheswaran, 2011). Local parks and libraries is hypothesized to promote social cohesion, trust and contact (Wavell et al., 2002), which in turn could protect against depression. Neighbourhoods that offer a variety of walking destinations also facilitate social contact and promote active transportation (Wendel-Vos et al., 2007), which is in turn associated with mental health (Mammen and Faulkner, 2013). The definition of neighbourhoods is also a point of debate in the literature (Osypuk and Galea, 2007). The majority of previous studies have employed administrative geographic units (e.g., census tracts) as a crude proxy to neighbourhoods, but neighbourhood definitions centered around the individual may more accurately capture the neighbourhood environment involved in health (Mair et al., 2008; Osypuk and Galea, 2007).

The neighbourhood context may be particularly important to individuals living with a chronic condition who may have limited mobility, and often rely on their local resources for disease management and support. Individuals with a chronic condition are a growing subpopulation and are particularly vulnerable to depression (Anderson et al., 2001; Lichtman et al., 2008; Yohannes et al., 2010). Patients are often told to self-manage their chronic illness through healthy lifestyle changes, such as diet and exercise. Yet, limited availability of healthy food stores or places to exercise may represent important barriers to managing a chronic disease (Brown et al., 2007), which could lead to distress. Limited availability of health care services may also hinder disease management, leading to greater risk of disease complications, loss of function, and depression. Depression can in turn substantially complicate the adjustment, disease course and health outcomes of people with a chronic condition. An understanding of the wider neighbourhood factors contributing to depression in people with a

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chronic condition therefore has important clinical and public health implications. Previous work exists on the association between neighbourhood features and depression in adults with arthritis (Martin et al., 2010), systemic lupus (Trupin et al., 2008), asthma (Yen et al., 2008, 2006) and diabetes (Gary-Webb et al., 2011), but information is missing on other common chronic conditions, such as cardiovascular disease and gastrointestinal problem. Evidence has so far been cross-sectional, except for one study (Yen et al., 2008), and little is known on the neighbourhood characteristics that might contribute to the risk of depression in subgroups of people with a chronic condition.

In addition to subgroups with a chronic illness, there may be sociodemographic groups that are more vulnerable to the effect of the neighbourhood environment. Studies report different associations by sex (Burke et al., 2009; van Praag et al., 2009), age group (Ahern and Galea, 2011), socioeconomic status (Burke et al., 2009; Stafford et al., 2008; Weich et al., 2003), and social support (Ross and Jang, 2000). For example, sex differences may exist because of gender-based societal expectations around family caregiving. Women may be more likely to be affected by neighbourhood factors that negatively impact their family, such as lack of safe play areas for children (Blocker and Eckberg, 1989; Burke et al., 2009). A sense of control over life is also known to protect against the deleterious effects of stress (Thoits, 1995), which may include environmental stress. There is also evidence that housing conditions are linked to psychological distress (Evans, 2003) and may amplify neighbourhood effects. Finally, neighbourhood characteristics may interact with one and another to affect depression.

In the present study, we combined 10 years of follow-up data from a large Canadian health survey with census, geospatial and satellite imagery data to investigate the effects of a wide range of neighbourhood characteristics on depression. We delineated neighbourhoods using a person-centered definition. Our first aim was to investigate the association of a comprehensive range of neighbourhood characteristics with the risk of depression in a representative sample. Our second aim was to study these associations in subgroups with a common chronic condition. Our third aim was to examine the potential moderating effect of individual-, household- and neighbourhood-level characteristics on the associations. We hypothesized that neighbourhood characteristics could be significant risk factors for depression and that this effect would be amplified in vulnerable subgroups, particularly in those with a chronic condition.

2. Methods

2.1. Study population

We used data from the National Population Health Survey (NPHS), a nationally representative cohort study of individuals across Canada ($n=17{,}276$). The NPHS used a stratified cluster sampling strategy (Statistics Canada, 2011). Follow-up interviews were conducted every 2 years. The NPHS collected data from 1994/95 to 2010/11. Because data on the neighbourhood environment were available starting in 2000/2001, we used NPHS data from 2000/2001 to 2010/2011 in this study, corresponding to NPHS cycles 4–9 (response rates 85%, 81%, 78%, 77%, 71% and 70%, for cycles 4 to 9, respectively). To insure comparability with other studies, we included adults who were between the ages of 18 and 80 at baseline ($n=13{,}618$). Because we were interested in incidence of depression, we excluded participants with depression during the previous survey cycles (1994/95 to 2000/01) ($n=2422$) and those with missing information on depression for 2 cycles or more ($n=2145$). We also excluded participants who were institutionalized at study baseline because we were interested in community-dwellers ($n=25$). Our final cohort included 9026 individuals with 10 years of follow-up. A flowchart of participant selection is available in Supplementary Table 1. Study protocols were approved by the Research Ethics Committee of the Douglas Mental Health University Institute.

2.2. Depression

The outcome of interest was depression, defined as meeting symptoms for either minor or major depressive disorder. This definition was selected because it captures the larger spectrum of depression disorder thought to be important to health outcomes (Kessler et al., 1997; Meeks et al., 2011; Rodriguez et al., 2012). Additional analyses using major depression only were also conducted. Past-year depressive symptoms were assessed using the Composite International Diagnostic Interview Short-Form (CIDI-SF), a clinically-validated screening instrument (Kessler et al., 1998). To meet criteria for depression, a person must have two or four depressive symptoms (minor depression) or five or more depressive symptoms (major depression), present for more than half of the days, for at least 2 weeks, with at least one of these symptoms being either depressed mood or loss of interest. The CIDI-SFMD diagnosis has good criterion validity compared with structured psychiatric interviews (sensitivity 90%, specificity 94%) (Kessler et al., 1998). Participants were also asked if they had been prescribed antidepressant medications during the last year. People taking antidepressants may not exhibit depressive symptoms at the time of the interview and be misclassified as not depressed. In sensitivity analysis, we changed the outcome to include those taking antidepressants as meeting the criteria for depression.

2.3. Neighbourhood characteristics

2.3.1. Definition of neighbourhood scale

We used a person-centered approach to define neighbourhoods. We created a radius buffer around the center of the postal code of each participant and measured the neighbourhood characteristics within the zone. The postal code is a six-character alphanumeric code that forms part of the postal address in Canada. It may indicate a specific city block, a single building, or a large volume mail receiver (Canada Post, 2014) and has been shown to be a good proxy for the full home address (Bow et al., 2004). The median number of individuals living in a postal code ranges between 8 and 25 across Canadian provinces (Electronic Health Information Technology, 2011). The radius buffer accounts for road networks and geographic obstacles (e.g., rivers). Because there is no consensus on the neighbourhood scale that is more important to depression, we conducted sensitivity analyses using 250 m, 500 m, 1000 m and 1500 m buffer radius sizes to determine which was most relevant to our study. We compared strengths of associations and goodness of fit indices (Akaike information criterion and the Bayesian information criterion) of univariate models using the different buffer sizes. Results suggested that the 500 m buffer radius had the best fit overall (Supplementary Table 2) and was therefore used in this study. The NPHS provided information on address change and we used the latest postal code of participants at each survey cycle. We used neighbourhood data that were closest in time to each survey cycle to approximate the neighbourhood characteristics at that time.

2.3.2. Material and social deprivation

The Pampalon et al. (2012) index was used to assess neighbourhood deprivation in 2001 and 2006. The index was constructed through a principal component analysis using six census variables resulting in two factors: material and social deprivation. We created quintiles for social and material deprivation, from least

deprived (1st quintile) to most deprived (5th quintile), in line with previous literature (Pampalon et al., 2012). Quintiles were entered as continuous variable in the model. Entering quintiles as categorical variables did not change results. The Pampalon index was available for 99% of the sample.

2.3.3. Density of services, resources and land use

Geospatial Canadian data from 2002, 2006 and 2010 were used to estimate density of businesses and services, parks and recreational facilities, and land-use patterns in neighbourhoods. Data were obtained from Desktop Mapping Technologies, Inc (DMTI Spatial Inc., 2010). Geospatial variables were computed using Geographic Information Systems software and linked to the NHPS data. Business and service data included number of health service providers, physical activity facilities, healthy food stores, fast-food restaurants, and cultural services (see Appendix 1 for details). Parks and recreation data were modelled as the proportion of an area used for parks, sports tracks, or swimming pools. We dichotomized density of businesses and parks and recreational facilities as present versus absent in the neighbourhood because data were extremely skewed. Land-use pattern was measured using the mix index, which varies between 0 and 1, where a higher score represents a greater mix of residential, commercial, parks, open area, industrial, and government and institutional land (Frank et al., 2005) (see Appendix 2 for details). Data on neighbourhood businesses were available for 99% of the sample and data on parks and recreation and land-use pattern data were available for about 72% of the sample.

2.3.4. Neighbourhood greenness

Canadian satellite imagery data from 2000–2002, 2004–2006 and 2009–2011 were used to estimate the average level of greenness in neighbourhoods (Canadian Council on Geomatics, 2009). We computed the Normalised Differential Vegetation Index (NDVI) using Landsat bands 3 (red) and 4 (near-infrared) and SPOT satellite images. The NDVI has been validated as a measure of neighbourhood greenness (Rhew et al., 2011). Satellite imagery data were available for about 46% of the sample due to blocking cloud cover and unavailability of data for most rural areas.

2.4. Covariates

2.4.1. Confounders

Based on our literature review, we adjusted for variables known to impact both neighbourhood selection and depression. We included information on sex, age, marital status (married/common law; single; widowed/divorced/separated), family income adequacy (low; middle/high), highest attained education level (less than high school; high school graduation; post high school education), employment status in past year (working full-time/part-time/student; not working/retired), family history of depression (yes/no) and childhood life events (none/any). Childhood life events included: two weeks or more in hospital; parents divorced; parents unemployed for a long time; traumatised for years; sent away from home; parents abused alcohol or drugs; was ever physically abused. Race was excluded because over 91% of the sample was white. We allowed marital status, family income adequacy and employment status to vary over time in the models.

2.4.2. Effect modifiers

We tested demographic (age, sex, marital status) and socioeconomic variables (highest attained education level, employment status, and family income adequacy), social support, sense of control, and household characteristics (type of housing, crowding index) as potential effect modifiers based on previous research (Burdette et al., 2011; Burke et al., 2009; Ross and Jang, 2000). We allowed for potential effect modifiers to vary over time in the model. Perception of social support was measured using the Medical Outcomes Study scale (Sherbourne, 1991) along 4 dimensions: (1) emotional and informational, (2) affectionate, (3) tangible, and (4) positive social interaction. Scores from the 4 subscales were summed and the overall score was linearly transformed from 0 to 100, where higher scores indicate more support. Sense of control was measured using the 7-item Pearlin Mastery Scale (Pearlin and Schooler, 1978). A sum score was calculated ranging from 0 to 28, where higher scores indicate higher sense of control. Information on household characteristics included type of dwelling (single detached house vs others) and crowding index (number of residents per bedroom and living areas) (Bennefield et al., 2003). Dwellings with a crowding index above 1 are considered crowded (Bennefield et al., 2003). We also tested interaction terms between neighbourhood characteristics.

In stratified analyses, we grouped participants by type of chronic condition into the following categories of common chronic conditions: cardiovascular disease (heart disease, high blood pressure) ($n=1849$), respiratory condition (asthma, bronchitis or emphysema) ($n=1071$), musculoskeletal problem (arthritis, back problems) ($n=3612$), migraine ($n=1048$), diabetes ($n=451$), gastrointestinal condition (intestinal or stomach ulcers, bowel problems) ($n=683$), and thyroid condition ($n=524$) based on whether the participant self-reported a doctor-diagnosis of the chronic condition during the first 4 cycles of the NPHS (1994/95–2000/2001). Categories were not mutually exclusive. We also conducted analyses on participants with any chronic condition ($n=5407$).

2.5. Statistical analysis

Following descriptive analyses, we ran survival regression models for each neighbourhood characteristic separately in a model adjusting for age and sex only and in a model adjusting for all individual-level confounders. Neighbourhood characteristics were entered as time-varying covariates in the models. Because the NPHS collected data every 2 years, we conducted survival analysis for discrete-time data using a generalized linear model with a complementary log–log link to calculate the hazard ratio of incident depression. We modelled time using non-parametric specification (dummy variables). Individuals with missing information on depression at one time point were right censored. We tested for the proportionality hazard assumption by testing an interaction terms between each variable and time. There was no evidence of violation. We checked for effect modification by adding interaction terms in the fully adjusted models. For significant interaction terms, stratified analyses by effect modifier were performed to further understand the direction of effect. We conducted stratified analyses by type of chronic condition (cardiovascular disease, respiratory condition, musculoskeletal problem, migraine, diabetes, gastrointestinal condition, and thyroid condition) and for those with any chronic condition. We did not use multilevel modelling because neighbourhoods were person-centered resulting in a unique neighbourhood per individual.

2.5.1. Additional analyses

We conducted stratified analyses by sex and by rural vs non-rural dwellers (determined from postal codes) because rural dwellers may have different life situations than urban dwellers (e.g., different access to healthcare) and data from rural areas are more difficult to accurately obtain. We conducted several sensitivity analyses in fully adjusted models to check the robustness of our results. To test for potential selection bias, we repeated analyses including those with depression at baseline but adjusting

for depression in the models. To check the sensitivity of the outcome measure, we examined incidence of major depression only and of depression that included those taking antidepressants.

2.5.2. Missing covariate values

In addition to some of the missing data on neighbourhood variables, preliminary analyses revealed that 27.3% of study participants had missing information on family history of depression, 16.0% on income adequacy and 17.4% on work status at baseline. Other covariates had between 0 and 6% of missing values. There was no systematic difference in sociodemographic characteristics between those with and without missing data, except that those with missing data on neighbourhood variables were more likely to have lower income and education at baseline. To test the impact of missing values, we ran analyses using multiple imputations. Imputed data provided similar results as those from the complete set (results not shown).

We used a two-sided p-value of <0.05. All regression analyses were conducted using study weights and bootstrapping (500 replications) provided by Statistics Canada to adjust for non-response, lost to follow-up and to account for the complex survey design of the survey. To check for possibility of type I error due to multiple testing, we calculated Bonferroni adjusted and False Discovery Rate adjusted p-values for significant results. Both methods provided similar results and Bonferroni adjusted p-values are presented here for simplicity. Statistical analyses were performed in STATA (version 12.1, StataCorp, College Station, TX).

3. Results

Characteristics of the study sample at baseline are presented in Table 1. The mean age was 49 years. The majority of participants had graduated from high school, were married and working, had middle to high income adequacy and were living in a single detached house. Over a third of neighbourhoods were in the 2 highest quintiles of material and social deprivation and less than a fifth had a healthy food store, health service, physical activity service or cultural service within its boundaries (Table 2). About two-thirds of participants reported having a chronic condition during NPHS cycles1–4. About a quarter of participants reported a family history of depression. A total of 927 new cases of depression were identified during the 10 year-follow up. The weighted 10-year cumulative incidence of depression in the NPHS cohort was 10.9%, with biannual incidence of 4.2%, 3.9%, 3.0%, 3.0% and 2.6% for NPHS cycles 5 to 9, respectively.

3.1. Neighbourhood risk factors for depression

In age- and sex-adjusted models, the presence of a park or recreation facilities in the neighbourhood was significantly associated with a lower risk of depression in the sample (HR 0.80, CI 0.65, 0.99) (Table 3). This association was no longer statistically significant after further adjusting for all confounders; however, point estimates still suggested a protective effect (HR 0.86, CI 0.69, 1.07). Presence of any health services (HR 0.85, CI 0.66, 1.09), any healthy food stores (HR 0.87, CI 0.67, 1.11) and level of greenness (HR 0.79, CI 0.27, 2.33) also showed protective but not statistically significant effects in fully-adjusted models (Table 3).

In sensitivity analyses investigating major depression incidences only, results were almost identical (Supplementary Table 3). In analyses where depression outcome included use of antidepressants, the presence of a park in the neighbourhood remained significant in the fully-adjusted model (HR 0.86, CI 0.74, 0.99) as did cultural services (HR 0.77, CI 0.62, 0.94) (Supplementary Table 3). Stratified analysis by sex did not reveal any significant sex differences

Table 1
Individual-level characteristics of study participants at study baseline (2000/01).

Variables	Study participants % (n) $n=9026$
Sex	
Female	50.7 (4123)
Male	49.3 (4238)
Age in years (mean, SE)	49.2 (0.2)
Education	
Less than secondary school	23.2 (1940)
Secondary school graduation	42.3 (3530)
Post-secondary graduation	34.4 (2874)
Employment status	
Worked in last year	76.0 (5369)
Did not work in last year	24.0 (1696)
Marital status	
Married/common law	71.5 (5495)
Single	13.3 (1023)
Divorced/separated/widowed	15.1 (1162)
Household income adequacy	
Low income	8.4 (590)
Middle/high income	91.6 (6433)
Family history of depression	
No	74.0 (4510)
Yes	26.0 (1585)
Childhood life events	
None	54.3 (4274)
1 or more	45.7 (3603)
Chronic condition	
No chronic condition	35.3 (2955)
1 or more	64.7 (5407)
Type of chronic condition	
Cardiovascular disease	22.1 (1849)
Respiratory disease	12.8 (1071)
Musculoskeletal problem	43.2 (3612)
Migraines	12.5 (1048)
Diabetes	5.4 (451)
Gastrointestinal problems	8.2 (683)
Thyroid problems	6.3 (524)
Type of housing	
Single detached	69.9 (5282)
Other	30.1 (2275)
Crowding index (mean, SE)	0.95 (0.43)
Social support score (mean, SE)	66.2 (0.2)
Mastery scale (mean, SE)	20.1 (0.1)

All estimates were weighted using statistics Canada survey weights.

Table 2
Characteristics of neighbourhoods of study participants at study baseline (2000/01).

Variables	Study participants % (n) $n=9026$
Material deprivation	
1st Quintile	16.5 (1366)
2nd Quintile	22.5 (1858)
3rd Quintile	24.7 (2041)
4th Quintile	23.0 (1905)
5th Quintile	13.3 (1097)
Social deprivation	
1st Quintile	14.8 (1219)
2nd Quintile	23 (1900)
3rd Quintile	24.5 (2025)
4th Quintile	23.7 (1956)
5th Quintile	14.1 (1167)
Any parks	43.8 (2863)
Land-use mixity index (mean, SE)	0.26 (0.20)
Any fast food store	23.9 (1979)
Any healthy food store	20.2 (1677)
Any health service	18.5 (1529)
Any physical activity service	14.5 (1205)
Any cultural service	10.2 (847)
Greenness (mean, SE)	0.06 (0.16)

All estimates were weighted using Statistics Canada survey weights.

(Supplementary Table 4). In subgroup analysis comparing rural to non-rural dwellers, point estimates suggested a stronger effects of living near a park, health services and physical activity services on risk of depression among rural dwellers, compared to non-rural dwellers, but results were not statistically significant (Supplementary Table 5).

Table 3
Hazard ratios of incident depression in relation to neighbourhood characteristics.

	Sex- and age-adjusted model HR (95% CI)	Fully adjusted model HR (95% CI)
Material deprivation (quintile)	0.98 (0.92,1.05)	1.01 (0.94,1.08)
Social deprivation (quintile)	0.99 (0.93,1.06)	0.96 (0.89,1.04)
Presence of any park and recreation	0.80* (0.65,0.99)	0.86 (0.69,1.07)
Land-use mix	1.24 (0.75,2.06)	1.22 (0.68,2.19)
Any fast food restaurants	1.02 (0.84,1.23)	1.00 (0.80,1.26)
Any health services	0.93 (0.75,1.16)	0.85 (0.66,1.09)
Any healthy food stores	0.90 (0.72,1.13)	0.87 (0.67,1.11)
Any physical activity facilities	1.02 (0.81,1.29)	0.95 (0.72,1.24)
Any cultural services	1.05 (0.81,1.36)	0.89 (0.65,1.21)
Greenness	0.89 (0.31,2.53)	0.79 (0.27,2.33)

All models adjusted for age, sex, education, family history of depression, childhood life events (time-fixed); marital status, employment status, family income (time-varying).
Estimates were weighted using Statistics Canada survey weights and bootstrap replications.

3.2. Effect modification analysis

In effect modification analyses of household factors (Supplementary Table 6), there was a significant interaction between the presence of a local park and household crowding index score, even after adjusting for confounders and correcting for multiple testing (Bonferroni corrected $p=0.018$). In stratified analyses, living in proximity to a park was associated with lower risk of depression specifically for those living in a more crowded household (fully-adjusted HR 0.64, CI 0.47, 0.87 for those living in a household with a crowding index ≥ 1). In analyses of interaction between neighbourhood factors (Supplementary Table 7), there was significant interaction between presence of health services and material deprivation (Bonferroni corrected $p=0.032$), such that the presence of local health services was significantly related to lower risk of depression specifically for people living in materially deprived neighbourhoods (fully-adjusted HR 0.46, CI 0.29, 0.74). The local presence of cultural services and neighbourhood social deprivation also significantly interacted together, even in the fully-adjusted model (Bonferroni corrected $p=0.048$). Nearby cultural services was significantly associated with a lower risk of depression for people living in socially advantaged neighbourhoods (fully-adjusted HR 0.56, CI 0.35, 0.90). In effect modification analyses of individual-level factors (Supplementary Table 8), we found no significant effect of socioeconomic variables, social support or sense of control on the associations between neighbourhood characteristics and depression after correcting for multiple testing.

3.3. Neighbourhood risk factors for depression by chronic condition

At study baseline, we identified 6024 adults reporting at least one common chronic condition in the preceding 6 years (NPHS cycles 1–4). Among them, 681 new cases of depression were identified during the 10 year-follow up. The weighted 10-year cumulative incidence of depression in the NPHS cohort with any chronic condition was 11.3%, with biannual incidence of 4.5%, 4.0%,

Table 4
Hazard ratios of incident depression in relation to neighbourhood characteristics by type of chronic condition.

	Any chronic condition $N=5407$ HR (95% CI)	Cardio-vascular condition $N=1849$ HR (95% CI)	Respiratory condition $N=1071$ HR (95% CI)	Musculo-skeletal problem $N=3612$ HR (95% CI)	Migraine $N=1048$ HR (95% CI)	Diabetes $N=451$ HR (95% CI)	Gastro-intestinal condition $N=683$ HR (95% CI)	Thyroid condition $N=524$ HR (95% CI)
Material deprivation (quintile)	0.99 (0.91,1.07)	1.03 (0.87,1.22)	0.98 (0.81,1.18)	1.00 (0.90,1.11)	1.00 (0.85,1.17)	0.98 (0.57,1.69)	1.00 (0.81,1.24)	1.00 (0.77,1.30)
Social deprivation (quintile)	0.99 (0.90,1.10)	1.00 (0.83,1.21)	1.08 (0.90,1.31)	1.00 (0.89,1.14)	0.94 (0.76,1.14)	0.87 (0.50,1.49)	0.81 (0.62,1.08)	1.05 (0.71,1.56)
Any parks and recreation	0.90 (0.70,1.17)	1.19 (0.75,1.89)	0.93 (0.53,1.65)	1.05 (0.78,1.41)	0.71 (0.39,1.28)	1.22 (0.00,2.5e+214)	0.83 (0.40,1.70)	0.71 (0.25,1.97)
Land-use mix	1.29 (0.67,2.50)	2.54 (0.70,9.25)	1.35 (0.31,5.90)	1.21 (0.57,2.53)	1.45 (0.32,6.48)	4.57 (0.00,3.3e+173)	2.94 (0.49,17.58)	5.00 (0.41,61.13)
Any fast food store	0.95 (0.73,1.22)	0.66 (0.38,1.13)	0.93 (0.51,1.69)	0.98 (0.73,1.32)	0.59 (0.30,1.16)	1.81 (0.09,36.10)	0.75 (0.39,1.45)	0.89 (0.27,2.98)
Any healthy food store	0.88 (0.66,1.17)	0.81 (0.45,1.45)	0.91 (0.48,1.73)	0.94 (0.67,1.32)	0.44 (0.17,1.12)	1.72 (0.01,476.5)	0.95 (0.47,1.92)	1.02 (0.25,4.16)
Any health services	0.86 (0.63,1.17)	0.76 (0.41,1.41)	0.56 (0.27,1.16)	0.72 (0.48,1.09)	0.73 (0.33,1.62)	0.60 (0.00,2.10e+07)	0.72 (0.30,1.78)	0.87 (0.21,3.51)
Any physical activity services	1.02 (0.76,1.37)	0.84 (0.45,1.57)	0.74 (0.34,1.60)	1.12 (0.79,1.59)	0.74 (0.37,1.49)	1.07 (0.00,155985)	0.69 (0.26,1.81)	0.97 (0.05,17.25)
Any cultural services	0.84 (0.59,1.20)	0.98 (0.49,1.96)	0.58 (0.23,1.45)	0.86 (0.55,1.35)	0.40 (0.16,0.97)	0.47 (0.00,5.58e+10)	1.09 (0.39,3.08)	0.54 (0.00,109.36)
Greenness	0.74 (0.17,3.18)	0.07 (0.00,1.21)	0.16 (0.01,4.68)	0.42 (0.07,2.68)	0.20 (0.01,3.12)	0.05 (0.00, > 9e+99)	0.51 (0.01,28.19)	0.77 (0.00,169242)

All models adjusted for age, sex, education, family history of depression, childhood life events (time-fixed); marital status, employment status, family income (time-varying).
Estimates were weighted using Statistics Canada survey weights and bootstrap replications.

3.1%, 3.1% and 2.7% for NPHS cycles 5 to 9, respectively. In participants with at least one chronic condition, none of the neighbourhood characteristics were significantly associated with risk of depression (Table 4). However, in subgroup analysis by type of chronic illness, we found a significant association between living in a neighbourhood with at least one cultural service and lower risk of depression in people with migraines (fully-adjusted HR 0.40, CI 0.16, 0.97), but results did not remain statistically significant after correcting for multiple testing (Bonferroni corrected $p=0.44$).

4. Discussion

This is the first study to use longitudinal data to examine the effect on depression of a wide range of neighbourhood characteristics in the general adult population, and the first study to examine this effect across several types of chronic conditions. It is also the first to provide evidence of effect modification by household and neighbourhood characteristics. In contrast to our hypothesis, results showed that neighbourhood characteristics were not statistically associated with risk of depression in the overall sample or in subsamples with a chronic condition. However, effect modification analyses revealed that living in proximity to a park was associated with lower risk of depression for those living in more crowded households and that local presence of health services was associated with lower risk of depression among those living in materially deprived neighbourhoods. Living in a neighbourhood that both was socially advantaged and offered local cultural services was also associated with lower risk of depression. Our results are comparable to those from previous cohort studies that found neighbourhood deprivation or poverty were not significant risk factors for depression (Buu et al., 2011; Glymour et al., 2010; Schootman et al., 2007; Wight et al., 2009), with a few exceptions (Beard et al., 2009; Galea et al., 2011; Lofors and Sundquist, 2007). This study adds to this body of literature by being the first longitudinal study to examine the presence of local businesses and services, land-use mix and proximity to parks and green spaces in relation to risk of depression. Results generally confirm those from cross-sectional data (Kubzansky et al., 2005; Miles et al., 2012; Saarloos et al., 2011; Stockdale et al., 2007).

Neighbourhood characteristics were not statistically significant factors associated with risk of depression in our sample. Although previous longitudinal studies have generally found similar results (Buu et al., 2011; Glymour et al., 2010; Schootman et al., 2007; Wight et al., 2009), several cross-sectional studies (Julien et al., 2012; Mair et al., 2008) report significant associations. Reverse causation might explain this discrepancy, wherein people with depression might be more likely to eventually live in poor quality neighbourhoods. However, in sensitivity analysis where people with depression at baseline were included in analyses, associations still did not reach statistical significance. It is possible that this study did not have sufficient power to detect neighbourhood effects. Neighbourhood characteristics are thought to be distal risk factors of depression compared to proximal factors such as personal level of stress. Neighbourhood effects are therefore expected to be small and may have been missed by this study. Data on some neighbourhood characteristics were also not available for all postal codes, further reducing study power. However, analyses using multiple imputations did not substantially change results. This study used objective measures of neighbourhood characteristics and a carefully selected person-centered neighbourhood definition. Nevertheless, measurement error of neighbourhood characteristics is possible and might have also affected power. These limitations could lead to type II error, whereby statistical analysis erroneously fails to reject the null hypothesis. In the largest cohort study to date on 4,516,787 residents of Sweden, authors found neighbourhood socioeconomic status was statistically significant in predicting first hospitalization with diagnosis of depression (Lofors and Sundquist, 2007). Future studies using larger samples are needed to confirm findings. Finally, it is possible that neighbourhood characteristics are not important risk factors for depression in Canadian adults. Neighbourhoods may be more homogeneous in Canada compared with other countries, such as the United States. For example, Canada offers universal healthcare to residents, making local access to health services less relevant to mental health when comparing neighbourhoods. Future research in different populations is recommended.

Aspects of the neighbourhood environment were significantly related to depression in some vulnerable subgroups in our sample. We found that residing near a park was an important protective factor for individuals living in a crowded household. Previous work has shown that living in a crowded space can be stressful for the individual (Evans, 2003). Local parks may therefore be beneficial by providing an escape from residential crowding and protect mental health. We also found that having local health services in the neighbourhood was a protective factor of depression among those living in high material deprivation neighbourhoods. Because materially deprived neighbourhoods have lower aggregate income and education level, residents may need to rely on resources outside of their local community members for physical and psychological problems. Availability of local health services may therefore be particularly valuable in this context. Finally, although social deprivation and cultural services were not independent factors in depression, living in a neighbourhood that both was socially advantaged and offered local cultural services was associated with lower risk of depression. Such a combination may promote community ties and social support which protect mental health (Bender and Lange, 2001). Previous efforts to identify vulnerable subgroups in neighbourhood research on depression have been limited to individual-level characteristics, such as sex and socioeconomic resources. This study is the first to examine housing characteristics and the combination of neighbourhood characteristics as other sources of vulnerability. Future research on neighbourhood effects that incorporates interactions of residential and neighbourhood variable is encouraged.

This study presented several strengths. It used data from a large representative sample of adults with 10 years of follow-up data. It covered a wide range of neighbourhood characteristics, many of which had not been examined in depression research. It used objective measures of the neighbourhood environment and a person-centred neighbourhood definition. Previous research has primarily delineated neighbourhoods using administrative regions which may not adequately reflect the surrounding neighbourhood environment of individuals (Osypuk and Galea, 2007). The study included several sensitivity analyses to check robustness of results.

Some limitations are however noteworthy. Survey data were self-reported, which might lead to measurement error. Depression was assessed using a validated screening questionnaire, not a psychiatric interview. Data on neighbourhood characteristics were only available at 2 or 3 time points. More frequent updates might provide different results. There was no information available regarding how long individuals lived at their address at baseline or how much time they spent in their neighbourhood. For example, individuals that lived for a long time in a deprived neighbourhood might have a greater risk of depression than those with a shorter exposure to neighbourhood deprivation. There was no information on the actual use of or access to neighbourhood parks, green spaces, businesses, and services, and the quality of these facilities. Missing data on some variables were important in our sample. However, sensitivity analyses with multiple

imputations resulted in similar estimates. As described previously in the discussion, the study might have been underpowered to test for statistical significance. Namely, effective sample sizes for stratified analyses by type of chronic condition were very small in some subgroups, such as those with diabetes. This study provided information on a range of neighbourhood factors, but other neighbourhood measures might also be important. For example, participants' perception of their neighbourhood might capture important aspects of the local environment that are not measured by census or geospatial data (e.g., social cohesion). The study used a nationwide Canadian sample and neighbourhood effects could vary between provinces. The sample was predominantly white, which may limit generalizability. Effects of household and neighbourhood characteristics in the study could also be unique to the Canadian context. Future research in other populations and subpopulations is encouraged. Larger studies are needed to confirm our findings.

5. Conclusion

Characteristics of the neighbourhood environment were not significantly associated with the risk of depression in a 10-year follow-up survey of Canadian adults. However, for people living in a crowded household, living in proximity to a park was associated with a lower risk of depression. For people living in a materially deprived neighbourhood, having a local health service nearby was also a factor associated with lower risk of depression. Intervention studies on these vulnerable living situations are needed for public health recommendations. Studies investigating other potentially high-risk subgroups are also encouraged. Evidence from this and previous longitudinal studies suggest that neighbourhood characteristics are not statistically significant risk factors of depression. However, neighbourhood research in depression faces several challenges, such as the need for sufficient statistical power to detect a potentially small effect size. While neighbourhood effects may be small, many argue that these effects may nonetheless be important because of the large number of people exposed to neighbourhood-level risk factors (Cubbin and Winkleby, 2005). Neighbourhood factors are also upstream determinants of health, thought to have an effect on a broad range of illnesses beyond depression (Diez Roux, 2010). Further, the health environment of deprived neighbourhoods is a significant contributor to health inequalities, a major concern for public health. Larger cohort studies are encouraged to confirm previous findings.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.healthplace.2014.10.009.

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5 | Associations between Neighbourhood Characteristics and Risk of Depression in People with Diabetes (Manuscripts II and III)

In Chapter 4, I presented results from a study using a large representative sample of the Canadian general population. Results from Manuscript I suggested that neighbourhood characteristics were not significantly associated with depression in the general sample or in subgroups with a chronic condition, but were important in some vulnerable subgroups. In this chapter, I narrow my focus to adults with diabetes and present the findings from a second and third manuscript (Manuscripts II and III). I used data from a community sample of adults with diabetes from Quebec (the DHS) to investigate the relationship between neighbourhoods and depression specifically in adults with diabetes and the potential moderators of this association. Later in Chapter 6, I specifically investigate some of the mediating pathways of this relationship in the DHS sample.

As described in Chapter 3, the DHS offers several advantages over the NPHS, including shorter intervals between follow-ups (1 year), detailed assessment on diabetes and diabetes management, and a more homogeneous sample from the same Canadian province. In addition, the DHS provides a large sample size of individuals with diabetes (n=2003). Sample sizes of subgroups with a chronic condition in the NPHS were small, particularly for those with diabetes (n=451). A larger sample of people with diabetes could uncover significant associations that were missed in the NPHS data because of limited study power. In addition, the DHS was an on-going study at the time of the thesis

project, which allowed me to collect additional information on perceived neighbourhood characteristics from a subsample of participants.

Manuscript II describes the development of the DHS neighbourhood questionnaire and the factorial analysis that I used to find latent neighbourhood factors. Analyses of the cross-sectional association between these latent neighbourhood factors and diabetes distress were then performed. In Manuscript III, I combined data on perceived neighbourhood factors with census, geospatial and satellite imagery data, to form a rich dataset on a wide range of neighbourhood characteristics. This dataset was then linked to DHS data to study neighbourhood characteristics and depression in people with diabetes.

Manuscripts II and III both make important contributions by being the first studies to examine the link between neighbourhood factors and mental health in a representative sample of people with diabetes. Manuscript III is also the first longitudinal study in neighbourhood and depression research using a sample with diabetes. Manuscript II is published in *Psychosomatic Research* (2013) and Manuscript III is in press in the journal *Diabetic Medicine* (2014).

Detailed Methods

Study Samples

I used data from the DHS and the DHS sub-study. Data from the sub-study were used because they provided additional information on perceived social and physical neighbourhood characteristics that were not available in the original DHS.

The DHS is a 5-year (2008-2013) prospective community-based study of 2,003 adults with diabetes, living in Quebec, Canada. The DHS was funded by a CIHR grant. The aim of the DHS was to study the role of social support, health, and lifestyle factors on depression and disability outcomes in people with diabetes. Participants were recruited through random digit dialling of residential phone numbers by a recognized polling firm (Bureau d'Intervieweurs Professionnels, Montreal, Quebec, Canada) between January 2008 and April 2008. The sampling frame consisted of all households with a listed telephone number in Quebec, Canada. Adults eligible to participate were 18 to 80 years of age at baseline, had a diagnosis of diabetes determined by a physician and could respond to the interview in either French or English. Telephone interviews were conducted using a computer-assisted interview system. Participants who agreed at baseline to participate in follow-up (n=1,755) were re-interviewed annually by telephone using the same baseline questionnaire. Further details of the DHS methodology and sample characteristics are described elsewhere.[47]

In 2011, I helped initiate the DHS sub-study, a 3-year cohort study (2011-2013) of 600 DHS participants with type 2 diabetes who live in the Montreal area (determined from postal codes). This study was funded by the Canadian Diabetes Association. The purpose of the study was to add missing information on diet, physical activity and neighbourhood environment to the DHS. DHS respondents who participated in the 2011 DHS follow-up were asked if they would be interested in participating in a supplementary phone-

interview 2-3 months following their annual DHS interview. A total of 680 participants accepted and provided verbal consent and 600 were subsequently interviewed.

Data Collection

Measurement of Depression

The outcome of interest was depression, defined as symptoms of either minor or major depressive disorder, consistent with the project using NPHS data. In the DHS, depressive symptoms in the past 2 weeks were assessed using the Patient Health Questionnaire (PHQ-9) screening scale.[132,133] The nine items of the PHQ-9 correspond to the DSM-IV criteria for depressive disorders. To meet criteria for depression, a person must have two or four depressive symptoms (minor depression) or five or more depressive symptoms (major depression), present for more than half of the days, for at least 2 weeks, with at least one of these symptoms being either depressed mood or loss of interest. Two meta-analyses[134,135] have shown the PHQ-9 diagnosis to have good sensitivity (80% and 77%, respectively) and specificity (92% and 94%, respectively) compared with diagnosis based on structured interviews.

Measurement of Neighbourhood Characteristics

Neighbourhood Definition

The neighbourhood definition for this project was the same as the project using NPHS data, described in Chapter 4. Briefly, I used a person-centered definition of neighbourhood and conducted sensitivity analyses for a range of buffer radii (500m,

1000m, 15000m). I linked neighbourhood data with DHS survey data using participant's postal code.

Neighbourhood Characteristics

Measurement of neighbourhood characteristics were the same as those described for the project using NPHS data, detailed in Chapter 4: I included information on neighbourhood social and material deprivation using the Pampalon Index; parks, land-use and density of businesses and services using geospatial data; and level of greenness using satellite imagery data.

Perceived Neighbourhood Characteristics

In addition to objective neighbourhood characteristics, I developed a neighbourhood questionnaire for the DHS sub-study to measure the perceived neighbourhood environment. I developed the questionnaire from previous work and items.[136-140] Items tapped into various neighbourhood constructs that have been proposed in the literature, such as neighbourhood order (14 items), land use (7 items), access to services and facilities (7 items), social norms (2 items) and social cohesion (5 items) (details in Appendix C). The measurement of residential environment from self-report is a relatively new area of research, and measures have shown overall moderate validity[56,77,139-142] and reliability[143]. After selection of items, I constructed the questionnaire to follow a logical sequence. The majority of questions required participants to answer on the same 4-point Likert scale (from strongly agree to strongly disagree). To avoid response set bias, I included items that were rated on a 5-point scale (from excellent to poor) and reversed

question wording for some items. I then conducted pre-testing of the neighbourhood questionnaire on a small convenience sample (n=10) to ensure clarity, simplicity and neutrality of questions. The questionnaire was revised in response to problems found. I found a low response rate for items related to social cohesion, likely because of the subjective nature of these items. One item was dropped ("Most of the people in my neighbourhood make efforts to stay healthy") because pre-test participants identified it as too difficult to answer. A total of 33 items was kept in the questionnaire. Questions were translated from English to French by two independent French-native professional translators and back-translated to English by an English-native professional translator. Final wording was approved by bilingual researchers.

Analysis of Neighbourhood Questionnaire Items

I dichotomized categorical responses (strongly agree/agree vs strongly disagree/disagree; excellent/very good/ good vs fair/poor) on the neighbourhood items to avoid potential for central tendency bias and because of small cell sizes for many of the extreme answer categories. To check the correlation between these dichotomized items, I used a tetrachoric correlation matrix (Appendix D). The tetrachoric correlation makes the assumptions that the neighbourhood trait on which ratings are based is continuous and that the latent trait is normally distributed. These were considered reasonable assumptions in this study. I smoothed the matrix to reduce the problem of negative latent roots, which is common with tetrachoric matrices, using TetMat[144] (available as a SAS macro).

Many of the neighbourhood items were correlated and their independent association with depression would not be reliably estimated. I therefore conducted a factor analysis to combine the neighbourhood items into a few meaningful constructs. Factor analysis is a method to examine the structure of items by identifying the smallest number of factors explaining the relationship among observed variables. I used a principal component analysis with an orthogonal varimax rotation. I used an exploratory factor analysis approach because previous research in neighbourhood latent constructs is limited. I selected the number of factors based on the scree plot (Appendix E) and the interpretability of the factors. Results suggested a 3-factor solution, representing three latent neighbourhood construct: 1) "order", represented physical and social order and included 13 items such as "there is a lot of graffiti in my neighbourhood"; 2) "society and culture", tapped into the social and cultural environment of the neighbourhood, and included 10 items such as "there are interesting things to do in my neighbourhood"; 3) "access" covered aspects of the land use and access to services, facilities and transportation. It grouped items related to access (access to park or walking trail, public transportation, shopping, medical care, fresh fruits and vegetables, healthy foods, fast food restaurants) and walkability. One item – "I really feel part of my neighbourhood" - was dropped because it did not significantly load on to any factor (loading factors < 0.15). Factor loadings (rotated loadings) for each neighbourhood items can be found in Appendix F. I conducted factor analysis again on neighbourhood data from 2012 and 2013 and found the same neighbourhood factors (Appendix G and Appendix H).

I calculated a summary score for each participant by summing the items related to each of the factors (Appendix I), which is the usual strategy in principal component analysis. Some items were reverse-coded so that higher scores indicated better neighbourhood qualities. I allowed for up to one missing item response per factor by replacing the missing value with the mean score of the other non-missing items.

Additional Testing of Neighbourhood Latent Factors

The latent neighbourhood factors showed good external and internal construct validity overall. I investigated the convergent construct validity of the 3 latent neighbourhood factors between each other, with the Pampalon Index and with individual-level socioeconomic variables. I estimated the association between the variables using Kendal tau-b correlation coefficients and the non-parametric Kruskal-Wallis test because the neighbourhood factors were not normally distributed and there were a large number of tied scores. The correlation matrix between the neighbourhood factors and Pampalon Index is presented in Appendix J. The strongest correlation (Kendal tau-b = 0.28) was found between the "culture" and "access" factors, while weak to moderate correlations were found between the other latent neighbourhood factors and deprivation indices from the Pampalon Index. The weak correlation may indicate that the neighbourhood factors are tapping into different constructs than the Pampalon Index. It may also be that the Pampalon Index from 2006 (latest available index during the thesis project) was no longer representative of neighbourhoods in 2011. As expected, results showed that higher socioeconomic status was associated with living in a better neighbourhood (Appendix K).

Marital status, working status, household income and education level were significantly related to the factors "order" and "culture" and education levels was also significantly related to the factor "access".

To check the internal consistency, I calculated the standardized Cronbach's alpha for each factor. Results showed good consistency for each factor (alphas between 0.78 and 0.86). As an approximate measure of reliability, I checked the intra-class correlation (ICC) of the neighbourhood factors by city of residence. I found a high ICC for all factors (order: 0.81; culture: 0.78; access: 0.78).

DATA ANALYSIS IN MANUSCRIPT III

RISK ANALYSIS

To meet the first thesis objective (Objective 1*: to assess the association of neighbourhood characteristics and risk of depression among adults with and without a chronic condition*), I used the same approach as the NPHS project, described in Chapter 4. I conducted proportional hazards regressions to estimate hazard ratios (HRs) of incident depression by neighbourhood characteristics, using a generalized linear model using the complementary log-log link function. I adjusted for important confounders and lagged time-varying covariates by 1 year.

MODERATOR ANALYSIS

To meet part of the second objective of the thesis project (Objective 2*: to investigate specific moderators of the association between neighbourhood characteristics and risk of depression in adults with and without a chronic condition*.), I used the same approach

described for the NPHS project in Chapter 4. I included interaction terms in the survival regression model. I conducted stratified analyses for significant interaction terms. In addition, I calculated marginal effects to check for the effect of scales on the significance and direction of interactions. Manuscript III presents results from moderator analysis of individual-level variables. Results of moderator analysis by household characteristics and between neighbourhood factors are available in appendix L.

Sensitivity Analyses

Assessing Missing Values

I used multiple imputations (MI) to assess the effect of missing data, in the same way described in Chapter 4 for the NPHS project.

Assessing Selection Bias

Censoring is assumed to be non-informative in survival analysis. I checked for this by computing study weights that were inversely proportional to the estimated probability of response.[129,145] People with a low probability of responding were given a higher weight in the analysis to represent the non-respondents with similar characteristics. I calculated the weights as a function of sociodemographic variables (age, sex, education, marital status), duration of diabetes (in years), number of diabetes complications, disability (substantial disability vs not), self-rated health (good/very good/excellent vs fair/poor), and smoking (current smoker vs former/never smoker) using a logistic model with censored status as the outcome variables. These covariates were chosen because they were risk factors for both censoring and depression based on substantive knowledge and data exploration. The

time-invariant covariates (age, sex, education, duration of diabetes) were used to stabilize the inverse probability of censoring weights. A necessary condition for correct model specification is that the stabilized weights have a mean close to one. I therefore tested several models and based model selection on the following criteria: Akaike information criterion (AIC), Bayesian information criterion (BIC), stabilized mean weight closest to 1, smallest standard deviation and the narrowest range (Appendix M). For inverse probability weighting (IPW) to be valid, it assumes consistency, positivity, and correct model specifications.[145] It also assumes no unmeasured confounding between censoring and the outcome, given the covariates. In additional sensitivity analysis, I also used imputed data from multiple imputations to calculate study weights.

In addition to losses to follow-up, preliminary analyses revealed that about 19% of the DHS sample screened positive for minor or major depression at baseline. The exclusion of these cases in the analysis may therefore create some selection bias. I therefore 1) compared characteristics between those depressed and not depressed at baseline, 2) included in the analyses those who were depressed at baseline but adjusted for baseline depression, and 3) used IPW of depression at baseline to attribute more weight to those who were not depressed but had similar characteristics to those who were. I used the same method to estimate IPW of depression as for IPW of censoring described above, except that the outcome was depression rather than censoring (Appendix N).

Assessing Information Bias

I conducted sensitivity analyses where the definition of depression included use of antidepressants. Data on neighbourhood parks, land-use and businesses were not available at study baseline in 2008, but were available for 2006 and 2010. I used 2010 data in Manuscript III, but investigated the effect of using data from 2006 instead in the analysis. This made no difference and was not described in the manuscript. Additionally, I tested the effect of excluding rural dwellers from analyses because they may have different life situations than urban dwellers (e.g., different access to healthcare) and data from rural areas are more difficult to accurately obtain.

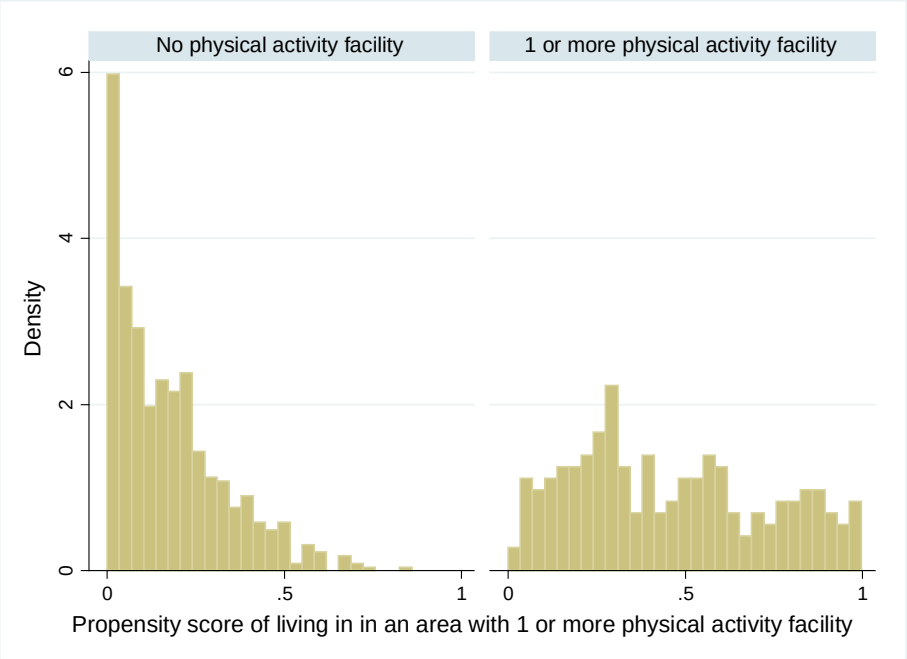
Assessing Structural Confounding

I assessed the potential for structural confounding using a propensity-score matched sample.[103,146] Structural confounding occurs when there is insufficient overlap in the background characteristics between residents of deprived and non-deprived neighbourhoods to estimate the effects of residency (e.g., only high SES individuals live in high SES neighbourhoods and low SES individuals in low SES neighbourhoods).[147] This could lead to off-support inference based purely on model extrapolation. Propensity score matching addresses this issue by matching together individuals that are as likely to live in a given neighbourhood given their individual characteristics. Individuals that are not matched are discarded from analysis. To compute propensity scores, I dichotomized neighbourhood characteristics to stay consistent with current practice of propensity scoring methods. I categorized variables by top 2 quintiles vs bottom 3 quintiles for

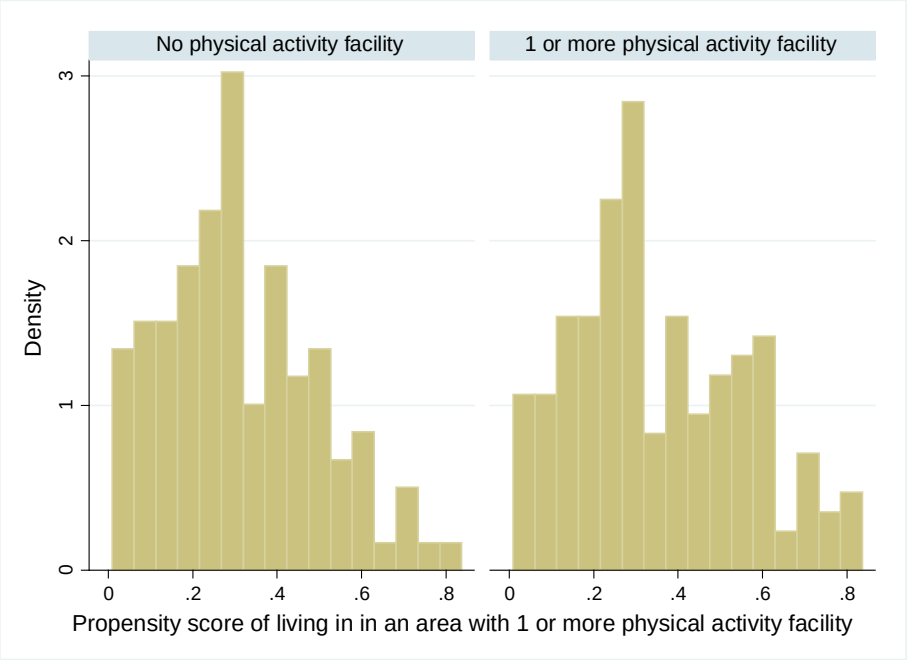
continuous values (e.g., top 2 quintiles on the greenness index vs bottom 3 quintiles) or by the presence vs absence of the characteristic for count values (e.g., one or more healthcare services vs none). For each neighbourhood characteristic, I calculated the probability that an individual would live in an area with the neighbourhood characteristic, compared to an area without, given their known individual-level variables.[103,146] I used multivariable logistic regression to model propensity scores as a function of all baseline individual-level variables described for previous models, as well as self-rated health (good/very good/excellent vs fair/poor), number of chronic conditions, body-mass index (kg/m^2), number of dependents, presence of disability (substantial disability vs not), and lifestyle factors including smoking (current smoker vs former/never smoker) and physical inactivity (<15 minutes of activity in last month vs ≥ 15 minutes). I included all possible two-way interaction terms in the model. I set a caliper of ± 0.05 and matched participants on their propensity score, with replacement, until no more matches were found. I then ran analyses for risk of depression with only matched participants and used weights for the number of times a participant was matched to another. Figure 5.1 provides an example of the distributions of propensity score for living in a neighbourhood with a physical activity facility before and after propensity-score matching. Propensity score was calculated using PSMATCH2 in STATA.[111]

FIGURE 5.1 DISTRIBUTIONS OF PROPENSITY SCORE FOR LIVING IN A NEIGHBOURHOOD WITH A PHYSICAL ACTIVITY FACILITY BEFORE AND AFTER PROPENSITY-SCORE MATCHING

a) Before propensity-score matching



b) After propensity-score matching



Manuscript II: Diabetes Distress and Neighbourhood Characteristics in People with Type 2 Diabetes

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Diabetes distress and neighborhood characteristics in people with type 2 diabetes

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ABSTRACT

Objective: Diabetes-specific distress is an important psychological issue in people with diabetes. The neighborhood environment has the potential to be an important factor for diabetes distress. This study investigates the associations between neighborhood characteristics and diabetes distress in adults with type 2 diabetes.

Methods: We used cross-sectional data from a community-based sample of 578 adults with type 2 diabetes from Quebec, Canada. Information on perceived neighborhood characteristics and diabetes distress was collected from phone interviews. We used factor analysis to combine questionnaire items into neighborhood factors. Information on neighborhood deprivation was derived from census data. We performed linear regressions for diabetes distress and specific domains of diabetes distress (emotional, regimen-related, physician-related and interpersonal distress), adjusting for individual-level variables.

Results: Factorial analysis uncovered 3 important neighborhood constructs: perceived order (social and physical order), culture (social and cultural environment) and access (access to services and facilities). After adjusting for individual-level confounders, neighborhood order was significantly associated with diabetes distress and all specific domains of distress; neighborhood culture was specifically associated with regimen-related distress; and neighborhood access was specifically associated with physician-related distress. The objective measure of neighborhood material deprivation was associated with regimen-related distress.

Conclusions: Neighborhood characteristics are associated with diabetes distress in people with type 2 diabetes. Clinicians should consider the neighborhood environment reported by their patients with diabetes when assessing and addressing diabetes-specific distress.

Introduction

The prevalence of diabetes in Canada is estimated at 5.5% and is expected to increase steadily in coming years [1]. Individuals living with diabetes often face lifelong self-management regimens often involving significant changes in their lifestyle and adherence to complex medication procedures. Individuals with diabetes also need to prevent and manage diabetes complications, concurrent health problems and functional limitations [1,2]. Diabetes distress is a multi-domain construct which captures the worry, frustration and discouragement that may accompany life with diabetes. It encompasses regimen-related distress, physician-related distress, emotional burden and diabetes-related interpersonal distress [3–5]. Distress over diabetes regimen relates to the worries and discouragements that patients may have about self-managing their disease, such as perceived difficulties in following their diet or maintaining their diabetes routine [6–8]. Distress related to physician includes concerns about access to healthcare and quality of care, such as worries that recommendations provided by healthcare professionals may be incomplete [6,9]. Emotional burden is another source of diabetes distress that refers to the negative mental and emotional aspects of life with diabetes. This includes feelings such as despair, anger or fear when thinking about a lifetime with diabetes or feeling overwhelmed by the demands of diabetes. Finally, interpersonal distress such as lack of social support may contribute to diabetes distress by limiting emotional support or making it more difficult to maintain a healthy lifestyle [6]. Diabetes distress is a psychological issue distinct from depression and anxiety [10]. It has been found to be more common and persistent than depression in people with diabetes [5,10,11]. It is associated with poorer glycemic control, self-care behaviors and medication adherence, even above and beyond depressive symptoms [12–16].

Although diabetes distress is an important outcome for people with diabetes, relatively little is known of the predictors and correlates of diabetes distress. One study identified individual-level variables associated with diabetes distress, including a greater number

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of diabetes complications, negative life events or chronic stress, a history of depression and an unhealthy lifestyle [17]. The neighborhood where people live could be an important additional factor for diabetes distress. People with diabetes are often recommended to exercise more frequently and improve their diet. Living in a neighborhood with limited access to healthy food and safe places to exercise can be an important barrier for diabetes self-care [18] and may be a source of diabetes distress. A lack of community resources and support may also limit a person's ability to manage and function with their diabetes [19]. Neighborhood factors have further been linked to physical health outcomes and complications in people with diabetes [19,20], which could affect distress. Only one study investigated the link between neighborhood environment and mental wellbeing in people with diabetes [21]. Results showed an association between neighborhood socioeconomic status and depressive symptoms in a clinical sample of obese patients with type 2 diabetes. No study has specifically focused on neighborhood factors in diabetes distress.

The primary objective of this study was to investigate the associations between a range of neighborhood characteristics and diabetes distress, in a representative sample of adults with type 2 diabetes. The secondary objective was to examine the association between neighborhood characteristics and the specific domains of diabetes distress (regimen-related, physician-related, emotional, interpersonal distress).

Methods

Study population

We used data from a sub-sample of the Diabetes Health and Well-being Study (DHS), a random digit-dialing survey of 2003 community-dwelling adults with diabetes, living in Quebec, Canada [22]. The DHS started in 2008 and follow-ups are annual. In 2011, we conducted a sub-study using a sub-sample of DHS participants with type 2 diabetes who lived in urban and semi-urban areas (determined from postal codes). The purpose of the sub-study was to add missing information on diet, physical activity and neighborhood environment to the DHS. A total of 680 participants accepted and provided verbal consent and 600 were subsequently telephone interviewed. For this study, we included participants with information on diabetes distress ($n = 578$). We found no significant differences in baseline socio-demographic and lifestyle characteristics between DHS sub-study participants and non-participants with type 2 diabetes living in urban or semi-urban areas, except that DHS sub-study participants were slightly more likely to be working (39.0% vs 31.5%, $p = 0.007$) and less likely to be smokers (17.5% vs 23.0%, $p = 0.006$) than non-participants.

Diabetes distress

Diabetes distress was measured using the 17-item Diabetes Distress Scale (DDS) [4]. The DDS has shown good validity and internal consistency ($\alpha = 0.93$) [4]. The scale explores four domains of distress potentially related to living with diabetes: emotional burden (5 items, such as "feeling that diabetes is taking up too much of my mental and physical energy every day"), physician-related distress (4 items, such as "feeling that my doctor doesn't give me clear enough directions on how to manage my diabetes"), regimen-related distress (5 items, such as "feeling that I am often failing with my diabetes routine") and diabetes-related interpersonal distress (3 items, such as "feeling that friends or family are not supportive enough of self-care efforts"). Items are rated on a Likert scale from 1 (not a problem) to 6 (very serious problem). We calculated a mean global diabetes distress score and mean scores for each domain-specific subscale by dividing the total score of the scales by the number of questions (range between 1 and 6). Previous research suggests a mean score of ≥ 2 to indicate moderate to high diabetes distress [3].

Neighborhood characteristics

Based on a review of the literature, we developed a 35-item neighborhood questionnaire using existing items from different works [23–28]. Items were rated on a yes/no scale or on a 4- or 5-point Likert scale. The questionnaire was pilot tested and translated to French. The measurement of residential environment from self-report is a relatively new area of research, and single item measures have shown overall moderate validity [23] and reliability [29].

Neighborhood deprivation was estimated using the Pampalon Deprivation Index [30]. The Pampalon Index uses aggregate census data to estimate material and social deprivation at the level of the dissemination area, the smallest census geographic unit in Canada. The index was calculated using data from the 2006 Canadian census, the most recently available census. Both material and social deprivation scores were divided into quintiles to stay consistent with previous literature [22]. Because we were interested in neighborhood deprivation, we compared the most deprived areas (4th and 5th quintiles) with the least deprived areas (1st to 3rd quintiles). The items in the Pampalon Index have good content validity [30]. The Pampalon index has been successfully used in several studies, including the DHS study sample [22].

Individual-level covariates

Based on our literature review, we selected variables that could confound the relationship between neighborhood selection and diabetes distress. We included socio-demographic information on sex, age, marital status, highest attained education (less than secondary school, secondary school graduation, some post-secondary school), working status (working, not working, retired) and family income (<$15,000, $15,000–$50,000 > $50,000), as well as information on number of chronic conditions (0, 1, >1) and duration of diabetes (in years). Race was not included because the majority of the sample was non-Hispanic Caucasian (94%).

Statistical analysis

Because many of the neighborhood items were highly correlated, their full inclusion in the model could lead to unstable estimates. We therefore performed a factor analysis to combine the neighborhood questionnaire items into a few meaningful constructs. Factor analysis is a method to examine the structure of items by identifying the smallest number of factors explaining the relationship among observed variables. We conducted the analysis using a principal component analysis with an orthogonal varimax rotation. Because of potential for central tendency bias and response set bias and because of small cell sizes for many of the extreme answer categories, we dichotomized the categorical responses of neighborhood items (strongly agree/agree vs strongly disagree/disagree; excellent/very good/good vs fair/poor). We used smoothed tetrachoric correlation matrices. The number of retained factors was based on the scree plot and interpretability of factors. A summary score for each neighborhood factor was calculated by summing the items related to each of the factors. We allowed for up to one missing item response per factor by replacing the missing value with the mean score of the other non-missing items. Some items were reverse-coded such that a higher score could be interpreted as better neighborhood qualities.

We performed linear regressions for each neighborhood construct. We used log transformed diabetes distress scores as the dependent variable because continuous scores were highly skewed. We reported the beta coefficient of each neighborhood construct for 3 models: 1) model 1 adjusted for age and sex only; 2) model 2 adjusted for

all individual-level variables (age, sex, socioeconomic and health variables); and 3) model 3 adjusted for all individual-level variables and the other neighborhood constructs. We checked for interactions between each neighborhood construct and age, sex and duration of diabetes by adding interaction terms to model 3. Statistical analyses were performed in SAS (version 9.3).

Missing values

In preliminary analysis, we found that 8% (n = 45) of the sample was missing information on household income. Other covariates had between 0 and 1% of missing values. We therefore conducted sensitivity analyses using multiple imputations for missing covariates and included data from the current study and previous DHS surveys. Imputations were done in STATA (version 12.1). Analyses using multiple imputations provided similar results as those from the complete set. Results from the non-imputed dataset are presented here.

Results

Characteristics of the study sample are described in Table 1. The mean age of the sample was 58 years old (SD 11.6 years). The majority of the sample was retired (51.1%), married (60.3%) and had an annual household income between 15,000 and 50,000 CAD (50.4%). More than three quarters of the sample (79.8%) had at least 1 comorbid chronic condition. The average diabetes distress score was 1.6 (SD 0.7), indicating low diabetes distress. However, about a quarter (23%) of the sample had scores suggestive of moderate to high diabetes distress (diabetes distress score ≥ 2).

Factor analysis of neighborhood items revealed three latent neighborhood factors (54.4% cumulative explained variance): 1) "order" represented physical and social order in the neighborhood, and included 13 items, such as "there is a lot of graffiti in my neighborhood" (score range 0–13; Cronbach's alpha 0.82); 2) "society and culture" tapped into the social and cultural environment of the neighborhood, and included 10 items, such as "most people in my neighborhood are friendly" (score range 0–10; Cronbach's alpha 0.86); and 3) "access" covered aspects of land use and access to services, facilities and transportation, and included 9 items (score range 0–9; Cronbach's alpha 0.78). Specific factor loadings for each neighborhood items can be found in Appendix 1.

Table 2 shows results of linear regression analyses for global diabetes distress. After adjusting for individual-level confounders, better perceived neighborhood order, culture and access were all significantly associated with lower global scores of diabetes distress. After further adjusting for other neighborhood constructs, only neighborhood order remained significant. The regression coefficient of neighborhood order suggests that every additional item of neighborhood order endorsed by a participant is associated with about a 3.1% lower diabetes distress score. Neighborhood social and material deprivation was not associated with diabetes distress.

Table 3 shows results of the regression analyses by specific domains of diabetes distress. After adjusting for individual-level covariates, better perceived neighborhood order was associated with better scores in all domains of diabetes distress. Better perceived social and cultural neighborhood environment was specifically associated with lower regimen-related distress. Better perceived neighborhood access was specifically associated with lower physician-related distress. Neighborhood material deprivation was associated with higher regimen-related distress. Neighborhood social deprivation was not significantly associated with any domains of diabetes distress.

We found significant interactions between perceived neighborhood culture and sex (β = −0.04) and diabetes duration (β = 0.002), suggesting that there is an association between better perceived neighborhood culture and lower diabetes distress for women but not for men, and that this association weakens slightly with each year spent living with diabetes. Interaction terms with age and with other neighborhood factors were not significant (results not shown).

Table 1
Characteristics of participants in the DHS neighborhood sub-study

Variables (%, n)	All participants n = 600
Age in years (mean, SD)	58.1 (11.6)
Gender	
Female	53.7 (322)
Male	46.3 (278)
Education	
Less than secondary school	38.5 (228)
Secondary school graduation	28.0 (166)
Post-secondary graduation	33.5 (198)
Work status	
Working full-time	32.4 (194)
Not working	16.5 (99)
Retired	51.1 (306)
Marital status	
Married/common law	60.3 (361)
Divorced/separated/widowed	26.5 (159)
Single	13.2 (79)
Income	
<15 k$	15.0 (83)
15 k$–50 k$	50.4 (279)
>50 k$	34.7 (192)
Number of chronic conditions	
0	20.2 (116)
1	28.4 (163)
>1	51.4 (295)
Diabetes duration in years (mean, SD)	11.5 (11.0)
Diabetes distress mean score (mean, SD)	
Global score	1.6 (0.7)
Domain-specific scores	
Emotional distress	1.8 (0.9)
Regimen-related distress	1.8 (0.9)
Physician-related distress	1.4 (0.8)
Interpersonal distress	1.4 (0.7)

Conclusion

The objective of this paper was to investigate the associations between a range of neighborhood characteristics and diabetes distress in adults with type 2 diabetes. Results suggest that individuals who report living in neighborhood with better physical and social order had lower overall diabetes distress than those who reported less favorably on neighborhood order, even after adjusting for socioeconomic and health variables. A better perceived neighborhood social and cultural environment was also associated with lower diabetes distress for women but not for men. Evidence suggests that different aspects of the neighborhood are associated with different domains of diabetes distress. Neighborhoods with less material deprivation and better perceived cultural and social environment were specifically associated with lower regimen-related distress and neighborhoods with better perceived access to resources and services were associated

Table 2
Multiple linear regressions of log-transformed global diabetes distress score

Neighborhood factors		β (95% confidence interval)
Order	Model 1	−0.04 (−0.05, −0.03)*
	Model 2	−0.03 (−0.04, −0.01)*
	Model 3	−0.03 (−0.05, −0.01)*
Culture	Model 1	−0.04 (−0.06, −0.03)*
	Model 2	−0.03 (−0.05, −0.01)*
	Model 3	−0.02 (−0.04, 0.00)
Access	Model 1	−0.02 (−0.04, −0.01)*
	Model 2	−0.02 (−0.04, −0.01)*
	Model 3	−0.02 (−0.04, 0.00)
Material deprivation	Model 1	−0.01 (−0.07, 0.06)
	Model 2	0.04 (−0.03, 0.11)
	Model 3	0.08 (0.00, 0.15)
Social deprivation	Model 1	−0.05 (−0.11, 0.01)
	Model 2	0.00 (−0.07, 0.07)
	Model 3	0.01 (−0.06, 0.08)

Model 1: adjusted for age and sex.
Model 2: adjusted for age, sex, marital status, highest attained education, working status, family income, number of chronic conditions and diabetes duration.
Model 3: adjusted for age, sex, marital status, highest attained education, working status, family income, number of chronic conditions, diabetes duration and the 4 other neighborhood factors.
* p-Value < 0.05.

Table 3
Multiple linear regressions of log-transformed diabetes distress score by specific domains of diabetes distress

Neighborhood factors		Emotional distress β (95% CI)	Regimen-related distress β (95% CI)	Physician-related distress β (95% CI)	Interpersonal distress β (95% CI)
Order	Model 1	−0.04 (−0.06, −0.03) *	−0.03 (−0.04, −0.01) *	−0.03 (−0.05, −0.02) *	−0.04 (−0.06, −0.03) *
	Model 2	−0.03 (−0.05, −0.02) *	−0.02 (−0.04, 0.00) *	−0.02 (−0.04, 0.00) *	−0.03 (−0.05, −0.01) *
	Model 3	−0.04 (−0.06, −0.02) *	−0.02 (−0.04, 0.00)	−0.02 (−0.04, 0.00)	−0.03 (−0.05, −0.01) *
Culture	Model 1	−0.04 (−0.06, −0.02) *	−0.04 (−0.06, −0.02) *	−0.04 (−0.06, −0.03) *	−0.04 (−0.06, −0.02) *
	Model 2	−0.03 (−0.05, 0.00) *	−0.04 (−0.06, −0.02)	−0.02 (−0.04, 0.00)	−0.03 (−0.04, −0.01) *
	Model 3	−0.01 (−0.04, 0.01)	−0.03 (−0.05, −0.01)	−0.01 (−0.04, 0.01)	−0.01 (−0.03, 0.01)
Access	Model 1	−0.02 (−0.04, 0.00)	−0.01 (−0.03, 0.01)	−0.04 (−0.05, −0.02) *	−0.02 (−0.04, 0.00)
	Model 2	−0.02 (−0.04, 0.00)	−0.02 (−0.04, 0.00)	−0.04 (−0.05, −0.02) *	−0.02 (−0.04, 0.00)
	Model 3	−0.01 (−0.03, 0.01)	−0.01 (−0.03, 0.01)	−0.03 (−0.05, −0.01) *	−0.01 (−0.03, 0.01)
Material deprivation	Model 1	0.00 (−0.08, 0.07)	0.02 (−0.05, 0.09)	−0.03 (−0.10, 0.04)	−0.03 (−0.10, 0.04)
	Model 2	0.04 (−0.04, 0.13)	0.06 (−0.02, 0.14)	0.02 (−0.06, 0.10)	0.02 (−0.06, 0.09)
	Model 3	0.06 (−0.02, 0.15)	0.10 (0.02, 0.19) *	0.05 (−0.04, 0.13)	0.05 (−0.02, 0.13)
Social deprivation	Model 1	−0.04 (−0.11, 0.03)	−0.08 (−0.15, −0.01) *	0.03 (−0.04, 0.10)	−0.03 (−0.10, 0.03)
	Model 2	0.00 (−0.08, 0.08)	−0.03 (−0.11, 0.05)	0.06 (−0.01, 0.14)	−0.02 (−0.09, 0.06)
	Model 3	0.02 (−0.07, 0.10)	−0.02 (−0.10, 0.06)	0.05 (−0.03, 0.13)	0.01 (−0.07, 0.08)

Model 1: adjusted for age and sex.
Model 2: adjusted for age, sex, marital status, highest attained education, working status, family income, number of chronic conditions and diabetes duration.
Model 3: adjusted for age, sex, marital status, highest attained education, working status, family income, number of chronic conditions, diabetes duration and the 4 other neighborhood factors.
* p-Value < 0.05.

with lower physician-related distress. Several studies have found a significant association between the neighborhood environment and psychological wellbeing in the general population [31,32] and in subgroups with diabetes and other chronic conditions [21,33]. Our study adds to this growing literature by being the first to examine aspects of the neighborhood associated with diabetes distress. It is the first to examine factors related to the specific sub-domains of diabetes distress. It is also the first to investigate a range of neighborhood characteristics that relate to mental health in people with diabetes.

Perceived neighborhood physical and social order was associated with lower global and domain-specific diabetes distress in our sample. The concept of neighborhood disorder in social psychology suggests that areas characterized by physical disorder (such as deteriorated buildings, graffiti, noise and trash) and social disorder (such as crime and vandalism) instill fear and mistrust in residents, which in turn affects their mental well-being, their interactions with each other and their view of the environment [34,35]. Conversely, living in communities with high physical and social order might protect against diabetes-related interpersonal distress by providing opportunities for social connection and community support in a perceived safe environment [36]. Neighborhoods perceived as safe and orderly might also protect against regimen-related diabetes distress by facilitating outdoor physical activities such as walking or other forms of active transportation [37].

The perceived cultural and social neighborhood environment was particularly important for regimen-related distress. This neighborhood factor captures aspects of social cohesion and social norms of health in the community. Numerous studies have shown that social norms and values are determinants of self-efficacy and healthy behaviors [38–41]. In spite of good knowledge of diabetes self-care recommendations, people with diabetes might struggle to maintain a healthy lifestyle when their efforts are not valued by their community. Evidence suggests that social cohesion also relates to healthy behaviors such as adherence to treatment [42]. Social cohesion represents the ties, solidarity and connectedness among individuals living in the neighborhood. Socially cohesive neighborhoods could provide people with diabetes with a wider social network, greater social support and locally available assistance to help deal with the burden of managing their diabetes. Further, it is hypothesized that social cohesion facilitates sharing of information among community members, which could provide people with diabetes with better knowledge of available services and resources to self-manage their illness. In addition to regimen-related distress, we found that the perceived cultural and social neighborhood characteristics were relevant to global diabetes distress specifically in women. Others have also reported social elements of neighborhood to be more important in women than in men for mental health outcomes [43]. Women may be more sensitive to the social cues and norms of health behaviors in their neighborhood environment or may derive greater benefits from neighborhood social cohesion than men [44,45].

Perceived neighborhood access to services and resources was specifically associated with physician-related diabetes distress. Physician-related diabetes distress is a measure of satisfaction and trust in the diabetes-related services provided by the physician. Access to medical services in the neighborhood, or access to transportation to medical services outside the neighborhood, might allow patients with diabetes to seek satisfactory healthcare for their diabetes.

Neighborhood deprivation was not associated with global diabetes distress, but material deprivation was related to regimen-related distress in our sample. Communities with more material resources may be better equipped to provide people with diabetes with the support that they need for their regimen.

Because data in this study were cross-sectional, it is not possible to make inferences on the direction of causality. Although the neighborhood environment could be a potential risk factor for diabetes distress, it is also possible that people with higher levels of diabetes distress report worse neighborhood characteristics because they are distressed. Individuals with high general distress could also be more likely to report poor neighborhood environments and diabetes distress. Additional information on general distress would help to determine whether people are distressed because of their diabetes, or because they are distressed in general. Further, the association between poorly perceived neighborhood environment and diabetes distress could be a due to lack of knowledge about the available neighborhood resources for people with diabetes. For example, individuals with high levels of regimen-related diabetes distress could report fewer neighborhood resources to help with diabetes management because they are unaware of these services and facilities in their communities.

All survey data were self-reported which has potential for measurement error. Perceived neighborhood characteristics may not reflect objective characteristics. For instance, some individuals may misestimate availability of healthy food in their neighborhood [46]. When measuring perceived neighborhoods, neighborhood geographic boundaries were defined by participants in the survey, which may depend on individual-level factors, such as physical mobility. This study focused on individuals living in urban and semi-urban areas and findings may therefore not be generalizable to rural areas. Finally, the list of neighborhood characteristics examined in this study was extensive but not exhaustive. Other elements of the neighborhood environment could be important to diabetes distress.

This study is the first to investigate the neighborhood characteristics that relate to diabetes distress. It used a large representative sample of adults with type 2 diabetes and used both objective and subjective measures to characterize the neighborhood environment. We adjusted for important individual-level confounders. We carefully considered correlation issues in our analysis by combining items using factorial analysis and we accounted for missing data using multiple imputations in sensitivity analyses.

Neighborhood characteristics are relevant to diabetes distress in adults with type 2 diabetes, above and beyond the characteristics of individuals. Findings from this study have important clinical and public health implications for the management of diabetes. Clinicians should consider the neighborhood environment of their patients when assessing and addressing diabetes distress. Namely, clinicians are encouraged to discuss available neighborhood resources to help their patients deal with the stress of life with diabetes. Clinicians should also consider potential barriers in the neighborhood environment of their patients to manage life with diabetes. For instance, patients that report living in an area that they perceive as unsafe or threatening could be referred to safer perceived neighboring community centers for the practice of physical activity. Perception of poor neighborhood resources could also be an indicator of diabetes distress. Policy-makers should also consider urban and community policies that enhance neighborhood physical and social capital to protect the mental wellbeing of individuals with diabetes. For example, evidence from this study suggests that diabetes distress could be reduced by improving physical order in neighborhoods, such as trash and graffiti clean-up and restoration of buildings and green spaces. Further research is recommended to elucidate the direction of causality between the neighborhood environment and diabetes distress and intervention studies may be warranted to investigate strategies by which to reduce diabetes distress under unfavorable neighborhood conditions.

Conflict of interest statement

All authors have completed the Unified Competing Interest form at http://www.icmje.org/coi_disclosure.pdf.

The authors have no competing interest to report.

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Appendix 1. Factor loadings of neighborhood questionnaire items using 3-factor solution factorial analysis

	Factor 1 "Order"	Factor 2 "Society and culture"	Factor 3 "Access"
Neighborhood is well maintained	−0.67548	0.36132	0.26288
Pleasant to walk in the neighborhood	−0.56958	0.40894	0.29834
Busy roads to cross when out for walks	0.52442	−0.08593	0.21122
A lot of noise	0.64163	−0.15532	0.12228
A lot of unpleasant smells	0.59698	0.07438	−0.18137
Presence of heavy traffic	0.60777	−0.12077	0.11379
A lot of trash and litter on the street	0.69151	−0.16789	−0.01850
Vandalism	0.76996	−0.07816	0.13299
A lot of graffiti	0.75637	0.11848	0.19446
Adequate policing	−0.66613	0.17395	0.32445
Neighborhood is safe	−0.68115	0.47919	0.19322
Violence is not a problem	−0.67125	0.23681	0.15000
Too many people hang around on the streets near my home	0.60840	−0.01116	0.09267
Many trees along the streets	−0.13925	0.45389	0.09944
Buildings and houses are interesting	−0.42107	0.65917	0.18724
Interesting things to do in the neighborhood	0.02377	0.62746	0.30843
Often see people walking in the neighborhood	−0.05708	0.59719	0.17699
Often see people exercising in the neighborhood	0.02636	0.70342	0.12812
Many places to be physically active in the neighborhood	0.03010	0.65808	0.39672
People are friendly in the neighborhood	−0.44647	0.76670	0.13944
People are willing to help their neighbors	−0.13424	0.86558	0.06846
People can be trusted in the neighborhood	−0.48814	0.72779	0.00810
People share the same values in the neighborhood	−0.34655	0.80118	−0.13354
Park or walking trail within a short walk from my home	0.20706	0.45841	0.46516
Sidewalks on most streets	0.44554	−0.04523	0.55924
Easy to walk to a bus stop, train, or subway station from my home	0.14899	−0.03630	0.59662
Many places to go within walking distance from my home	0.16654	0.32548	0.56034
Access to shopping	−0.05643	0.12780	0.81494
Access to medical care	−0.17530	0.28253	0.60335
Access to a large selection of fresh fruits and vegetables	−0.13552	0.31041	0.66869
Access to large selection of healthy foods	−0.13281	0.38636	0.72178
Access to many fast food restaurants	−0.04630	0.04079	0.66209

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Manuscript III: Place and Health in Diabetes: the Neighbourhood Environment and Risk Of Depression in Adults with Type 2 Diabetes

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Place and health in diabetes: the neighbourhood environment and risk of depression in adults with type 2 diabetes

Running title: Neighbourhoods and depression in diabetes

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Conflict of interest disclosure

The authors report no conflicts of interest.

Novelty statement

- This 5-year cohort study is the first to examine neighbourhood effects on the risk of depression in type 2 diabetes.

- Data include a wide range of objective and subjective neighbourhood characteristics taken from several data sources, many of which have not yet been examined in diabetes.

- Results demonstrate that several neighbourhood characteristics impacted the risk of depression in a sample of people with type 2 diabetes.

- Interaction analysis further shows that some subgroups with diabetes were more vulnerable to the effect of neighbourhood on depression.

Abstract

Background: Depression is a common co-illness in people with diabetes. Evidence suggests that the neighbourhood environment impacts the risk of depression, but few studies have investigated this effect in those with diabetes. We examined the effect of a range of neighbourhood characteristics on depression in people with type 2 diabetes.

Methods: This cohort study used 5 waves of data from 1298 participants with type 2 diabetes from the Diabetes Health Study (2008-2013). We assessed depression using the Patient Health Questionnaire. We measured neighbourhood deprivation using census data; density of services using geospatial data; level of greenness using satellite imagery; and perceived neighbourhood characteristics using survey data. The effect of neighbourhood factors on risk of depression was estimated using survival analysis, adjusting for socio-demographic variables. We tested effect modification by age, sex and socioeconomic characteristics using interaction terms.

Results: A greater number of physical activity facilities, cultural services and level of greenness in the neighbourhood were associated with lower risk of depression in our sample, even after adjusting for confounders. Material deprivation was associated with increased risk of depression, particularly in participants who were older or retired.

Conclusions: Characteristics of neighbourhoods were associated with the risk of depression in people with type 2 diabetes and there were vulnerable subgroups in this association. Clinicians are encouraged to consider the neighbourhood environment of their patients when assessing the risk of depression. Future intervention research is needed for health policy recommendations.

Introduction

Diabetes is an increasingly prevalent chronic condition. In Canada, prevalence of diabetes was estimated at 9% in 2013 and is expected to reach 11% by 2020 [1]. Depression is a common co-illness in diabetes, affecting 10 to 30% of patients [2]. For individuals with diabetes, depression can substantially complicate their adjustment, disease course and health outcomes [3]. An understanding of the risk factors contributing to depression in diabetes has important clinical and public health implications.

Several clinical and behavioural risk factors for depression in diabetes have already been identified [4]. The broader neighbourhood context could be an important additional risk factor. Previous studies have reported neighbourhood effects on depression in the general population [5]. Individuals with diabetes could be a vulnerable group in this context. Dietary and exercise recommendations can be difficult to achieve in neighbourhoods with limited access to healthy food and safe places to exercise [6]. Neighbourhood deprivation has also been linked to poor medication adherence [7]. Neighbourhoods lacking social resources could limit the ability of individuals to socially function with their diabetes [8]. Living in a disadvantaged area also impacts physical health [9] and functioning [10], adding to the burden of diabetes and the vulnerability to depression. Only one cross-sectional study has examined neighbourhood and mental health in diabetes [11]. Using a sample of overweight individuals with type 2 diabetes, the authors found no significant association between neighbourhood deprivation and depressive symptoms. The study however focused on neighbourhood deprivation, but other neighbourhood characteristics

could also be important. There may be vulnerable subgroups within the population with diabetes for whom the effect of neighbourhood on depression is particularly salient. Evidence from samples of the general population suggests that gender, socioeconomic characteristics and social support could be relevant effect modifiers of neighbourhood effects on mental health [12, 13]. Longitudinal data are also needed to examine the impact of neighbourhood factors on the risk of depression. In short, there is a need for more evidence concerning the possible neighbourhood effects on mental health among people with diabetes [14].

In this study, we combined data from a representative sample with type 2 diabetes with census, geospatial and satellite imagery data to investigate the effect of a range of neighbourhood characteristics on the 5-year risk of depression in adults with type 2 diabetes and the potential moderating effect of socioeconomic variables and social support. We hypothesized that neighbourhood characteristics would be important risk factors for depression and that this effect would be amplified in some subgroups.

Methods

Study population

We used data from the Diabetes Health Study (DHS) [10] and the DHS sub-study [15]. Data from the sub-study were used because they provided information on perceived social and physical neighbourhood characteristics that were not available in the DHS. The DHS is a 5-year (2008-2013) population-based telephone survey of adults with diabetes from Quebec, Canada. Details on the DHS design can be found elsewhere [10].

Participants were recruited in 2008 through random digit dialling (n=2003, 62% response rate among those eligible) and followed-up annually. Eligible participants were between 18 and 80 years old and reported a diagnosis of diabetes (any type). Participants who agreed to be followed-up at baseline formed the sample of the cohort study (n= 1757). There was no sociodemographic difference between those who accepted and refused follow-up. In sensitivity analyses, including those who refused follow-up had minimal impact on results. Response rates were 74%, 66%, 66%, 61% and 59% for follow-ups 1 to 5, respectively. The final sample included 1298 participants with type 2 diabetes and without depression at baseline.

In 2011, we initiated a 3-year sub-study (2011-2013) using a sample of DHS participants. Participants with type 2 diabetes, who lived in non-rural areas, and participated in the 2011 DHS follow-up were asked to participate in a supplementary phone-interview 2-3 months following their DHS interview. A total of 680 participants accepted and 600 were subsequently interviewed. Follow-up interviews were conducted annually (response rates 81% and 76% for follow-ups 1 and 2, respectively). There were no differences in baseline socio-demographic characteristics between DHS sub-study participants and non-participants with type 2 diabetes, except that participants were more likely to be working (39.0% vs 31.5%, $p = 0.007$). For analysis of the DHS sub-study, we excluded participants with depression detected during a previous DHS survey (n=228), for a final sample of 372 individuals.

Study protocols were approved by the Research Ethics Committee of the Douglas Mental Health University Institute. All subjects participated voluntarily and provided informed consent.

Depression

The outcome of interest was depression. Depressive symptoms in the past 2 weeks were assessed using the Patient Health Questionnaire (PHQ-9) [16]. To meet criteria for depression, a person must have minor depression (2-4 symptoms) or major depression (>4 symptoms), present for more than half of the days, for at least 2 weeks, with at least one symptom being either depressed mood or loss of interest. In two meta-analyses [17, 18], the PHQ-9 diagnosis has shown good sensitivity (80% and 77%, respectively) and specificity (92% and 94%, respectively) compared with diagnosis based on structured interviews. Participants were asked if they had been prescribed antidepressants in the last year. Individuals taking antidepressants may not exhibit depressive symptoms and be misclassified as not depressed. In sensitivity analyses, we classified antidepressants use as meeting the criteria for depression.

Neighbourhood characteristics

Neighbourhoods were defined using a person-centered approach. We created a radius buffer around the centre of the postal code of participants to measure neighbourhood characteristics within the zone. Postal codes are alphanumeric codes that form part of the postal address in Canada. The median number of individuals living in a postal code is 17 in Quebec [19]. We conducted sensitivity analyses using different radius sizes (500m,

1000m, 1500m) and compared the strengths of associations and goodness of fit indices in univariate models. Results suggested that the 500m buffer radius had the strongest associations and overall best fit (appendix 1).

Neighbourhood deprivation

The Pampalon index was used to estimate neighbourhood material and social deprivation separately [20]. The index was constructed through a principal component analysis of six variables from 2006 census data. We constructed quintiles of deprivation, from least deprived (1^{st} quintile) to most deprived (5^{th} quintile), to stay consistent with previous literature.

Neighbourhood resources

Geospatial Canadian data [21] from 2008 were used to obtain information on density of businesses, parks and recreations, roads and land-use patterns. Businesses included number of health services, physical activity facilities, healthy food stores (stores offering fresh produces), fast-food restaurants and cultural services (museums, libraries and botanical gardens). Parks and recreation was modelled as the percentage of the neighbourhood used for parks and sports tracks. Density of express highways was used as proxy for traffic. Land-use pattern was measured using the land-use mix index, which varies between 0 and 1, where a higher score represents a greater mix of residential, commercial, parks, open area, industrial, and government and institutional land [3] (see Appendix 2 for details).

Neighbourhood greenness

Satellite imagery data from 2009 were used to estimate the level of greenness of neighbourhoods [22]. We computed the Normalised Differential Vegetation Index (NDVI), a validated measure of neighbourhood greenness [23]. The NDVI was transformed into deciles for ease of interpretation.

Perceived neighbourhood

We administered a neighbourhood questionnaire to participants in the DHS sub-study [15]. A factor analysis was used to combine the questionnaire items into three neighbourhood constructs: 1) "order" represented physical and social order in the neighbourhood (13 items; score range 0-13; standard deviation (SD) 1.7); 2) "society and culture" tapped into the social and cultural environment of neighbourhoods (10 items; score range 0-10; SD 1.7) "access" covered land use and access to services (9 items; score range 0-9; SD 1.7). A score for each neighbourhood factor was calculated by summing the number of endorsed items related to each factor.

Confounders

We included sex, age, marital status (married/common law; single; widowed/divorced/separated), family income (<15,000 CAD; 15,000-29.999 CAD; 30,000 to 49,999 CAD; 50,000 to 79,999 CAD; >80,000 CAD), educational level (low: < secondary school; medium: secondary school graduation; high: >secondary school) and employment (working full-time/part-time/student; not working; retired). We modelled marital status and employment as time-varying covariates lagged by 1 year. Race was not

included because the majority of the sample was white (94%).

Effect modifiers

We included age, sex, marital status, educational level, employment, family income and social support as potential effect modifiers based on previous research [12, 13]. Perception of social support was measured using the Medical Outcomes Study scale [24].

Statistical analysis

We ran analyses for each neighbourhood characteristic using an unadjusted and adjusted model controlling for confounders. We plotted Kaplan-Meier survival curves for depression onset and conducted survival analysis for discrete-time data using a generalized linear model with a complementary log-log link. We used a non-parametric specification for time using dummy variables for each survey cycle. Individuals with missing information on depression at one time point were right censored because a hiatus $\geq$ 2 years might contain a depression event which would be missed. We tested for the proportional hazard assumption by including an interaction term between each covariate and time variables. There was no evidence of assumption violation. We tested for non-informative censoring using weights inversely proportional to the probability of responding (see appendix 2 for description). There was no evidence of non-informative censoring (appendix 3). We checked for effect modification by adding interaction terms in fully adjusted models. For significant terms, we conducted stratified analyses and calculated marginal effects to check for effect modifications on the additive scale. We conducted several sensitivity analyses (methods and results in appendices 2-5). Results

were overall robust to sensitivity analyses. Preliminary analyses revealed 20% missing values on household income. Other covariates had <2% missing values. We used multiple imputations to test the impact of missing data on estimates. Results were similar to non-imputed data (appendix 3). We did not use multilevel modelling because neighbourhoods were person-centered resulting in a unique neighbourhood per individual.

We used a two-sided p-value of 0.05. Confidence intervals were estimated using bootstrapping (1000 iterations). To check for type II error due to multiple testing, we calculated a Bonferroni adjusted p-values from Monte Carlo permutation test (1000 iterations) for main effects. Statistical analyses were performed in STATA (version 12.1, StataCorp).

Results

Characteristics of the samples are presented in table 1. The mean baseline age of DHS participants was 60 years. The majority of participants was retired, partnered and reported a household income between 15,000 and 49,999 CAD. Participants in the DHS sub-study had similar characteristics. The 5-year cumulative incidence of depression in the DHS was 29%, with annual incidence of 14%, 11%, 12%, 8% and 5% for each follow-up year since the previous, respectively.

Table 2 presents hazard ratios of depression by neighbourhood characteristic. In fully adjusted models, the number of physical activity facilities (adjusted hazards ratio (AHR) 0.71, CI 0.55-0.91) and cultural services (AHR 0.75, CI 0.57-0.99) were significantly

associated with lower risk of depression. Estimate for physical activity facilities was robust to multiple testing correction (Bonferroni adjusted p-value = 0.01). A Kaplan-Meier survival curve for onset of depression by presence of physical activity facilities (none vs any) is illustrated in Figure 1. Level of greenness and material deprivation also had important effect sizes, but their confidence intervals crossed the null (AHR 0.94, CI 0.88-1.01 and AHR 1.12, CI 0.99-1.27, respectively). Other neighbourhood features were not associated with depression.

Analyses of effect modification revealed significant interactions between material deprivation and being older and retired. The effect of material deprivation on risk of depression was 1.01 higher for every additional year of age (p=0.014) and 1.28 higher for retired individuals compared to those working (p=0.042). In stratified analyses by age group, material deprivation increased the risk of depression only in those 65-80 years old (AHR 1.31, CI 1.05-1.64), not in those 18-44 (AHR 0.81, CI 0.56-1.18) and 45-64 years old (AHR 1.02, CI 0.88-1.19).The difference in hazard rate of depression for those aged 65-80 years old living in a high deprivation neighbourhood compared to those of the same age group living in a low deprivation area was 0.07 (CI 0.03, 0.10), all else being equal. This difference in hazard rate was smaller and not significant for those aged 45-64 (0.03, CI -0.002, 0.06) and 18-44 years old (-0.03, CI -0.11, 0.06). In stratified analyses by employment, material deprivation was significant only in people who were retired (AHR 1.27, CI 1.06-1.24), but not in those working (AHR 0.95, CI 0.77-1.16) and those not working (0.97, CI 0.74-1.28). The difference in hazard rate of depression for those

retired living in a high deprivation neighbourhood compared to those retired living in a low deprivation area was 0.05 (CI 0.02, 0.08). The difference in hazard rate was not significant for those employed (0.01, CI -0.02, 0.04) and those not working (0.00, CI -0.10, 0.10).

Discussion

This is the first cohort study to investigate the effect of a range of neighbourhood characteristics on the risk of depression in a sample of people with type 2 diabetes. Our results show that living in a neighbourhood with greater availability of physical activity facilities and cultural services was associated with lower risk of depression in people with type 2 diabetes from Quebec, Canada. There was also evidence that living in an area with higher levels of greenness reduced the risk of depression. Residing in a neighbourhood with higher material deprivation was a significant risk factor for depression, specifically in people with type 2 diabetes who were older and retired. These findings add to the body of evidence that characteristics of the neighbourhood environment matter for the risk of depression [5]. In the only previous study focused on people with diabetes [11], neighbourhood deprivation was not significantly associated with depressive symptoms. However, our findings suggest that it may be material deprivation specifically that affects depression in type 2 diabetes.

Living in a neighbourhood with more physical activity facilities was associated with lower risk of depression in our sample. This effect was robust to several sensitivity analyses. Results were particularly large and suggest that living in a neighbourhood with

one additional physical activity service was associated with a 30% reduction in risk of depression. People with type 2 diabetes are encouraged to exercise to manage their diabetes, but living in an area with few places to exercise may make it difficult to maintain an active lifestyle [25], which could be distressing for patients, and lead to diabetes complications and subsequent depression [26].

Residing in an area with more cultural services was associated with lower risk of depression. Cultural services have been hypothesized to promote social cohesion and trust [27], known to increase resilience to depression. In contrast to this hypothesis, better perceived social and cultural neighbourhood environment was not significantly associated with risk of depression in our sample, although point estimates supported a protective effect. It is possible that number of cultural services is a proxy for other neighbourhood characteristics, such as neighbourhood aesthetics. Future research in the pathways linking cultural services and depression is recommended.

Neighbourhood greenness was associated with a lower risk of depression in our study. Although green spaces have been shown to reduce stress, only one study investigated neighbourhood greenness specifically in depression [28]. The latter found that people living in areas with a moderate amount of green space had fewer depressive symptoms than those living in areas with no green space. Interestingly, the density of parks and recreational space was not associated with depression in our study. This suggests that living in a green environment, such as an area rich in tree cover, may have a stronger effect than living only in proximity to a park for people with diabetes.

Neighbourhood material deprivation was associated with a greater risk of depression in our sample. Several longitudinal studies have reported associations between neighbourhood socioeconomic characteristics and depressive symptoms [5], but not all [29]. Differences in measurement of deprivation might explain discrepancies. For instance, we found that material deprivation rather than social deprivation was an important risk factor for depression. We also found that participants who were older and retired were more vulnerable to this effect. Both the multiplicative and additive effects of material deprivation were larger in these subgroups. Older and retired individuals might spend more time in their neighbourhood thereby having a stronger exposure to local material deprivation.

Findings from our study should be interpreted in light of some limitations. Data on perceived neighbourhood characteristics could be biased, although measurement of residential environment from self-report has shown moderate validity [30]. There was no information on residential history. We only examined neighbourhood characteristics at one time point. Some neighbourhoods might have changed and participants could have moved during the study. Because effect modifiers were measured at the same time as neighbourhood characteristics, direction of effect modification could not be established. The PHQ-9 is a validated screening tool for depression, but it is not a clinical interview. The power to detect some neighbourhood effects was limited by the small effect neighbourhood environments have on depression and the small sample size of the DHS

sub-study. The study was conducted in Canada and may have limited generalizability. Replication of results in larger studies and in other neighbourhoods is warranted.

This study is strengthened by its use of a large population-based sampling of people with diabetes, a comprehensive range of neighbourhood characteristics and measurement of neighbourhood area using a person-centered approach. The use of several sensitivity analyses and appropriate analysis techniques are other strengths of our approach.

Characteristics of the neighbourhood contributed to the risk of depression in a sample of people with type 2 diabetes. Some vulnerable subgroups were identified. For clinicians, results suggest that the neighbourhood environment should be taken into account when assessing the risk of depression, particularly for some subgroups. For policy-makers and urban planners, this study identified neighbourhood characteristics and subgroups that were important for depression in adults with type 2 diabetes. Future research on the effect of a policy or program to change the characteristics of neighbourhoods is needed to infer if changing neighbourhood characteristics would have a causal effect on risk of depression.

Conflicts of Interests

The authors report no conflicts of interest.

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Figure 1. Kaplan-Meier survival curve of depression by presence of physical activity facility (none vs any) in DHS participants without depression at baseline

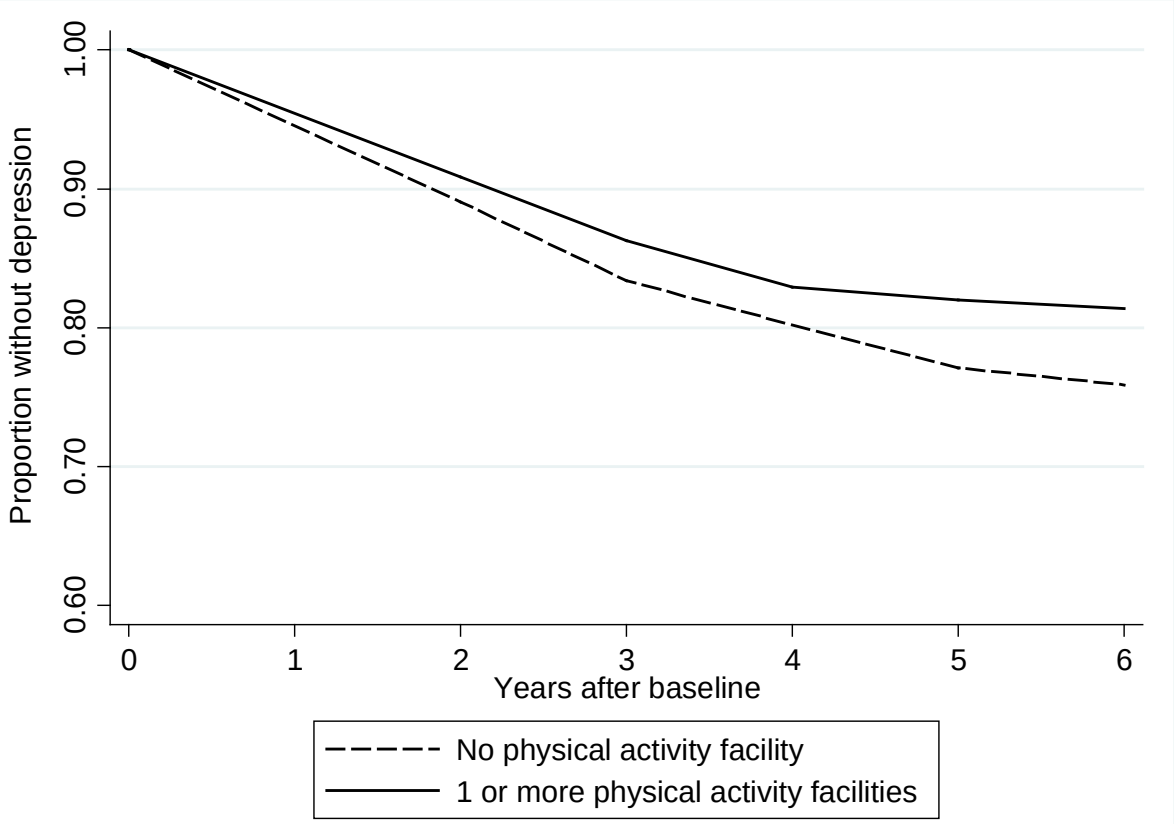

Table 1. Characteristics DHS and DHS sub-study participants without baseline depression

Variables (%, n)	DHS participants *n=1298*	DHS sub-study participants *n=348*
Sex		
Female	51.2 (664)	48.1 (179)
Male	48.8 (634)	51.9 (193)
Age in years (mean, SD)	59.8 (11.0)	58.7 (11.43)
Educational level		
Low: < secondary school	39.3 (501)	34.0 (124)
Middle: secondary school graduation	28.1 (358)	27.7 (101)
High:>secondary school	32.7 (417)	38.3 (140)
Employment		
Working full-time/part-time/student	39.1 (506)	42.5 (158)
Not working	13.8 (179)	11.0 (41)
Retired	47.1 (610)	46.5 (173)
Marital Status		
Married/Common law	64.7 (839)	67.2 (250)
Divorced/ Separated/Widowed	23.8 (308)	21.0 (78)
Single	11.5 (149)	11.8 (44)
Family income		
No income and less than $15,000	14.4 (151)	9.7 (29)
$15,000 to $29,999	23.9 (250)	17.8 (53)
$30,000 to $49,999	27.0 (282)	28.5 (85)
$50,000 to $79,999	17.2 (180)	22.8 (68)
$80,000 or more	17.5 (183)	21.1 (63)
Social support score (mean, SD)	65.9 (27.5)	68.9 (27.7)

Table 2. Hazard ratios of incident depression in relation to census-based, and geospatial neighbourhood characteristics

Neighbourhood variable (sample size)	**Unadjusted model** HR [95% CI]	**Fully adjusted model** HR [95% CI]
Material deprivation (quintile)	1.21***	1.12
(n=1197)	[1.09,1.35]	[0.99,1.27]
Social deprivation (quintile)	1.07	1.00
(n=1197)	[0.96,1.19]	[0.88,1.14]
Express highways (per km^2)	1.37	1.22
(n=1197)	[0.99,1.90]	[0.72,2.08]
Parks and recreation (% per area)	1.12	1.38
(n=1052)	[0.15,8.43]	[0.17,10.95]
Land-use mix index	1.78	1.63
(n=1052)	[0.91,3.46]	[0.72,3.70]
Fast food restaurants (number/area)	1.01	0.98
(n=1198)	[0.95,1.07]	[0.91,1.06]
Health services (number/area)	1.00	0.98
(n=1198)	[0.96,1.04]	[0.92,1.04]
Healthy food stores (number/area)	1.01	0.98
(n= 1198)	[0.93,1.10]	[0.88,1.09]
Physical activity facilities (number/area) (n= 1198)	0.74** [0.59,0.93]	0.71** [0.55,0.91]
Cultural services (number/area)	0.82	0.75*
(n= 1198)	[0.64,1.05]	[0.57,0.99]
Vegetation Index (decile)	0.92**	0.94
(n=716)	[0.87,0.97]	[0.88,1.01]

Source: DHS 2008-2013
Fully-adjusted model adjusted for age, sex, educational level (time-fixed); marital status, employment status, family income (time-varying, lagged 1 year)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3. Hazard ratios of depression of perceived neighbourhood characteristic

Neighbourhood variable (sample size)	**Unadjusted model** HR [95% CI]	**Fully adjusted model** HR [95% CI]
Physical and social order (n=343)	0.97 [0.78,1.20]	1.01 [0.75,1.39]
Cultural and social environment (n=328)	0.89 [0.72,1.11]	0.93 [0.70,1.15]
Access to services (n=346)	0.93 [0.77,1.13]	0.96 [0.79,1.24]

Source: DHS sub-study 2011-2013

Fully-adjusted model adjusted for age, sex, educational level (time-fixed); marital status, employment status, family income (time-varying, lagged 1 year)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendices

Appendix 1. Hazard ratio, Akaike information criterion (AIC) and Bayesian information criterion (BIC) of univariate model using 500m, 1000m and 1500m

	500m	**1000m**	**1500m**
Material deprivation (quintile)			
HR	1.21***	1.23***	1.20**
AIC	1842.46	1841.82	1846.34
BIC	1879.03	1878.39	1882.90
Social deprivation (quintile)			
HR	1.07	1.02	1.05
AIC	1854.18	1855.67	1855.17
BIC	1890.75	1892.23	1891.73
Express highways (per km^2)			
HR	1.37	1.10	0.99
AIC	1853.15	1855.05	1855.97
BIC	1889.72	1891.62	1892.53
Parks and recreation (% per area)			
HR	1.12	0.90	0.15
AIC	1627.36	1628.83	1636.77
BIC	1663.16	1664.65	1672.59
Land-use mix index			
HR	1.78	1.66	1.06
AIC	1624.51	1627.21	1638.61
BIC	1660.31	1663.02	1674.43
Fast food restaurants (number/area)			
HR	1.01	1.00	1.00
AIC	1855.88	1855.76	1855.88
BIC	1892.45	1892.33	1892.45
Health services (number/area)			

HR	1.00	1.00	1.00
AIC	1855.98	1855.87	1855.83
BIC	1892.55	1892.44	1892.39
Healthy food stores (number/area)			
HR	1.01	1.01	1.01
AIC	1855.89	1855.89	1855.24
BIC	1892.46	1892.46	1891.81
Physical activity facilities (number/area)			
HR	0.74**	0.97	1.01
AIC	1847.44	1855.09	1855.76
BIC	1884.00	1891.66	1892.33
Cultural services (number/area)			
HR	0.82	0.97	0.99
AIC	1853.01	1855.36	1855.77
BIC	1889.58	1891.92	1892.33
Vegetation Index (decile)			
HR	0.92**	0.90***	0.89***
AIC	1006.43	1003.38	1001.94
BIC	1039.87	1036.82	1035.38

Source: DHS 2008-2013

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

AIC: Akaike information criterion (lower scores indicate better fit)

BIC: Bayesian information criterion (lower scores indicate better fit)

Appendix 2. Methods and Results of Sensitivity Analyses

Methods

We tested for non-informative censoring using weights inversely proportional to the probability of responding, as a function of sociodemographic variables, duration of diabetes (in years), number of diabetes complications, disability (substantial disability vs not), self-rated health (good/very good/excellent vs fair/poor), and smoking (current smoker vs former/never smoker). The exclusion of individuals with depression at baseline could result in selection bias. We 1) compared characteristics between those depressed and not depressed at baseline, 2) included in the analyses those who were depressed at baseline but adjusted for baseline depression, and 3) used inverse probability weighting of depression. We conducted additional analyses where use of antidepressants was classified as meeting the criteria for depression. We examined the effect of excluded rural dwellers on estimates because data from rural areas may be less accurate. We assessed the potential for structural confounding using a propensity-score matched sample. Structural confounding occurs when there is insufficient overlap in the background characteristics between participants residing in different neighbourhoods to estimate the effects of neighbourhoods (e.g., only individuals with high socioeconomic position live in rich neighbourhoods, and individuals with low socioeconomic position live in poor neighbourhoods). This could lead to off-support inference based purely on model extrapolation. Propensity score matching addresses this issue by matching together individuals that are as likely to live in a given neighbourhood given their individual characteristics. Individuals that are not matched are discarded from analysis. To compute propensity scores, we dichotomized each neighbourhood characteristics to stay consistent

with current practice of propensity scoring methods. We dichotomized variables by top 2 quintiles vs bottom 3 quintiles for continuous variables or by the presence vs absence of the characteristic for count values. For each neighbourhood characteristic, we calculated the probability that an individual would live in an area with the neighbourhood characteristic, compared to an area without, given their known individual-level variables[56,57]. We used multivariate logistic regression to model propensity scores as a function of all baseline individual-level variables described for previous models, as well as other variables thought to affect risk of depression, including duration of diabetes (in years), self-rated health (good/very good/excellent vs fair/poor), diabetes control (good/very good/excellent vs fair/poor), number of diabetes complications, number of chronic conditions, presence of disability (substantial disability vs not) and lifestyle factors of smoking (current smoker vs former/never smoker), physical inactivity (<15 minutes of activity in last month vs more ≥ 15 minutes) and body-mass index (kg/m^2). We included all possible two-way interaction terms in the model. We set a caliper of ± 0.05 and matched participants on their propensity score, with replacement, until no more matches were found. In sensitivity analysis, we used a ± 0.01 caliper width which did not result in any appreciable difference. We then ran analyses for risk of depression with only matched participants and used weights for the number of times a participant was matched to another. Propensity score was calculated using PSMATCH2 in STATA.

Results

Results were robust to several sensitivity analyses. In assessing selection bias by depression status, we found some differences in baseline characteristics between people with and without depression at baseline (appendix 4); however, weighted analyses using

inverse probability of depression provided results consistent with unweighted analyses (appendix 3). Analyses that included people with baseline depression and adjusted for baseline depression also provided similar results, except that neighbourhood greenness was significant. Effect sizes were similar when we defined the outcome as either depression or taking antidepressants (appendix 3), although results were no longer statistically significant. Results were not substantially changed when excluding rural-dwellers (appendix 5). Propensity score matched samples provided similar estimates to non-matched samples (appendix 3), except that coefficients were larger and statistically significant for material deprivation, land-use mix and greenness.

Appendix 3. Results of sensitivity analyses using multiple imputations for missing values, weights for inverse probability of censoring, broader definitions of depression and propensity-score matching

	Using complete data HR [95% CI]	Using MI data HR [95% CI]	Weighted sample using complete data and complete data for weight calculations HR [95% CI]	Weighted sample using complete data and MI data for weight calculations HR [95% CI]	Weighted sample using MI data and MI data for weight calculations HR [95% CI]	Outcome defined as depression or past-month use of antidepressant HR [95% CI]	Weighted sample using inverse probability of depression HR [95% CI]	Propensity score matched analyses HR [95% CI]
Material deprivation (quintile)	1.12 [0.99,1.27]	1.14 [0.96,1.34]	1.04 [0.88,1.23]	1.06 [0.91,1.23]	1.07 [0.93,1.24]	1.05 [0.95,1.17]	1.19* [1.01,1.40]	1.69*** [1.47,1.94]
Social deprivation (quintile)	1.00 [0.88,1.14]	1.00 [0.84,1.17]	0.98 [0.83,1.15]	0.94 [0.81,1.09]	0.94 [0.81,1.09]	1.00 [0.90,1.12]	1.00 [0.84,1.20]	1.02 [0.91,1.14]
Express highways (per km^2)	1.22 [0.72,2.08]	1.26 [0.77,2.05]	0.79 [0.34,1.85]	0.87 [0.45,1.67]	0.87 [0.45,1.67]	1.14 [0.82,1.58]	0.70 [0.36,1.39]	1.07 [0.84,1.36]
Parks and recreation (% per area)	1.38 [0.17,10.95]	2.58 [0.29,22.87]	2.00 [0.09,45.64]	1.87 [0.30,11.75]	1.83 [0.28,12.03]	1.75 [0.29,10.41]	0.52 [0.02,11.44]	12.93 [0.62,270.89]
Land-use mix index	1.63 [0.72,3.70]	2.16 [0.86,5.44]	1.43 [0.55,3.73]	1.41 [0.56,3.56]	1.48 [0.63,3.44]	1.61 [0.83,3.10]	1.63 [0.63,4.21]	4.93** [1.49,16.37]
Fast food restaurants (number/area)	0.98 [0.91,1.06]	0.99 [0.91,1.08]	1.00 [0.92,1.08]	0.98 [0.91,1.06]	0.98 [0.91,1.06]	1.03 [0.98,1.09]	1.04 [0.98,1.11]	0.97 [0.88,1.07]
Health services (number/area)	0.98 [0.92,1.04]	0.98 [0.91,1.06]	0.99 [0.93,1.06]	0.97 [0.93,1.02]	0.98 [0.93,1.02]	0.98 [0.93,1.03]	1.01 [0.95,1.07]	1.00 [0.92,1.08]
Healthy food stores	0.98 [0.88,1.09]	0.98 [0.86,1.11]	1.00 [0.87,1.15]	0.97 [0.85,1.10]	0.97 [0.86,1.09]	1.02 [0.94,1.11]	1.01 [0.89,1.15]	1.01 [0.89,1.14]

(number/area)								
Physical activity facilities (number/area)	0.71**	0.68*	0.73*	0.71**	0.70**	0.85	0.76*	0.86
	[0.55,0.91]	[0.49,0.94]	[0.55,0.97]	[0.54,0.92]	[0.53,0.90]	[0.71,1.02]	[0.59,0.99]	[0.64,1.15]
Cultural services (number/area)	0.75*	0.93	0.77	0.78	0.83	0.86	0.84	0.90
	[0.57,0.99]	[0.69,1.24]	[0.57,1.04]	[0.58,1.04]	[0.61,1.13]	[0.69,1.08]	[0.63,1.11]	[0.63,1.29]
Vegetation Index (decile)	0.94	0.94	0.95	0.97	0.97	0.96	0.93	0.94*
	[0.88,1.01]	[0.87,1.02]	[0.86,1.03]	[0.89,1.05]	[0.89,1.05]	[0.91,1.02]	[0.85,1.01]	[0.88,0.99]

Exponentiated coefficients; 95% confidence intervals in brackets
Source: DHS 2008-2013 and MEGAPHONE data
All models adjusted for age, sex, education (time-fixed); marital status, employment status, family income (time-varying, lagged 1 year)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix 4. Characteristics of DHS participants without depression at baseline (cohort of current study) and with depression (excluded from study) and who agreed to follow-up
Source: DHS 2008

Variables (%, n)	DHS participants without baseline depression *n=1298*	DHS participants with baseline depression *n=322*
Sex		
Female	51.2 (664)	62.4 (201)
Male	48.8 (634)	37.6 (121)
Age in years (mean, SD)	59.8 (11.0)	58.7 (11.9)
Education		
Less than secondary school	39.3 (501)	52.6 (169)
Secondary school graduation	28.1 (358)	27.4 (88)
Some post-secondary school	32.7 (417)	19.9 (64)
Work status		
Working full-time/part-time/student	49.1 (506)	21.7 (70)
Not working	13.8 (179)	32.9 (106)
Retired	47.1 (610)	45.3 (146)
Marital Status		
Married/Common law	64.7 (839)	52.6 (169)
Divorced/ Separated/Widowed	23.8 (308)	33.3 (107)
Single	11.5 (149)	14.0 (45)
Income		
No income and less than $15,000	14.4 (151)	31.7 (85)
$15,000 to $29,999	23.9 (250)	26.5 (71)
$30,000 to $49,999	27.0 (282)	22.0 (59)
$50,000 to $79,999	17.2 (180)	11.9 (32)
$80,000 or more	17.5 (183)	7.8 (21)
Social support score (mean, SD)	65.9 (27.5)	58.7 (25.6)

Appendix 5. Hazard ratios of depression of census-based and geospatial neighbourhood characteristics by urbanicity

	Urban and semi-urban n=1034 HR [95% CI]	**Rural** n=264 HR [95% CI]
Material deprivation (quintile)	1.12 [0.98,1.29]	1.09 [0.69,1.74]
Social deprivation (quintile)	1.02 [0.89,1.17]	1.00 [0.72,1.40]
Express highways (per km^2)	1.25 [0.83,1.88]	1.00 [1.00,1.00]
Parks and recreation (% per area)	1.29 [0.17,9.81]	50934.92 [0.03,8.99e+10]
Land-use mixity index	1.82 [0.84,3.98]	0.20 [0.01,4.46]
Fast food restaurants (number/area)	1.00 [0.93,1.07]	0.20 [0.03,1.38]
Health services (number/area)	0.98 [0.94,1.04]	0.46 [0.14,1.45]
Healthy food stores (number/area)	1.00 [0.90,1.11]	0.57 [0.21,1.52]
Physical activity facilities (number/area)	0.70** [0.54,0.91]	0.89 [0.29,2.77]
Cultural services (number/area)	0.73* [0.55,0.98]	1.50 [0.48,4.66]
Vegetation Index (decile)	0.94 [0.88,1.01]	N/A[a]

Source: DHS 2008-2013
Fully-adjusted model adjusted for age, sex, education (time-fixed); marital status, employment status, family income (time-varying, lagged 1 year)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] Vegetation index was unavailable for rural areas

6 | Mechanisms Linking Neighbourhood Characteristics and Depression in People with Diabetes

There has long been a call for researchers to derive theories and test some of the mechanisms by which neighbourhood characteristics affect depression and other health outcomes.[31-34,58] In Chapter 2, I developed a conceptual framework that laid ground for this thesis research. Chapter 2 highlights potential mediators that have been proposed in the literature. In this chapter, I tested mediating pathways using a method recently developed by Lange and Hansen.[148] Van Ham and Manley argued that unpacking the black-box that is neighbourhood effect is the first challenge for furthering neighbourhood research.[58] Mair, Diez Roux and Galea echoed this call by stating that this type of research is "fundamental to strengthening causal inference".[31] In addition to furthering research, identification of the pathways linking neighbourhood characteristics to depression can help identify which proximal risk factors of depression, such as lifestyle behaviours, are influenced by the neighbourhood environment. An understanding of these intermediate variables may assist future research to identify where neighbourhood interventions or policies would likely be most effective.

As described in Chapters 2 and 3, part of the original objective 3 of this thesis was to test for pathways in adults with and without a chronic condition. However, analyses did not find any significant associations between neighbourhood characteristics and risk of depression in samples of adults with and without a chronic condition in the NPHS, except in specific vulnerable subgroups (Manuscript I). Consequently, I focused mediation analysis on the sample of adults with type 2 diabetes from the DHS, where significant associations were found between neighbourhood physical activity facilities and cultural services with risk of depression (Manuscript III).

Results of this chapter were presented at the 2014 Society of Epidemiology Conference in Seattle (oral presentation) and are in preparation for submission to the *International Journal of Methods in Psychiatric Research*.

METHODS

STUDY SAMPLE AND DATA COLLECTION

This analysis used the DHS sample and dataset as described in Manuscript III. The study here focused only on the two neighbourhood characteristics that were found to be significant risk factors for depression in people with type 2 diabetes: neighbourhood physical activity facilities and cultural services.

MEDIATING VARIABLES

Based on the conceptual model outlined in Chapter 2, I included the following mediating variables that were available in the DHS dataset:

Health behaviours (available all DHS cycles) included smoking (current smoker vs former/never smoker), physical inactivity (<15 minutes of activity in last month vs ≥ 15 minutes) and perceived diabetes control (good/very good/excellent vs fair/poor). Physical inactivity was measured by asking participants to estimate the number of days they exercised or participated in sports activity for at least 15 minutes in the last month. Participants that reported 0 day were classified as inactive. Perceived diabetes control was assessed by asking participants "in the past month, would you say that the control of your diabetes was…". Responses were dichotomized as excellent/very good/good vs fair/poor. In a previous study, we found this single-item measure to have good validity in the DHS study sample.[149]

Health and functions (available all DHS cycles): Self-rated health was captured by the question "In general, would you say your health is excellent, very good, good, fair or poor?" This single item is a strong and independent predictor of morbidity and mortality.[150] Number of diabetes complications was measured through the Diabetes Complications Index (DCI), a 17-item survey used to assess diabetes complications based on patient self-report.[151] The variable was dichotomized in the analysis (no complication vs 1 or more). Body-mass index (BMI; kg/m^2) was calculated from self-reported weight and height. Obesity was ascertained using a BMI cut-off ≥ 30, in accordance with international standards adopted by the WHO.[152] Global disability level was assessed using the 12-item World Health Organization Disability Assessment Schedule II.[153] The scale disability domains include self-care, mobility, understanding and communication, interpersonal relations, work/domestic responsibilities, and participation in activities. The instrument provides a reliable and valid measure of global disability.[154] Scores on the disability scale were log-transformed (log of score+1) because distribution was highly skewed in the sample.

CONFOUNDING VARIABLES

As recently highlighted in the causal inference literature, mediation assessment requires a specific set of assumptions regarding confounding to estimate natural indirect effects, including no unmeasured confounding for the exposure-outcome, exposure-mediator and mediator-outcome relationships; and no exposure-dependent confounders.[155-157] Other assumptions are discussed later in this chapter. I therefore adjusted for confounding variables of the relationships that were available in the DHS, including age, sex, marital status (married/common-law; single/never married; divorced/separated/ widowed), education level (less than secondary school graduation; secondary school graduation; post-secondary school), and household income

(<15,000 CAD; 15,000-29.999 CAD; 30,000 to 49,999 CAD; 50,000 to 79,999 CAD; >80,000 CAD). Time-varying variables were lagged by 1-year to better take into account time order.

Data Analysis: Mediation analysis

For the neighbourhood characteristics that were previously found to be significant risk factors for depression in people with diabetes (i.e., neighbourhood physical activity facilities and cultural services), I estimated their direct effect on depression and their indirect effect as mediated by behavioral and health factors. I conducted mediation analyses using the Aalen additive hazards model[158] and the approach described by Lange and Hansen[148,159]. Similar to the proportional hazards model, the Aalen additive hazards model is a flexible model appropriate for survival data, but it estimates hazards difference instead of hazard ratios. It models the hazard as a linear function of the explanatory variables plus an unspecified baseline hazard. Effect estimates can therefore be directly interpreted as the number of additional cases of depression per person-year associated with the covariate. The additive hazards model approach allows both the covariates themselves and the effect of these variables to change with time, which is relevant in the study (e.g., health status is likely to change over time since diabetes is a progressive disease). The use of hazard difference is useful when conducting mediation analysis because it does not suffer from the problem of non-collapsibility that hazard ratios might have.

The indirect effect of neighbourhood on depression through the mediator is estimated using two steps. In a first step, I estimated the effect of the neighbourhood factor on the mediator, adjusted for confounders (age, sex, education (time-fixed); marital status, employment status, family income (time-varying, lagged 1 year)). I used logistic regression for mediators that were binary variables and linear regression for those that were continuous variables. I checked if the

coefficients of the covariates needed to be time-dependent. None of the covariates were significantly time-dependent and I therefore modelled coefficients as time-fixed in the model to increase power. In a second step, I estimated the effect of both the neighbourhood factor and the mediator on the risk of depression by fitting the additive hazards model using year as the time scale. I tested for proportional hazard assumption using the Kolmogorov-Smirnov test. None of the variables violated the proportionality assumption. The indirect effect through a mediator was given by the product of the parameter estimate of the neighbourhood factor on the mediator from the logistic or linear regression model and the parameter estimate of the mediator on depression from the additive hazards model. The direct effect of the neighbourhood exposure was given directly from the additive hazards model. Confidence intervals were calculated using the bootstrap method and 20,000 replications. Analyses were conducted in R (version 2.15.2; www.r-project.org) using the timereg package.[160] Because the function breaks ties with random noise, the sum of the direct and indirect effect using the additive hazards model may not exactly equate the total effect estimated from the model without the mediator.[161] Implementation details were provided in the appendix of the paper by Lange and Hansen[148] and elsewhere[162].

ASSUMPTIONS

The additive hazards approach to mediation analysis attempts to estimate the natural direct effect and natural indirect effect of a neighbourhood characteristic on depression after accounting for a mediator.[157] Specifically, the natural direct effect estimates how much the outcome would change on average if the neighbourhood exposure was set at level $a=1$ versus level $a=0$ but each individual the mediator was kept at the level it would have taken if $a=0$. The natural indirect effect shows how much the outcome would change on average if the neighbourhood exposure was controlled at level $a=1$, but the mediator was changed from the level it would take if $a=0$ to

the level it would take if *a=1*. In order to reasonably estimate the nature direct and indirect effects, the following assumptions, conditional on covariates, are required to be met: 1) no confounding in the exposure-outcome association, 2) no confounding in the mediator-outcome association, 3) no confounding in the exposure-mediator association, 4) no mediator-outcome confounder that is affected by the exposure, and 5) no interaction between the exposure and the mediator.[155-157] In this study, I assumed that conditions 1) to 4) were met after adjusting for relevant confounders, although, as in most observational studies, it is possible that unmeasured confounding still be a problem. For assumption 5), I tested for interaction between the neighbourhood exposure and the potential mediator using an interaction term in the model. None of the interaction terms were significant.

ADDITIONAL ANALYSES

I compared the traditional difference method approach[163] (i.e. testing the effect of adding a mediator in the model on the estimate of the exposure) to assess whether results from the additive hazards model approach were dependent on model assumptions. I used the fully-adjusted clog-log model described in Chapter 5 and added a mediator one at a time in the model to check the effect this would have on the coefficient of the neighbourhood characteristic. I also assessed mediation using marginal structural modelling (MSM).[164] The mediators in the association between neighbourhood factors and depression might also be time-dependent confounders of the relationship. The MSM can overcome this situation by using weights to take into account the probability that individuals are exposed to the mediator to which they were actually exposed to. Further details on implementation of MSM can be found elsewhere.[145] I accounted for both probabilities of exposure to the mediator and of censorship in the MSM weights. I used the probability of censorship model that was previously developed in the DHS

(described in Chapter 5). I developed different models for propensity of exposure for each potential mediator. The traditional difference approach and MSM were performed using STATA (version 12.1). Confidence intervals for coefficients using the traditional difference approach were estimated using the robust option in STATA and confidence intervals in the MSM were estimated using the cluster option in STATA to allow clustering of data on the same person.

RESULTS

PATHWAYS FROM PHYSICAL ACTIVITY FACILITIES TO DEPRESSION

Table 6.1 presents results of the mediation analysis using the additive hazards approach, the traditional difference approach and MSM. The first line of the table shows the total effect of physical activity facilities on risk of depression, without any mediator. The following lines of the table show the direct and indirect effects of physical activity facilities when each mediator is included in the model. Mediators were included in the model one at a time. In the additive hazards approach, a mediator is considered significant if the coefficient of the indirect effect of physical activity through the mediator is significant. In the traditional differences and MSM method, a mediator is considered important if the total effect of the estimate changes when the mediator is accounted for in the model. Results of the additive hazards model are presented on an additive scale, where a negative coefficient represents a reduction in the number of cases of depression per 1000 person-year; results of the traditional differences approach and MSM are based on the proportional hazards model and are on a multiplicative scale, where a coefficient less than 1 represents a lower relative risk of depression.

Using the additive hazards model, I found that living in a neighbourhood with more physical activity facilities significantly decreased the number of depression cases by an average of 16 per

year per 1000 individuals with diabetes (HD -16.1, 95% CI -27.2, -5.0). Of these 16 cases, 5 cases (HD -5.3, 95% CI -11.5, -0.4) could be attributed to the effect of neighbourhood physical activity resources on diabetes complications and 4 cases (HD -3.7, 95% CI -7.1, -0.7) on disability score. Surprisingly, physical activity facilities negatively affected self-rated health in the sample, which resulted in an increased number of depression cases through this pathway (HD 21.6, 95% CI 2.3, 44.0).

Using the traditional approach to mediation analysis, the coefficient for the total effect of physical activity facilities on depression remained largely unchanged even after adjusting for time-varying physical inactivity, smoking, diabetes control, self-rated health, obesity, diabetes complication and disability score. Using MSM, the coefficient for the total effect also remained relatively unchanged, except that the protective effect of neighbourhood physical activity facilities on depression became stronger after adjusting self-rated health.

PATHWAYS FROM CULTURAL SERVICES TO DEPRESSION

Table 6.2 presents results of the mediation analysis for cultural services. Using the additive hazards model, living in a neighbourhood with more cultural services significantly decreased the number of depression cases by an average of 17 per year per 1000 individuals with diabetes (HD -17.5, 95% CI -32.3, -2.8). None of these cases could be significantly attributed to a specific mediator. These results were also found using the traditional difference approach and MSM, where the total effect of cultural services remained largely unchanged after adjusting for the mediators in the models.

TABLE 6.1 ESTIMATES OF THE INDIRECT AND DIRECT EFFECT OF NUMBER OF **PHYSICAL ACTIVITY FACILITIES** ON DEPRESSION USING THE ADDITIVE HAZARDS APPROACH AND THE DIRECT EFFECT USING THE TRADITIONAL DIFFERENCE METHOD' AND MARGINAL STRUCTURAL MODELLING.

	Indirect effect	**Direct effect**		
Mediator	Additive hazards method HD (and 95% CI) by 1,000 person-year	Additive hazards method HD (and 95% CI) by 1,000 person-year	Traditional difference method HR (and 95% CI)	MSM method[a] HR (and 95% CI)
No mediator		-16.1 (-27.2, -5.0)	0.71 (0.55, 0.91)	0.71 (0.55, 0.91)
Physical inactivity	1.2 (-6.1, 9.1)	-16.8 (-28.4, -5.9)	0.71 (0.55, 0.92)	0.63 (0.43, 0.92)
Current smoking	-2.7 (-10.3, 2.1)	-14.8 (-27.4, -3.5)	0.74 (0.57, 0.95)	0.72 (0.53, 0.98)
Fair to poor diabetes control	0.8 (-7.6, 9.4)	-16.5 (-27.9, -5.2)	0.74 (0.58, 0.94)	0.64 (0.47, 0.87)
Fair to poor self-rated health	21.6 (2.3, 44.0)	-20.0 (-31.5, -8.6)	0.69 (0.54, 0.88)	0.48 (0.26, 0.89)
Obesity	0.1 (-0.3, 0.6)	-16.8 (-28.1, -5.7)	0.74 (0.58, 0.95)	0.71 (0.52, 0.97)
Presence of diabetes complications	-5.3 (-11.5, -0.4)	-14.6 (-25.7, -3.4)	0.75 (0.58, 0.97)	0.67 (0.48, 0.94)
Disability score (log)	-3.7 (-7.1, -0.7)	-14.1 (-25.4, -2.8)	0.73 (0.56, 0.94)	0.64 (0.46, 0.90)

All models adjusted for age, sex, education, marital status, employment status, and household income.
[a]Physical activity facilities dichotomized as present vs absent in MSM analysis
[b]Disability is dichotomized as substantial vs not substantial in MSM analysis

TABLE 6.2. ESTIMATES OF THE INDIRECT AND DIRECT EFFECT OF NUMBER OF **CULTURAL SERVICES** ON DEPRESSION USING THE ADDITIVE HAZARDS APPROACH AND OF THE DIRECT EFFECT USING THE TRADITIONAL DIFFERENCE METHOD' AND MARGINAL STRUCTURAL MODELLING.

	Indirect effect	**Direct effect**		
Mediator	Additive hazards method HD (and 95% CI) by 1,000 person-year	Additive hazards method HD (and 95% CI) by 1,000 person-year	Traditional difference method HR (and 95% CI)	MSM method[a] HR (and 95% CI)
No mediator		-17.5 (-32.3, -2.8)	0.75 (0.57,0.99)	0.80 (0.57,1.10)
Physical inactivity	-4.5 (-13.9, 2.4)	-20.7 (-34.5, -6.5)	0.71 (0.53,0.95)	0.74 (0.51,1.05)
Current smoking	-4.3 (-14.0, 1.8)	-16 (-31.7, -1.0)	0.75 (0.57,0.99)	0.83 (0.44,1.59)
Fair to poor diabetes control	-6.3 (-18.7, 3.4)	-16.8 (-31.1, -2.1)	0.75 (0.56,0.99)	0.84 (0.45,1.55)
Fair to poor self-rated health	-6.6 (-33.1, 16.4)	-17.7 (-32.4, -3.4)	0.73 (0.55,0.96)	0.88 (0.50,1.54)
Obesity	0.0 (-0.4, 0.3)	-18.7 (-34.0, -4.3)	0.73 (0.56,0.97)	0.80 (0.44,1.46)
Presence of diabetes complications	2.0 (-4.4, 8.8)	-17.6 (-32.0, -3.6)	0.72 (0.53,0.97)	0.97 (0.53,1.79)
Disability score (log)	-2.8 (-6.6, 1.0)	-19.3 (-34.1, -4.7)	0.77 (0.58,1.01)	0.92 (0.52,1.64)[b]

All models adjusted for age, sex, education, marital status, employment status, and household income.
[a]Cultural services dichotomized as present vs absent in MSM analysis
[b]Disability is dichotomized as substantial vs not substantial in MSM analysis

DISCUSSION

This chapter investigated potential mediators in the pathways between neighbourhood characteristics and risk of depression in a sample of people with type 2 diabetes. I used the novel additive hazards approach for mediation analysis, but also compared results with the traditional difference approach and MSM using the proportional hazards model. Greater availability of physical activity facilities in the neighbourhood was associated with a reduction in the number of cases of depression in adults with type 2 diabetes in the additive hazard model, and this association was in part through less diabetes complications and disability. Self-rated health was another significant mediator, but results from the additive hazard model and MSM paradoxically suggest that living in a neighbourhood with more physical activity facilities was associated with poorer self-rated health which resulted in more cases of depression. Greater number of cultural services was also associated with a reduction in the number of depression cases, but none of the tested mediators significantly explained this association. Few studies have investigated mediating pathways in neighbourhood and depression research.[72-76] Previous evidence suggests perception of neighbourhoods and social support mediate some of the associations between neighbourhoods and depression.[35] This study contributes to knowledge by being the first to test behavioral and health factors as mediators between neighbourhood characteristics and depression. It is also the first to investigate pathways of the neighbourhood effect specifically in people with diabetes.

The association between neighbourhood physical activity facilities and depression in adults with type 2 diabetes was mediated in part by diabetes complications and disability level in the additive hazards mediation analysis. One explanation is that having a greater availability of physical activity resources could facilitate diabetes self-management. Diabetes complications

and disability levels could be good indicators of diabetes self-care. Another explanation is that neighbourhoods offering a greater number of physical activity resources could have other characteristics that protect against depression through reducing diabetes complications and disability. For example, neighbourhoods with more physical activity facilities could be composed of residents who value health and encourage good self-care, which can protect against diabetes complications, disability, and depression. In the mediation analyses using the traditional difference approach and MSM approach, diabetes complications and disability levels did not appear to be important mediators. The lack of clear results with these approaches could be in part due to the issue of non-collapsibility of the hazard ratio, which is not problematic with the hazard difference.[165] This issue could be particularly problematic in this study where the outcome is common (29% incident depression). An unexpected finding is that neighbourhood physical activity facilities contributed to additional cases of depression by increasing the number of cases of poor/fair self-rated health. Explanation for this pathway is not clear. Mediation analyses for the effect of neighbourhood cultural services on depression did not find any significant mediators among those tested in the study.

The study presented several strengths, including the use of a representative sample of adults with diabetes, objective measures of the neighbourhood and the use of advanced epidemiologic methods. However, several limitations should be noted. Measurement error could have been a problem. For example, the range of physical activity level was limited in this study (inactive vs not inactive) and a greater precision could have led to different results. Depression was measured using a screening tool and not a clinical interview. There was no information on residential history or time spent in the neighbourhood. The models in this study were based on several assumptions which could not all be tested and may not be met.

In conclusion, more physical activity facilities in the neighbourhood was associated with less cases of depression in adults with type 2 diabetes in part through less diabetes complications and less disability. Future intervention research is recommended to test whether increasing the number of physical activity facilities in the neighbourhood would have a causal effect on diabetes complications, disability and depression.

7 | Changes in Neighbourhood and Changes in Depression in Adults from the General Population (Manuscript IV)

Chapters 4, 5 and 6 were concerned with neighbourhood factors associated with incidence of depression. The identification of risk factors contributing to the onset of depression is important. However, depression is not a permanent health state, but a dynamic condition that can change over time. Depression is a treatable condition, although often recurring.[166] In this chapter, I expanded the conceptualization of depression to include its changing nature into the model. The aim of this chapter is to investigate the association between changes in neighbourhood characteristics and changes in depression over time (objective 3 of the thesis). Manuscript IV is the first study to address this question and a next step in neighbourhood and depression research. I used a relatively novel method in psychiatric research, latent class growth modelling, to identify groups that followed a similar trajectory of depression over time and to test the effect of time-varying neighbourhood characteristics on the trajectories. I used NPHS data in this research because neighbourhood data were available for 3 time points for the NPHS and because the sample size was large. I focused on the characteristics of the built environment, for which data were available for 99% of the sample, to increase the power to run the complex analyses.

Detailed Methods

Study Sample and Data Collection

This analysis used the NPHS sample and dataset as described in Chapter 4. Individuals with depression at baseline were not excluded from the study. The outcome of interest was symptoms of major depression. I focused only on characteristics of the built environment in this study, including the presence of parks and recreations, health services, fast-food restaurants, healthy food stores, physical activity facilities and cultural services. Results from physical activity

facilities were not included in the manuscript because of convergence problems with this variable in the analysis.

Data Analysis

I used latent class growth modelling (LCGM)[167] (sometimes called group-based trajectory modelling) to identify different trajectories of major depression symptoms in the sample and then examined the association between neighbourhood characteristics and depression trajectories over time. LCGM is a semi-parametric technique used to uncover distinct groups of individuals who follow a similar pattern of change. LCGM assumes that every member of the group follows the same trajectory. All groupings, or classes, are mutually exclusive and exhaustive. For each trajectory, a probability of group membership is calculated for each individual. The aggregate of probabilities corresponds to the percentage of the sample that belongs to each trajectory.

In contrast to a traditional regression or growth curve model that models only one mean trajectory within the population, one of the main advantages of LCGM is that it allows different trajectories to emerge. This is relevant when investigating depression trajectories because different longitudinal patterns of depression may exist which vary both in strength and direction of change. In the NPHS, it would not be reasonable to assume that all participants experience the same pattern of depression over time. Modelling a single averaged growth trajectory would therefore hide relevant subgroups of depression trajectories. Since depression is not a frequent outcome, a single mean depression trajectory for all could also lead to the erroneous conclusion that there is no change in depression over time in people. Another advantage of LCGM is that it makes no assumption about the distribution of the observed variables; in contrast to traditional latent growth curves require normally distributed continuous variables. This type of analysis can

also accommodate dichotomous and time-varying variables, which is relevant for this study where depression was modelled as a dichotomous variable (presence or absence of major depression) and neighbourhood characteristics were allowed to vary over time.

One drawback, of the LCGM is that it does not take into account random effects due to individual variations within each subgroup. It assumes that every person in the group follows the same trajectory. A related limitation is that it is possible for LCGM to find classes because of non-normal distribution of random effects rather than because of true unique subgroups. Careful selection of the number of classes is therefore essential. The final number of classes was selected based on the Bayesian Information Criterion (BIC), interpretability and meaningfulness of each class. The model with the smallest absolute BIC was preferred. The shape of the trajectories was then selected based on the significance of the polynomial components of each class.

In a first step, I selected the appropriate number of groups and the shape of trajectory of major depression for each group. The trajectory shapes of each group was determined in a step-wise manner starting with all groups set to have a cubic order, and comparing change in BIC and the significance of parameters, as their polynomial orders were made less complex (from quadratic to linear to intercept only). I compared the sociodemographic and health characteristics of each group to provide insight into the classes and additional evidence that the differences between classes are meaningful. In a second step, I examined whether neighbourhood characteristics significantly alter the depression trajectory over time within each group, by including time-varying neighbourhood characteristics into the LCGM.

Manuscript IV: The Neighbourhood Built Environment and Trajectories of Major Depression Symptoms in Adults: a Latent Class Growth Analysis

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The neighbourhood built environment and trajectories of major depression symptoms in adults: a latent class growth analysis

Running title: Neighbourhood effect on trajectories of depression

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Abstract

Aim: To investigate the effect of the neighbourhood built environment on trajectories of major depression symptoms in adults from the general Canadian population.

Research Design and Methods: We used 10 years of data collection (2000/01-2010/11) from the Canadian National Population Health Study (n= 13,618). Major depression symptoms were identified using the Composite International Diagnostic Interview Short-Form. We assessed the presence of local parks, healthy food stores, fast food restaurants, health services and cultural services using geospatial data. We used latent class growth modelling (LCGM) to identify different trajectories of major depression symptoms in the sample and tested for the effect of neighbourhood variables on the trajectories over time.

Results: LCGM uncovered three distinct trajectories of major depression symptoms: low prevalence of depression symptoms (85.5%, n=12,941), moderate decreasing prevalence of depression symptoms (10.8%, n=402) and high persistent prevalence of depression symptoms (3.4%, n=275). Living in an area with parks or cultural services was associated with a significant shift in the trajectory towards lower probability of depression symptoms in the group with high persistent prevalence of depression symptoms. Local parks were also associated with a shift in the trajectory of low prevalence of depression symptoms towards lower probability of depression symptoms. Healthy food stores, fast food restaurants and health services in the neighbourhood were not associated with trajectories of major depression symptoms.

Conclusions: For individuals following a trajectory of high persistent prevalence of major depression symptoms, living in an area with parks and cultural services was associated with a shift in the trajectory towards lower probability of major depression symptoms. Future intervention studies are recommended to make policy recommendations.

Introduction

Depression is a prevalent public health concern and the leading cause of disability in the world[1]. It is estimated that about 5% of the population in Canada and other Western countries currently have major depression [2,3]. Research has identified several individual-level risk factors of major depression, but there has been growing interest in the larger neighbourhood-level factors that contribute to depression. Several studies have shown neighbourhood characteristics to be significantly associated with depression[4,5]; however, evidence has been mainly cross-sectional. In studies using longitudinal data, findings have been less consistent, with about half of studies reporting a significant association[4-6]. Variation in depression and neighbourhood over time might explain some of the mixed findings. Longitudinal studies have typically measured neighbourhood characteristics at baseline, and modelled depression event at only one time point. Neighbourhoods may change over time and people may change which neighbourhood they live in. Depression also follows a dynamic process characterized by different trajectories[7]. Research that takes into account the changing nature of neighbourhoods and depression over time has therefore been recommended as the next step for clarifying the role of neighbourhood in depression[4,7,8]. This line of research could not only provide insight into the risk factors of depression, but also into what contributes to certain long-term depression patterns.

Among the different characteristics of neighbourhoods, studies have found that the built environment – the physical structures and infrastructures in the local environment, such as parks, buildings, and stores – appears to be linked to mental health[9,10]. Neighbourhood features such as local parks could offer respite from stress and a place to foster social connections [11]. The proximity to certain local businesses and services could also be important, such as nearby health services which could facilitate access to mental healthcare. Nonetheless, research on the effect of

the built environment specifically in the context of depression has been limited. Evidence from only two cross-sectional studies currently exists. Kubzansky et al. reported no significant association between depressive symptoms and neighbourhood services promoting social engagement, services providing care, and undesirable amenities, in an elderly sample[12]. Stockdale et al. found no association between depression and number of alcohol outlet and number of alcohol, drug, and mental-health facilities in a sample of adults[13]. Longitudinal evidence is missing and the effect of other aspects of the built environment (such as parks and healthy food stores) on depression over time has not been examined.

Using 10 years of data collection from a large national population health survey, the objective of this study was to identify trajectories of major depression symptoms in adults and assess whether built environment affects the trajectories over time. We used latent class growth modelling to identify different trajectories of major depression symptoms.

Methods

Study population

We used 10 years of data from the National Population Health Survey (NPHS)[14]. The NPHS is a large population-based health survey of individuals across Canada (baseline n=17,276), with 9 cycles of data collected from 1994/95 to 2010/11. Participants were selected using a stratified cluster sampling strategy. Follow-up interviews were conducted every 2 years. Details on the NPHS can be found elsewhere[14]. For this study, we used data from 2000/2001-2010/2011, corresponding to 6 survey cycles (cycles 4 to 9), because data on the neighbourhood built environment were available from 2000/2001 onwards. Response rates were 85%, 81%, 78%, 77%, 71% and 70%, for each of the survey cycles, respectively. To insure comparability with

other studies, we included adults who were between the ages of 18 and 80 at baseline (n=13,618).

Ethics Statement

This study was approved by the Research Ethics Committee of the Douglas Mental Health University Institute.

Measures

Major depression symptoms

The outcome of interest was past-year major depression symptoms, assessed using the validated Composite International Diagnostic Interview Short-Form for Major Depression (CIDI-SFMD), a brief screening scale for depression[15]. Participants were asked whether they experienced depressed mood or loss of interest for at least 2 consecutive weeks in the past year. Those who endorse one of these two key depression symptoms were then asked about eight other depressive symptoms. Criteria for major depression symptoms require the endorsement of at least five depressive symptoms, including depressed mood or loss of interest, as described in the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV)[16]. The CIDI-SFMD is a screening tool used to identify major depression symptoms, but is not a clinical interview that yields a full diagnosis of major depression. Validation studies based on the full CIDI have shown 75% to 90% positive predictive values[15,17].

Neighbourhood characteristics

We used a person-centered approach to define neighbourhoods. We created a 500m radius buffer around the center of the 6-digit postal code of each participant and measured the neighbourhood characteristics within the zone. Geospatial Canadian data from 2002, 2006 and 2010 were used

to estimate density of businesses and services, as well as parks and recreational facilities[18]. Business and service data included number of health services, healthy food stores, fast-food restaurants and cultural services (see Appendix S1 for details). Parks and recreation data were modelled as the proportion of an area used for parks, sports tracks, or swimming pools. We dichotomized density of businesses and parks and recreational facilities as present versus absent in the neighbourhood because data were extremely skewed. Neighbourhood data that were closest in time to each survey cycle were used to approximate the neighbourhood characteristics of that survey. Data on neighbourhood businesses were available for 99% of the sample and data on parks and recreation were available for 72% of the sample.

Sociodemographic and health variables

Based on our literature review, we investigated variables known to be important to both neighbourhood selection and depression symptoms. We used these variables to characterize and compare the different trajectories of depression symptoms. We included sex, age, marital status (married/common law; single; widowed/divorced/separated), race (white; non-white), education (less than high school; high school graduation; post high school education), employment status in past year (working full-time/part-time/student; not working/retired), family income adequacy (based on the number of people in the household and on Statistics Canada's low-income cut-offs[19]; low vs middle/ high), family history of depression (yes/no), chronic condition (none; any of the following: asthma, chronic bronchitis, heart disease, arthritis, cancer, back pain, high blood pressure, migraines, stomach/intestinal ulcers, bowel disorder, thyroid condition) and childhood life events (none; any of the following: two weeks or more in hospital; parents divorced; parents unemployed for a long time; traumatised for years; sent away from home; parents abused alcohol or drugs; was ever physically abused).

Statistical analysis

We identified trajectories of prevalence of major depression symptoms in the sample from latent class growth modelling (LCGM)[20] using a logistic model. LCGM is a semi-parametric technique used to uncover distinct groups of individuals who follow a similar pattern of change over time. We started by fitting a one-class solution to the data, equivalent to the null hypothesis that all participants in the NPHS follow the same trajectory of probability of major depression symptoms. We then added more classes until the number of groupings reached a good fit with the data. The final number of classes was selected based on the Bayesian Information Criterion (BIC), interpretability of the model, and meaningfulness of each class. The shape of the trajectories in the final model was selected based on the significance of the polynomial components of each class. We classified participants in the trajectory group for which they had the highest probability of belonging. We compared the sociodemographic and health characteristics of members of the different trajectories to gain further insight into the classes and evidence that the differences between classes were meaningful. We tested for differences between classes using the chi-square test for categorical variables and analysis of variance for continuous variables. Formal statistical tests should however be interpreted with caution because they do not take into account the uncertainty of group assignment based on probabilities[21]. Due to the complex analysis, sociodemographic and health variables were not directly included in the estimation of the trajectory classes of major depression symptoms, in accordance with the usual strategy for LCGM analysis[22,23]. We then examined how changes in neighbourhood characteristics over time altered the trajectory of major depression symptoms within a group by introducing time-varying neighbourhood characteristics in the model. The coefficients of the time-varying neighbourhood variables are interpreted the same way as an ordinary logistic

regression, but within each trajectory group, and represent the deviation in the long-term probability of depression of members of that group. Neighbourhood variables were entered one at a time.

LCGM was performed in SAS (SAS Institute, Cary, NC, version 9.3) using the procedure PROC TRAJ [24].The procedure assumes that missing data on the dependent variable (major depression symptoms) are missing at random and therefore includes subjects with some missing data on the dependent variable in analysis. All analyses were conducted using study weights provided by Statistics Canada to adjust for non-response and lost to follow-up, and to account for the complex survey design[14].

Results

Participants in the sample were 43 years old on average at baseline (2001/01) and the majority were partnered, working and had middle to high income (table 1). Prevalence of major depression symptoms at each survey cycle were 4.5%, 4.9%, 4.7%, 4.5%, 4.3% and 4.2% in 2000/01, 2002/03, 2004/05, 2006/07, 2008/09 and 2010/11, respectively.

We selected a three-class solution for the LCGM, based on BIC values (Tables S1 and S2), interpretability, and meaningfulness. The final model included three linear trajectories (figure 1). Characteristics of members of the different trajectories of major depression symptoms are presented in table 1. Trajectory 1 was the largest class (85.8% of the sample) and represented individuals who followed a trajectory of low prevalence of major depression symptoms during the study period. Expected prevalence of major depression symptoms stayed consistent at 1% for every survey cycle within this group. Compared to the two other groups, members of this group were on average older, more likely to be married and more likely to have middle/high household

income. Trajectory 2 represented individuals who had a moderate and decreasing prevalence of major depression symptoms (10.8% of the sample). Expected prevalence of major depression symptoms of trajectory 2 was 22%, 20%, 18%, 16%, 14% and 12% in 2000/01, 2002/03, 2004/05, 2006/07, 2008/09 and 2010/11, respectively. The average member of this group had 2.1 episodes of major depression symptoms during the study. Compared to trajectory 1, those in trajectory 2 were less likely to be married and more likely to have low household income. They were also more like to report a family history of depression, a traumatic childhood life events and to be living with a chronic condition. Trajectory 3 grouped individuals who had a high persistent prevalence of major depression symptoms during the study (3.4% of the sample). Expected prevalence of major depression symptoms of trajectory 3 was 39%, 42%, 46%, 49%, 53% and 57% in 2000/01, 2002/03, 2004/05, 2006/07, 2008/09 and 2010/11, respectively. Members of this group had an average of 3.5 events of major depression symptoms during the study. Compared to trajectory 1, individuals who followed trajectory 3 were on average younger, more likely to be female, white, single and to have low household income. Members of this group were more likely than any other group to report a family history of depression, a traumatic event during childhood and to have a chronic condition.

When introducing time-varying neighbourhood characteristics into the LCGM (table 2), living in a neighbourhood with a park at a time point during the study was associated with a significant shift in trajectories of persistent high prevalence and of low prevalence of major depression symptoms towards lower probability of major depression symptoms at that time point. Figure 2 illustrates the probability of major depression symptoms when local parks are modelled as absent throughout the study period compared to when local parks are modelled as present for the latter half of the study period. Confidence intervals suggest that the presence of local parks was

associated with a 33% to 99% reduction in odds of major depression symptoms for the group following high persistent major depression symptoms, and 18% to 55% for the group following low prevalence of major depression symptoms (table 2). Presence of a cultural service was also significantly associated with a shift in the trajectory of persistent high prevalence of major depression symptoms towards lower probability of major depression symptoms. Confidence intervals suggest the presence of a local cultural service was associated with a 39% to 99% decrease in the odds of major depression symptoms (table 2). Presence of local healthy food stores, fast-food stores and health services was not associated with trajectories of major depression symptoms.

Discussion

This study sought to examine the association between aspects of the neighbourhood built environment and trajectories of major depression symptoms over time in a representative sample of adults from the Canadian population. Analyses revealed three distinct trajectories of major depression symptoms in the sample: low prevalence of major depression symptoms, moderate but decreasing prevalence, and high persistent prevalence. Others have found similar trajectories of prevalence of depression symptoms in representative samples of adults[22,25]. Living in an area with a local park or cultural service during a time point of the study was significantly associated with a shift in the trajectory of high persistent prevalence of major depression symptoms downwards to a lower probability of symptoms. Living in a neighbourhood with parks was also associated with a shift in the trajectory of low prevalence of major depression symptoms towards an even lower probability of symptoms. Presence of local healthy food stores, fast food restaurants and health services in the neighbourhood was not significantly associated with trajectories of major depression symptoms. This study is the first to provide evidence that

neighbourhood characteristics are associated with the trajectories of major depression symptoms over time in adults. These findings lend support to the notion that some aspects of neighbourhoods play a role in depression in adults[4,5].

Living in proximity to a park or cultural service during the course of the study was significantly associated with a change in the trajectory of major depression symptoms towards lower depression symptoms probability in those following a pattern of high persistent probability of major depression symptoms. Similar to our results, previous studies report that about 20% of patients with major depression develop a chronic course of depression[26,27]. Individuals who have persistent and recurrent major depression symptoms are a particularly vulnerable group to a host of poor health outcomes, functional problems and lost life opportunities[28,29]. Results from this study suggest that the neighbourhood environment could be an important contributing factor to the trajectory of chronic depression symptoms, in addition to other known factors[26]. Local parks could offer those with high probability of depression symptoms a place to unwind from stress, to engage socially with others or in physical activities, all of which could decrease the risk of recurrent depression symptoms[10,30,31]. In this study, presence of parks was shown to be associated with a decrease in the probability of major depression symptoms even in those who followed a trajectory of low prevalence of depression symptoms during the study period, although associations were much smaller. Cultural services could be a local destination that acts in a similar fashion to protect mental health, by allowing individuals to escape from daily stress and connect with others[32]. This is the first study to link cultural services to trajectory of depression symptoms in the literature. In contrast, presence of healthy food stores, fast food restaurants and health services in the neighbourhood was not significantly associated with trajectories of major depression symptoms in our sample. Previous studies have shown these

neighbourhood characteristics to impact physical health[33], but our study suggests that the impact may be smaller for mental health.

This study is strengthened by the use of a large representative sample of Canadian adults, longitudinal data covering 10 years of data collection with multiple assessment points, and the careful consideration of the time-varying nature of neighbourhood characteristics and depression. We used objective measures of the neighbourhood built environment and a person-centered definition of neighbourhoods. We uncovered important depression trajectories using latent class growth modelling, a relatively novel method in longitudinal analyses.

Several limitations should nonetheless be noted. The latent class growth model identified three trajectory groups of major depression in the sample, but these groups are not fixed and members of these groups are not expected to follow the same trajectory permanently. Different trajectories may be identified in different populations and within the same population at different time points. Research replicating findings in other populations is recommended. Although the CIDI-SFMD is a validated instrument to assess major depression symptoms, it is a screening tool and not a clinical interview. The study examined a range of characteristics of the neighbourhood built environment, but other aspects of the neighbourhood could also be important. There was also no information on residential mobility, such as when people moved to a specific neighbourhood or what neighbourhood factors they were previously exposed to. Nonetheless, the study covered up to 10 years of residential history.

Characteristics of the built environment were significant associated factors in shifting the trajectories of probability of major depression symptoms over time in a sample of Canadian adults, particularly those with high persistent prevalence of major depression symptoms.

Clinicians might consider the neighbourhood characteristics of their patients when assessing and intervening on major depression symptoms, particularly in those with a pattern of recurrent major depression symptoms. From a public health point of view, findings potentially suggest that providing cultural services and park spaces in neighbourhoods, or transforming unused spaces into parks, could positively impact the course of major depression of residents. Future intervention and impact studies are recommended to make public health recommendations.

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Competing interest

None declared.

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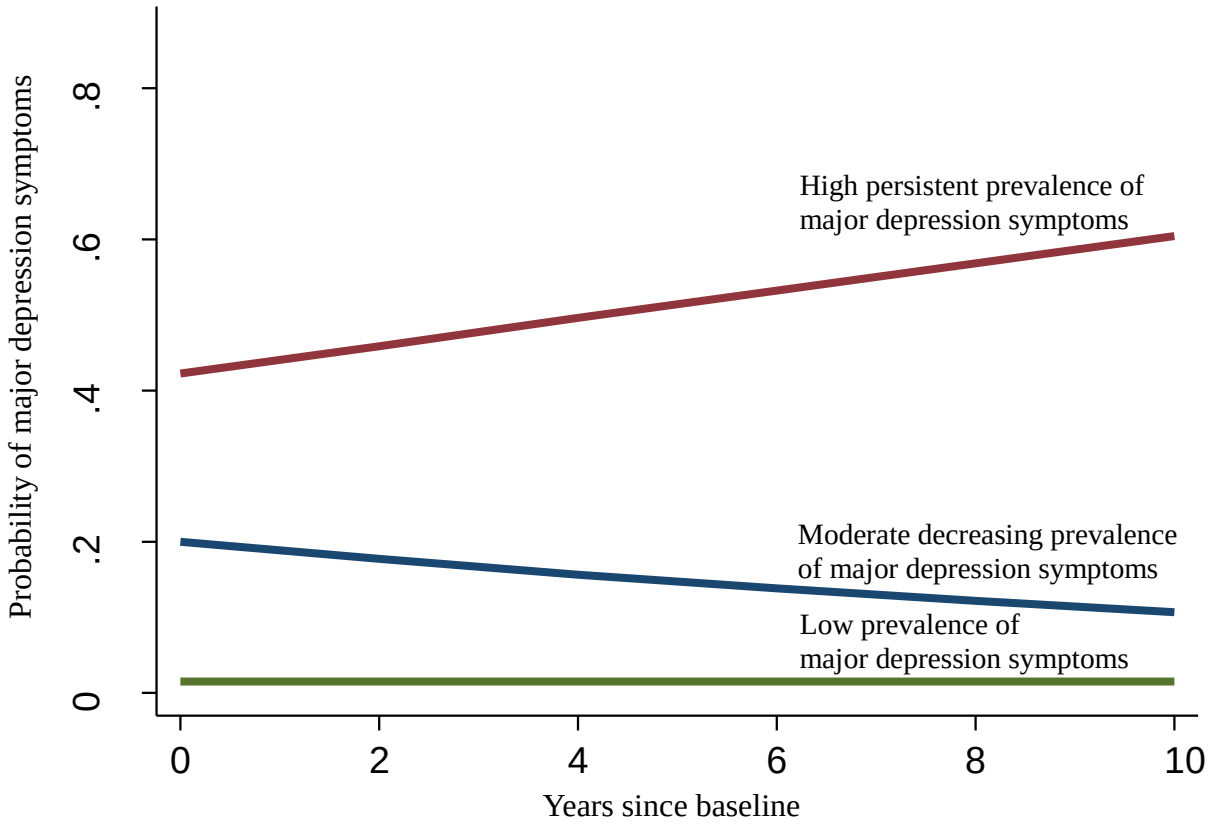
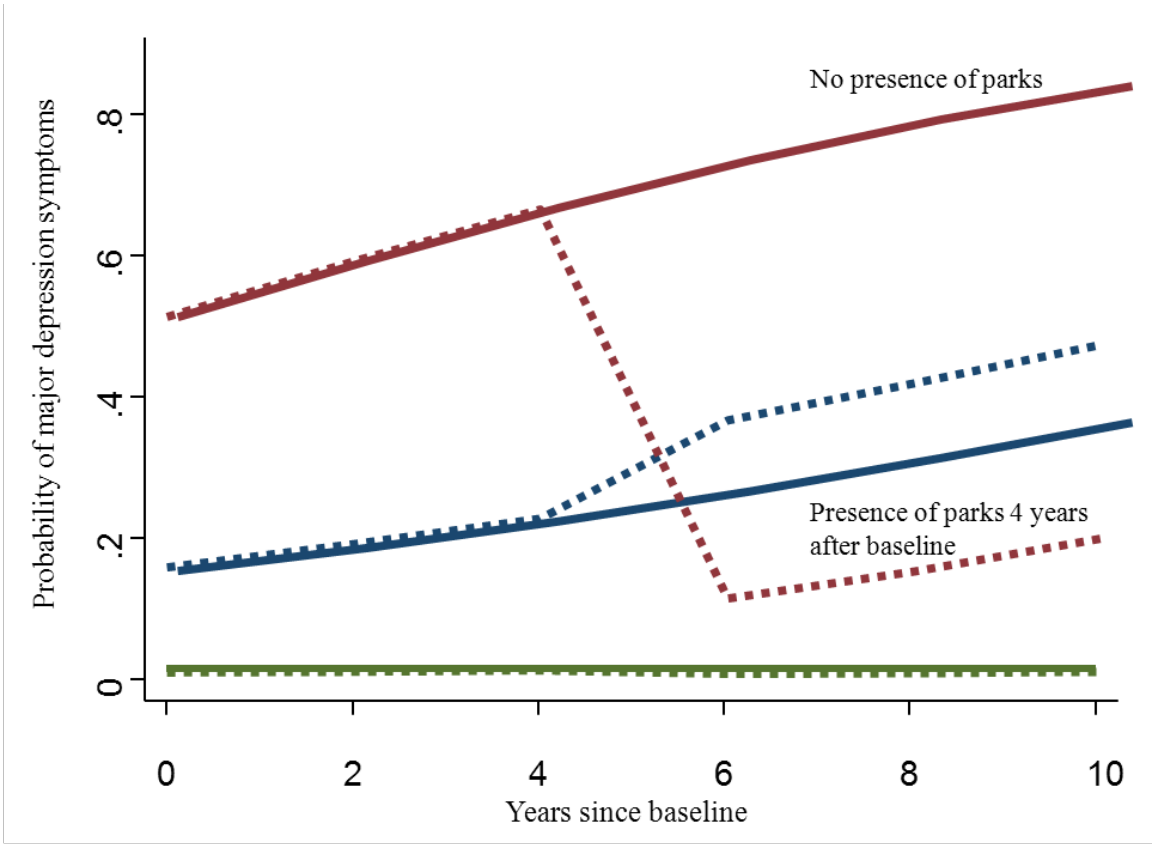
Figure 1. Trajectories of prevalence of major depression symptoms over time in the NPHS (2000/01-2010/11)



Legend figure 1. Trajectories of prevalence of major depression symptoms over time in the NPHS (2000/01-2010/11). The red line represents the trajectory with high persistent prevalence of major depression symptoms (3.4% of sample). The blue line represents the trajectory with moderate decreasing prevalence of major depression symptoms (10.8% of sample). The green line represents the trajectory with low prevalence of major depression symptoms (85.8% of sample)

Figure 2. Trajectories of prevalence of major depression symptoms over time in the NPHS (2000/01-2010/11) including time-varying presence of parks in the growth model



Legend figure 2. Trajectories of prevalence of major depression symptoms over time in the NPHS (2000/01-2010/11), including time-varying presence of parks in the growth model. The solid lines represent trajectories when presence of park is set to "no park" across the study period. The dotted lines represent trajectories when presence of park is set to "no park" for the first 4 years of the survey and "presence of park" for the last 6 years of the survey. The red line represents the trajectory with high persistent prevalence of major depression symptoms. The blue line represents the trajectory with moderate decreasing prevalence of major depression symptoms. The green line represents the trajectory with low prevalence of major depression symptoms

Table 1. Baseline characteristics and number of depression events by depression trajectory class

Variable **% (n)**	**All participants** **N=13,618**	**Trajectory 1** ***Low prevalence of major depression symptoms*** **N=12,941**	**Trajectory 2** ***Moderate decreasing prevalence of major depression symptoms*** **N=402**	**Trajectory 3** ***High persistent prevalence of major depression symptoms*** **N=275**	***p-value***
Proportion of sample	100%	85.8%	10.8%	3.4%	
Average probability of latent class membership (mean, SE)		0.90 (0.01)	0.51 (0.02)	0.74 (0.04)	
Sex					<0.001
Male	49.3 (6217)	49.9 (6473)	41.6 (157)	31.8 (86)	
Female	50.7 (6389)	50.1 (6496)	58.4 (220)	68.2 (185)	
Age in years (mean, SE)	43.1 (0.2)	43.5 (0.2)	37.5 (0.9)	34.9 (0.9)	<0.001
Race/ethnicity					0.086
White	90.0 (11,339)	10.2 (1317)	7.3 (27)	5.3 (14)	
Non-white	10.0 (1258)	89.8 (11642)	92.7 (350)	94.7 (257)	
Marital Status					<0.001
Married/Common law	68.3 (6779)	69.2 (7021)	55.0 (199)	51.1 (131)	
Single	14.7 (1461)	14.2 (1438)	21.2 (77)	27.2 (69)	
Divorced/ Separated/Widowed	17 (1691)	16.7 (1692)	23.8 (86)	21.7 (55)	
Education					0.044
Less than secondary school	25.2 (3166)	25.4 (3289)	23.8 (90)	15.8 (43)	
Secondary school graduation	42.2 (5301)	42.0 (5425)	44.3 (167)	50.6 (137)	
Post-secondary graduation	32.6 (4097)	32.6 (4216)	31.9 (120)	33.7 (91)	
Employment status					0.444
Worked in last year	75.7 (6866)	24.1 (2181)	27.9 (96)	24.2 (59)	
Did not work in last year	24.3 (2201)	75.9 (6852)	72.1 (248)	75.8 (185)	
Household income adequacy					<0.001
Low	9.8 (879)	9.3 (860)	16.8 (56)	15.3 (37)	
Middle/high	90.2 (8132)	90.7 (8339)	83.2 (280)	84.7 (205)	
Family history of depression					<0.001
No	70.9 (5535)	72.5 (5781)	48.0 (124)	35.8 (77)	
Yes	29.1 (2275)	27.5 (2187)	52.0 (134)	64.2 (137)	

Childhood life events					<0.001
None	50.6 (5795)	51.7 (6212)	29.3 (108)	27.4 (68)	
1 or more	49.4 (5660)	48.3 (5797)	70.7 (261)	72.6 (181)	
Chronic condition					<0.001
No chronic condition	33 (3999)	33.7 (4213)	20.4 (77)	17.2 (47)	
1 or more	67 (8135)	66.3 (8296)	79.6 (299)	82.8 (226)	

All estimates were weighted using Statistics Canada survey weights. P-values are derived from the chi-square test for categorical variables and analysis of variance for continuous variables.

Table 2. Association of time-varying neighbourhood variables with the log-odd of major depression symptoms within each class of depression trajectory

Neighbourhood characteristic Coefficient (95% CI)	**Trajectory 1** ***Low prevalence of major depression symptoms***	**Trajectory 2** ***Moderate decreasing prevalence of major depression symptoms***	**Trajectory 3** ***High persistent prevalence of major depression symptoms***
Presence of any park	-0.5 (-0.8, -0.2)	0.5 (-0.6, 1.5)	-3.0 (-5.6, -0.4)
Presence of any healthcare service	0.1 (-3.5, 3.8)	-0.3 (-1.7, 1.1)	0.0 (-1.3, 1.3)
Presence of any healthy food store	0.0 (-0.3, 0.3)	-0.3 (-0.8, 0.3)	-2.1 (-6.7, 2.4)
Presence of any fast food restaurant	0.3 (-0.4, 0.9)	-0.6 (-1.6, 0.4)	-0.1 (-1.1, 1.0)
Presence of any cultural service	0.2 (-0.1, 0.6)	1.5 (-0.5, 3.5)	-2.7 (-4.8, -0.5)

Supporting Information

Appendix S1. Details on classification of business and service data.

Desktop Mapping Technologies Inc. (DMTI software, Markham, Ontario, Canada, 2010) provided data on operating businesses across Canada. We developed specific algorithms using Standard Industrial Classification (SIC) codes in the DMTI databases to identify the number of healthcare services, healthy food stores, fast-food restaurants, and cultural services in neighbourhoods. Healthcare services include those covered by the Canada Health Act, which largely includes care delivered in hospitals and by physicians. Healthy food stores included stores that offer a selection of fruits and vegetables, meats, fish and/or seafood. Fast-food restaurants were restaurants that served food prepared and served quickly and often high in fat and caloric content. We identified fast food restaurants, outlets and retailers using keywords that corresponded both to fast food chain names as well as qualifying terms such as “fried”. Cultural services were establishments that contributed to the local culture, including libraries, museums and botanical gardens. Keywords were searched for anywhere in the “name” field of the DMTI database. Unequivocal keyword terms or chain names were searched regardless of SIC code to maximize coverage. Potentially equivocal keyword terms were searched only under relevant SIC codes, avoiding countless false positives. Although seemingly relevant SIC classification exist in the database (e.g., SIC for health services), some did not meet our needs (e.g., too many missing or unwanted entities), and were therefore not included in their entirety.

Table S1. Comparison of fit statistics for 1- to 4-class solutions

Number of classes	Polynomial order of coefficients for best model	BIC[1]
1	2	-9208.81
2	2 2	-8437.08
3	**1 1 1**	**-8437.06**
4	2 2 2 2	-8453.25

[1] The BIC strives to identify the most parsimonious model with the best fit by adjusting for the number of parameters in the model. Smaller absolute values indicate a better balance between fit and parsimony

Table S2. Parameter estimates for latent class growth model of major depression using 3-class solution

Group	Parameter	Estimate	Standard Error
1 Low prevalence of major depression symptoms			
	Intercept	-4.21	1.36
	Linear	0.00	0.13
2 Moderate decreasing prevalence of major depression symptoms			
	Intercept	-1.24	1.74
	Linear	-0.15	0.09
3 High persistent prevalence of major depression symptoms			
	Intercept	-0.46	0.34
	Linear	0.15	0.14

8 | Discussion and Conclusions

SUMMARY OF FINDINGS

In the first manuscript, I used a wide general population perspective to investigate the association of neighbourhood characteristics with risk of depression in a representative sample of Canadian adults and subsamples with a chronic condition (NPHS data). I used a discrete time proportional hazards model. Findings revealed that neighbourhood characteristics were not statistically significantly related to the 10-year risk of depression in adults from the general population or in subgroups with a chronic condition. However, point estimates suggested a protective effect of neighbourhood parks (HR 0.86, CI 0.69, 1.07), health services (HR 0.85, CI 0.66, 1.09), healthy food stores (HR 0.87, CI 0.67, 1.11) and greater level of greenness (HR 0.79, CI 0.27, 2.33) on depression. Moderator analysis identified significant associations in some subgroups living in vulnerable situations: for those living in more crowded households, the presence of a neighbourhood park was associated with lower risk of depression (HR 0.64, CI 0.47, 0.87 for those living in crowded households); for those living in materially deprived neighbourhoods, the presence of local health services also was associated with lower risk of depression (HR 0.46, CI 0.29, 0.74 for those living in a materially deprived neighbourhood).

In the second and third manuscript, I narrowed the focus of my research on a specific group with a chronic condition - those with type 2 diabetes (DHS data). The second manuscript describes a factor analysis that I performed to group items of the neighbourhood questionnaires into relevant neighbourhood factors (perceived neighbourhood order; perceived culture; and perceived access). This cross-sectional study found that perceived neighbourhood factors were associated with diabetes distress in a sample of people with type 2 diabetes. The third manuscript expands on the second manuscript to include longitudinal data and a wider range of neighbourhood

characteristics, including geospatial and satellite imagery data, and their associations with risk of depression. Results showed that several neighbourhood characteristics were significantly associated with risk of depression in the sample, including number of physical activity facilities (adjusted hazards ratio (HR) 0.71, CI 0.55-0.91) and cultural services (HR 0.75, CI 0.57-0.99), and important association with level of greenness (HR 0.94, CI 0.88-1.01). Material deprivation was also significant in subgroups with type 2 diabetes who were older (HR 1.31, CI 1.05-1.64 in those 65-80 years old) or retired (HR 1.27, CI 1.06-1.24 in those who were retired). These results contrast with those from Manuscript I where no significant association was found in the subsample of adults with diabetes, though directions of association were generally similar. One consideration is that the sample size was three times greater in DHS (n=1298) than in the subsample with diabetes in the NPHS (n=451). Other explanations may include differences in assessment of depression (the DHS used the PHQ-9, which measures depression symptoms in the past 2 weeks, and the NPHS used the CIDI-SFMD, which measures past-year depression); differences in operationalization of neighbourhood characteristics; differences in follow-up time (DHS was 5 years, NPHS was 10 years); and possible differences in attrition rates.

In chapter 6 (manuscript in preparation), I narrowed my focus on significant results from manuscript III (i.e., neighbourhood physical activity facilities and cultural services) and investigated potential mediators through which neighbourhood physical activity facilities and cultural services could affect risk of depression in people with type 2 diabetes (DHS data). I conducted mediation analysis using the additive hazards model approach. The relationship between neighbourhood physical activity facilities and reduction in number of depression cases was partly explained by a reduction in cases of diabetes complications and of disability score.

None of the tested mediators explained the relationship from cultural services to reduction in depression cases in the sample.

Finally, in the fourth manuscript, I expanded my research by taking into account the changing nature of both depression and neighbourhood characteristics. I used latent class growth modelling to find distinct patterns of major depression prevalence in a sample of the general population (NPHS data) and I investigated the effect of including time-varying neighbourhood characteristics on the trajectories of major depression. I found 3 trajectories of major depression symptoms in the sample: low prevalence of major depression symptoms (85.5%, n=12,941), moderate decreasing prevalence of major depression symptoms (10.8%, n=402) and high persistent prevalence of major depression symptoms (3.4%, n=275). Living in an area with parks or cultural services was associated with a significant shift in the trajectory of those in the group with high persistent prevalence of depression symptoms towards lower probability of depression symptoms.

Results from the thesis lend evidence to the notion that aspects of the neighbourhood environments are associated with risk of depression. Yet, there did not appear to be a specific neighbourhood characteristic that was consistently associated with depression in the general population sample and in subsamples with diabetes and other chronic illnesses (Appendix O). Instead, findings suggest that different neighbourhood characteristics were important to different subgroups, including subgroups with a chronic condition such as diabetes (Manuscript III), and other vulnerable subgroups such as individuals living in a crowded household (Manuscript I) or individuals with persistent major depression symptoms (Manuscript IV).

MAIN LIMITATIONS

Several study limitations have been described in Manuscripts I to IV and Chapters 4 to 7. This section highlights some of the main thesis limitations, which are often common to neighbourhood and depression research.

MEASUREMENT OF NEIGHBOURHOODS

One of the challenges in neighbourhood research is accurately measuring neighbourhood exposure. There is no agreement regarding which geographical area constitutes a neighbourhood. Arguments exist for the use of administrative geographic units (such as census tracts)[168], person-centered neighbourhoods[59] and person-perceived neighbourhoods[169]. This thesis used person-centered neighbourhoods, and conducted several sensitivity analyses using different radius sizes, but other measures of neighbourhood units may yield different results. I had no information on the intensity, frequency or duration of exposure to neighbourhood characteristics. For example, people who frequently travelled outside their area for work and activities were less exposed to their local environment than those who spent most of their time at home. However, analyses were adjusted for several socioeconomic variables that predict mobility (e.g., age, employment status). Results were therefore somewhat robust to this potential misclassification. There was no information on residential mobility, such as when people moved to a specific neighbourhood or what neighbourhood factors they were previously exposed to. Nonetheless, the NPHS and the DHS data cover up to 10 years and 5 years of residential history, respectively. I also allowed neighbourhood characteristics to vary over time in longitudinal data analysis. Another key challenge is that there was no information on why individuals chose to live in their neighbourhoods. Namely, the social drift hypothesis suggests that persons with poor mental health are more likely to move to neighbourhoods with poor quality environments. Risk analysis

however excluded individuals with depression at baseline, and controlled for socioeconomic factors, such as income and education, which contribute to social drift.

Neighbourhood measurement was not perfect in this thesis, but there is an argument that "what gets measured gets done". Results from this thesis contribute to the scientific understanding of the multifactorial nature of the neighbourhood environment and the features or combinations of features that are relevant to depression. Previous studies have mainly focused on specific and often difficult to modify neighbourhood characteristics, such as neighbourhood deprivation. In this thesis, I studied a broad range of neighbourhood characteristics and included several neighbourhood characteristics that have not yet been studied, many of which could be amenable to intervention, such as the presence of a local park and cultural services.

Measurement of Depression

Identification of depression symptoms were based on screening tools in my thesis. The PHQ-9 and CIDI-SFMD are brief screening instruments intended to differentiate persons likely to have minor or major depression according to DSM-IV criteria from those at lower risk. They are however not clinical interviews designed to diagnose depression. Although there is a good agreement between these instruments and clinical interviews, it is possible that some of the participants were misclassified. For example, some depression symptoms overlap with symptoms of chronic conditions (e.g., low energy, fatigue); identification of depression in people with a chronic condition may therefore be overestimated. Manuscripts I and III included minor and major depression in the definition of depression. Some controversy exists on the use of minor depression in research. One the one hand, minor depression is not a clinical diagnosis per say, but is a mood disorder classified under "Depressive Disorder Not Otherwise Specified" in the

DSM-IV. Clinical treatment for minor depression is also currently limited.[170] One the other hand, minor depression is considered an important health outcome linked with suffering, reduced functioning and impaired quality of life, and a significant risk factor for major depression disorder.[94-97,171] Additionally, there is no available data on history of depression and other psychiatric disorders, which may play a role in where people chose to live and their risk of depression.

Statistical Modeling and Model Assumptions

Results from the studies are based on statistical models which have their own limitations and set of assumptions. As described in manuscript I, study power is one issue which could exist across all studies, in spite of large sample sizes. This may be particularly problematic for subgroup analysis of smaller sizes (e.g. stratified analyses by chronic condition) and with more complex analysis (e.g., mediation analysis using the additive hazards model). Results were interpreted with this in mind. In addition to specific model assumptions, a set of basic assumptions is required to make causal inference from the data, including exchangeability (exposed and unexposed are interchangeable), positivity (nonzero probability of receiving every level of exposure for every combination of covariates) and consistency (a well-defined intervention).[172] Some of these assumptions were tested. For example, I addressed exchangeability by adjusting for known confounders (conditional exchangeability) and using study weights for informative censoring. Unmeasured confounding may however still exist. I tested for positivity by using propensity score matching to check for structural confounding. It may also be reasonable to assume consistency given that the main focus of the studies was on neighbourhood-level characteristics amenable to intervention, such as features of the local built environment, rather than the effects of individuals moving from one neighbourhood to another. Exchangeability,

positivity and consistency are however never fully certain in observational studies. Further discussion on limitations to causal inference for neighbourhood research with observational data can be found elsewhere.[147,173] Despite these limitations, the studies in this thesis contribute to the evidence that environmental factors above and beyond individual-level behaviours and characteristics are relevant to depression.

Implications for Research and Public Health

Mental health research has traditionally focused on the biological and behavioural risk factors for disease, but the last three decades has brought an increasing interest in the wider, contextual factors that affect mental health. The general message from neighbourhood health research is that where people live matters to their health.[31-34,174] While the effect of neighbourhood may be small, many argue that this effect is significant because of the large number of people exposed to neighbourhood-level risk factors.[175] Neighbourhood factors are also upstream determinants of health, thought to have an effect on a broad range of illnesses beyond depression.[174] Further, the health environment of deprived neighbourhoods is a significant contributor to health inequalities, a major concern for public health.

Policymakers have already responded with growing efforts to improve neighbourhoods for population health. Urban regeneration initiatives have started to incorporate mental health impacts in their planning and development.[176-180] Information regarding which neighbourhood characteristics are important to common mental health problems, such as depression, is therefore needed now. Previous studies have found that aspects of the neighbourhood, particularly neighbourhood SES, were significant factors in depression. The studies in this thesis contribute to this growing body of research by adding evidence from high-quality longitudinal data, using

advanced statistical methods, and investigating a broad range of neighbourhood characteristics. Work for this thesis also examined several physical neighbourhood features which are amenable to public health interventions, such local parks and cultural services.

Findings from this thesis lend themselves to general public health recommendations. However, evidence was not directly from intervention research and should be interpreted with caution. Results suggest that local park and recreation facilities are important neighbourhood factors associated with depression, particularly for those living in crowded households (Manuscript I) and those with persistent major depression symptoms (Manuscript IV). When renewing and building the neighbourhood environment, urban planners and policy-makers might plan to include a park and recreation facility, particularly in communities where household crowding in known to be problematic or where mental health problems such as depression are prevalent. Neighbourhoods with more green spaces were also found to be associated with less depression symptoms in the general population, across subpopulations with a common chronic condition (Manuscript I) and significantly in those with type II diabetes (Manuscript III). Policies that increase neighbourhood greenness, such as local tree planting programs and community gardens, could be beneficial to the mental health of local residents. Policies to increase the availability of certain local businesses and services could also be potential interventions that protect populations against depression. Specifically, the presence of local health services were found to be associated with lower risk of depression for the general population and across all subpopulations with a chronic conditions (Manuscript I), and significantly for people living in materially deprived neighbourhoods (Manuscript I). Promoting availability of health services is already an important public health concern and results from this thesis further emphasis its role in depression. Availability of physical activity facilities was also found to be a significant factor associated with

lower risk of depression in people with type II diabetes (Manuscript III), partly through its protective effect on diabetes complications and disability score (Chapter 6). Policies to increase community access to local gyms and fitness facilities, particularly in neighbourhoods where diabetes is prevalent, could help lower the risk of depression of residents. Finally, cultural services in the neighbourhood were associated with lower risk of depression in the sample of the general population and across subsamples with a chronic illness (Manuscript I), and significantly in people with type II diabetes (Manuscript III), and those with persistent major depression symptoms (Manuscript IV). Local cultural services, such as museums and botanical gardens, may offer residents a space to escape from daily stress and connect with others[118], while other cultural services, like libraries, may be a local resource for information and education. Urban planners might consider allocating more spaces to local cultural services when designing and renewing neighbourhoods. Future intervention and impact studies are needed to test the effect of these policy recommendations on depression.

The decision to intervene to improve neighbourhoods for depression should not only consider evidence presented in this thesis and other studies, but also in consultation with the neighbourhood residents. A useful example is the implementation of public parks. Although this thesis found the presence of local parks to be a protective factor in depression, building parks may not have any effect if residents are not interested in using them. The addition of a park may also be contextually inappropriate in some areas. In a focus-group study by Wilbur and al., women living in low-income urban areas viewed nearby parks as dangerous places to be rather than spaces to exercise.[181] Another qualitative study among mainly Latino women report similar findings [182]. Collaboration between urban planners, public health workers and community residents is an important next step in this field.

Because of their broad implications, neighbourhood interventions may also impact communities beyond population mental health and depression. Some of these externalities may be positive, such as improvement in physical health, while others may be negative, such as inequality. Neighbourhood interventions often require residents to tolerate disruption and change into their life; to adapt to new circumstances; and to suffer the stress of this process. Researchers suggest that, within communities, this burden tends to be heaviest on those who have the least resources.[183] As Meyer and Schwartz have warned, "public health may have unintended consequences that, paradoxically, serve to preserve disparities rather than eliminate them".[184] For example, a regeneration program aimed at improving infrastructure and services relating to transportation and employment was associated with a worsening of well-being among adults living in a disadvantaged neighbourhood of South Manchester, England.[179] In deciding on whether to intervene at the neighbourhood-level, social and economic consequences beyond depression should be considered.

As reported in the literature review from Chapter 2, almost all evidence for a neighbourhood effect on depression comes from observational studies, which are not fully able to answer causal questions. In order to make policy recommendations, intervention studies are needed. These might include natural experiments or quasi-natural experiments, such as studies involving neighbourhood regeneration programs. For example, the presence of a cultural service, such as a library, was related to lower risk of depression in this thesis, yet public libraries are currently being closed down across Canada. The depression status of residents living in a neighbourhood where the local library closed down could be compared with the depression status before the closure (e.g., model change before and after) as well as with residents from other nearby neighbourhood where libraries remained open (e.g., model difference in differences). This

example assumes that library closure was done randomly. Randomized experiments could also be conducted. Researchers and policy-makers might purposefully test the effect of changing specific neighbourhood characteristics hypothesized to affect depression in the literature. For example, a randomized study could investigate the effect of a new park on depression levels of residents. Other methods such as the use of instrumental variables to estimate neighbourhood causal effects could also be exploited. Qualitative research could also be useful to better understand the role of individuals and neighbourhood context in depression in ways that research may have missed or may not currently be able to study.

Despite some of the limitations of scientific evidence on neighbourhoods and depression, and the potential ethical challenges in neighbourhood interventions, public health should not give up on the goal of improving neighbourhood environments. Some would even argue that it is the very role of public health to ensure that residents have equally opportunities and access to resources to lead a healthy life.[185,186] Resnik posits that broad public health strategies, such as urban planning or neighbourhood programs, offer many advantages from a societal viewpoint.[186] They have the potential to be highly cost-effective because of their wide impact on prevention and health; they can address problems that are beyond the abilities of the individual to influence, such as addressing physical features of neighbourhoods; and they may enhance individual responsibility for health by giving people the resources and tools to make healthy choices. Continued work in neighbourhood research is important to help produce effective public health strategies and is relevant now more than ever in the current context of increasing rates of diabetes, obesity and other chronic conditions, and the aging population.

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Appendices

APPENDIX A. SEARCH TERMS FOR UPDATE OF LITERATURE REVIEW

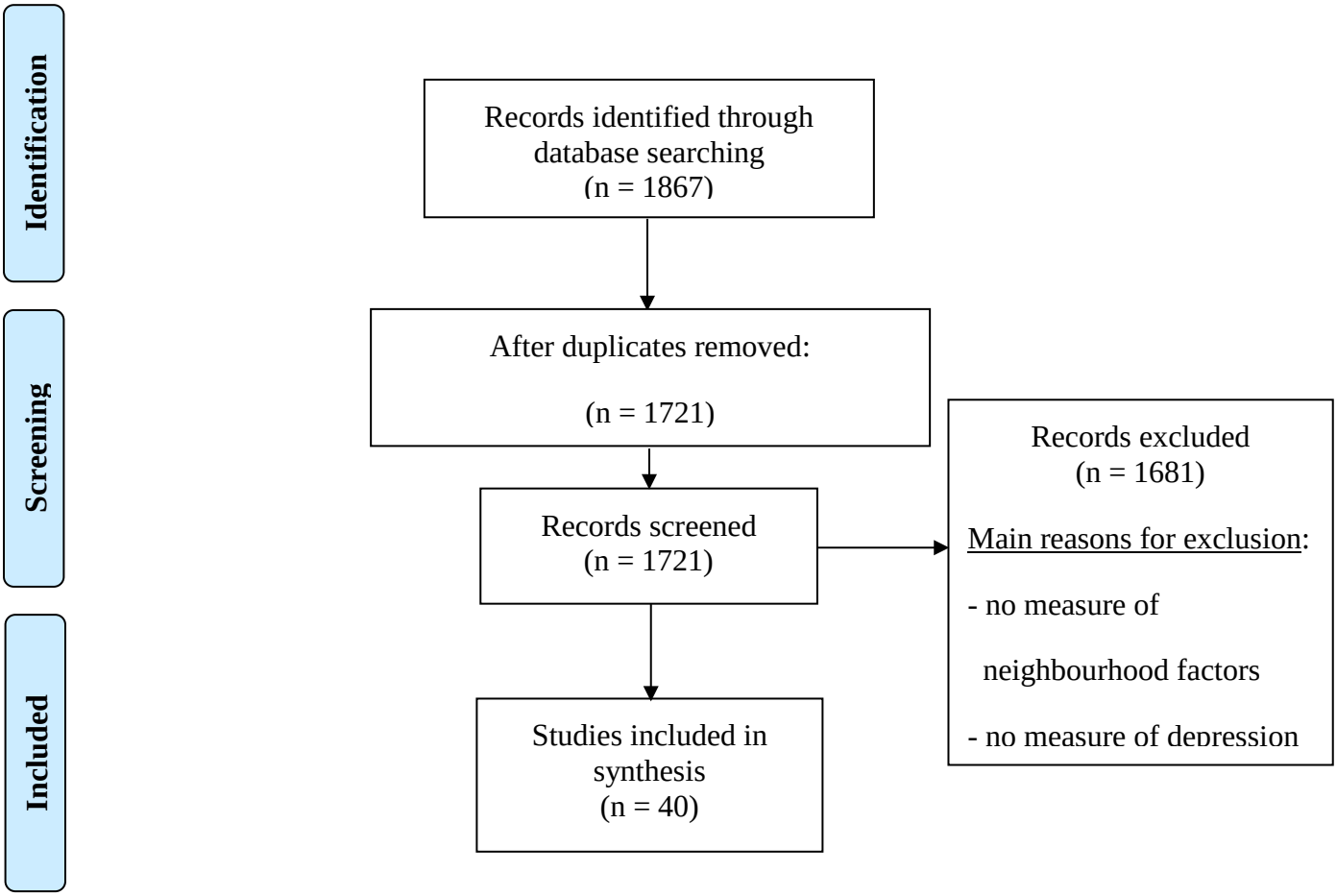
PUBMED:

("Residence Characteristics"[Mesh] OR neighbor* OR "environment design" OR "built environment" OR "urban environments" OR "residence characteristics" OR "urbanization" OR "social cohesion" OR "neighborliness" OR " neighbourhood social capital" OR " neighbourhood social environment" OR "collective efficacy" OR " neighbourhood disorder*" OR " neighbourhood problem*" OR " neighbourhood poverty" OR " neighbourhood income" OR " neighbourhood socioeconomic disadvantage" OR " neighbourhood socioeconomic status" OR "Carstairs deprivation score" OR "Gini coefficient" OR "county-level income inequality" OR "Townsend index" OR "Townsend score" OR "Townsend deprivation index" OR "Pampalon Index" OR "Pampalon deprivation" OR " neighbourhood environmental quality" OR "residential stability" OR "population density" OR " neighbourhood quality" OR " neighbourhood affluence" OR " neighbourhood socioeconomic advantage" OR "racial composition" OR "ethnic composition" OR "racial heterogeneity" OR "ethnic heterogeneity" OR " neighbourhood walkability" OR " neighboring behavior") AND ("Depression"[Mesh] OR "Depressive Disorder"[Mesh])

ISI Web of Science

((depress*) AND (neighb*)

APPENDIX B. FLOW DIAGRAM OF STUDY SELECTION FOR UPDATE OF LITERATURE REVIEW



APPENDIX C. NEIGHBOURHOOD CONCEPTS AND EXAMPLE OF SURVEY ITEMS OF THE DIABETES HEALTH STUDY (DHS) SUB-STUDY.

General concept	Description of concept	Example of questionnaire item
Physical order	Physical order refers to the physical aspect of a neighbourhood. Places with high levels of physical disorder are noisy, dirty, and run down; buildings are in disrepair; and vandalism and graffiti are common. Physical disorder is often interpreted as an indication that social control has broken down.	"My neighbourhood is well maintained"
Social order	Social order involves people. It reflects social control in an area. Visible signs of social disorder include fights among neighbors, presence of people hanging out on the streets, drinking, taking drugs, panhandling, and creating a sense of danger.	"Violence is not a problem in my neighbourhood."
Land use	Land use usually refers to the level of diversity of destinations. A highly mixed land use provides residents with a variety of residential and non-residential destinations, such as businesses, parks and green spaces.	"There are many places to go within walking distance from my home"
Access to services and facilities	This concept measures perceived accessibility to specific services and facilities, including medical care, shopping, healthy foods and fast-foods.	"I have easy access to large selection of healthy foods in my area"
Social cohesion	Social cohesion attempts to capture the quality of the social network within a neighbourhood. It is measured by the levels of trust, norms of reciprocity and the formation of strong social bonds within the local social structure.	"I really feel part of my neighbourhood"

APPENDIX D. TETRACHORIC CORRELATION MATRIX OF NEIGHBOURHOOD QUESTIONNAIRE ITEMS

i. Neighbourhood questionnaire items Q73 to Q89

	Q73	Q74	Q75	Q76	Q77	Q78	Q79	Q80	Q81	Q82	Q83	Q84	Q85	Q86	Q87	Q88	Q89
Q73) neighbourhood is well maintained	1.00	0.65	0.17	0.54	-0.38	-0.41	-0.41	-0.63	-0.51	-0.42	0.29	0.17	0.28	0.24	-0.15	0.13	-0.36
Q74) pleasant to walk in neighbourhood.	0.65	1.00	0.39	0.59	-0.24	-0.40	-0.21	-0.45	-0.35	-0.28	0.25	0.12	0.25	0.25	0.03	0.00	-0.24
Q75) many trees along the streets	0.17	0.39	1.00	0.46	-0.19	-0.21	-0.20	-0.18	-0.16	0.32	0.33	0.11	0.24	0.19	0.07	0.16	-0.11
Q76) buildings and houses are interesting.	0.54	0.59	0.46	1.00	-0.40	-0.35	-0.34	-0.43	-0.29	-0.16	0.59	0.20	0.42	0.30	-0.08	0.03	-0.16
Q77) a lot of noise	-0.38	-0.24	-0.19	-0.40	1.00	0.27	0.72	0.56	0.41	0.37	0.02	0.00	-0.09	0.03	0.32	0.12	0.43
Q78) a lot of unpleasant smells.	-0.41	-0.40	-0.21	-0.35	0.27	1.00	0.26	0.31	0.36	0.32	0.08	0.09	0.10	-0.05	0.02	-0.18	0.17
Q79) has heavy traffic.	-0.41	-0.21	-0.20	-0.34	0.72	0.26	1.00	0.50	0.44	0.40	-0.12	-0.05	-0.12	0.04	0.30	0.06	0.47
Q80) a lot of trash and litter on the street	-0.63	-0.45	-0.18	-0.43	0.56	0.31	0.50	1.00	0.45	0.48	-0.12	0.11	-0.11	0.16	0.32	0.07	0.42
Q81) vandalism	-0.51	-0.35	-0.16	-0.29	0.41	0.36	0.44	0.45	1.00	0.64	-0.03	0.15	0.02	0.03	0.57	0.15	0.23
Q82) a lot of graffiti	-0.42	-0.28	0.32	-0.16	0.37	0.32	0.40	0.48	0.64	1.00	0.11	0.16	0.17	0.29	0.53	0.28	0.42
Q83) interesting things to do	0.29	0.25	0.33	0.59	0.02	0.08	-0.12	-0.12	-0.03	0.11	1.00	0.45	0.58	0.34	0.05	0.09	0.00
Q84) many places to go within walking distance from my home	0.17	0.12	0.11	0.20	0.00	0.09	-0.05	0.11	0.15	0.16	0.45	1.00	0.53	0.53	0.30	0.24	0.03
Q85) many places to be physically active	0.28	0.25	0.24	0.42	-0.09	0.10	-0.12	-0.11	0.02	0.17	0.58	0.53	1.00	0.52	0.10	0.17	-0.08
Q86) park or walking trail within a short walk from my home	0.24	0.25	0.19	0.30	0.03	-0.05	0.04	0.16	0.03	0.29	0.34	0.53	0.52	1.00	0.33	0.39	0.06
Q87) sidewalks on most streets	-0.15	0.03	0.07	-0.08	0.32	0.02	0.30	0.32	0.57	0.53	0.05	0.30	0.10	0.33	1.00	0.45	0.30
Q88) easy to walk to a bus stop, train, or subway station from my home	0.13	0.00	0.16	0.03	0.12	-0.18	0.06	0.07	0.15	0.28	0.09	0.24	0.17	0.39	0.45	1.00	0.21
Q89) busy roads to cross when out for walks	-0.36	-0.24	-0.11	-0.16	0.43	0.17	0.47	0.42	0.23	0.42	0.00	0.03	-0.08	0.06	0.30	0.21	1.00

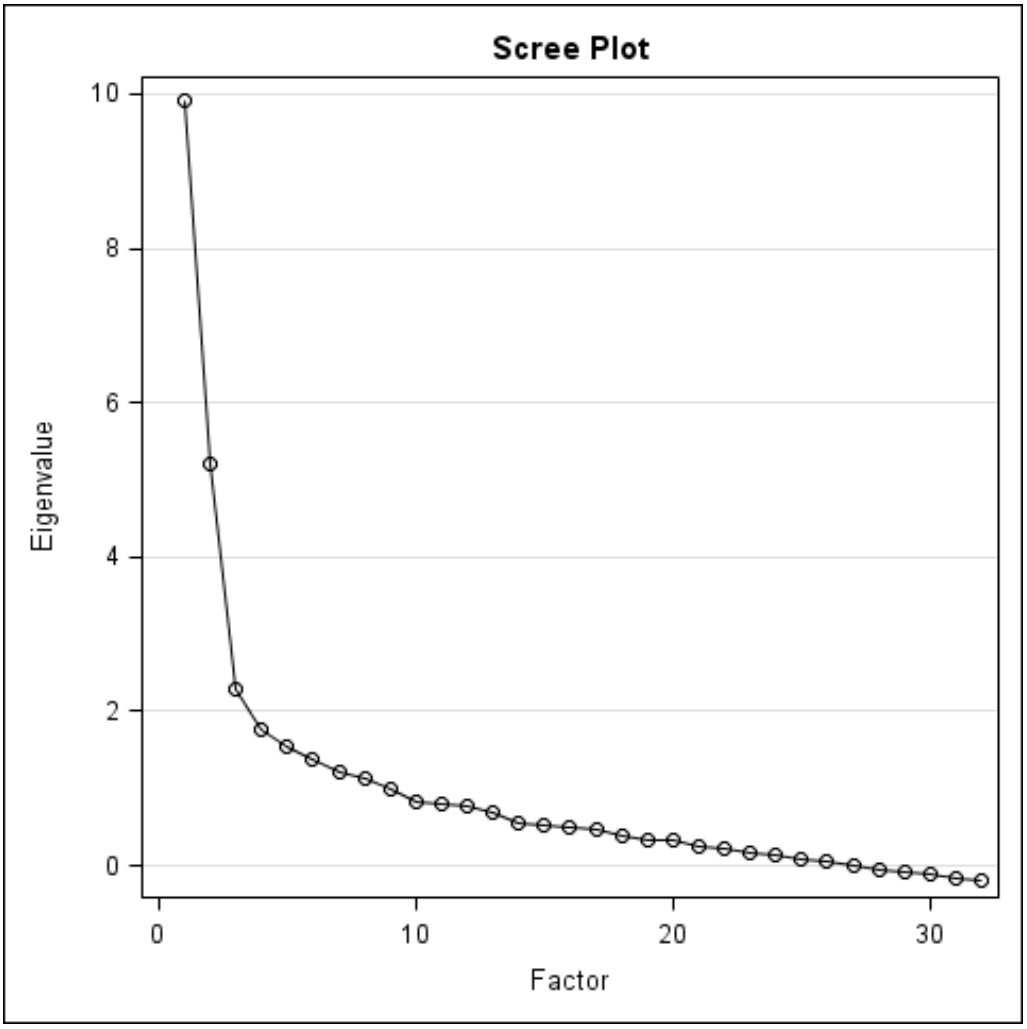
Q90) access to shopping	0.18	0.30	-0.02	0.20	0.01	-0.10	0.05	-0.19	0.16	0.08	0.37	0.50	0.42	0.27	0.36	0.30	0.11
Q91) access to medical care	0.36	0.35	0.22	0.36	0.02	-0.09	0.04	-0.20	-0.06	0.01	0.37	0.27	0.31	0.27	0.35	0.33	0.02
Q92) policing	0.48	0.57	0.33	0.45	-0.36	-0.40	-0.22	-0.48	-0.46	-0.37	0.25	0.10	0.21	-0.05	0.06	0.09	-0.20
Q93) access to a large selection of fresh fruits and vegetables	0.37	0.30	0.26	0.33	-0.12	-0.08	-0.10	-0.12	-0.15	0.10	0.39	0.42	0.43	0.38	0.05	0.21	0.02
Q94) access to large selection of healthy foods	0.47	0.32	0.21	0.38	-0.12	-0.07	-0.05	-0.22	-0.05	0.06	0.38	0.47	0.52	0.40	0.21	0.27	0.04
Q95) access to many fast food restaurants	0.09	0.22	0.03	0.19	0.05	0.01	0.06	-0.05	-0.02	-0.03	0.21	0.30	0.35	0.24	0.15	0.21	0.17
Q96) often see people walking	0.29	0.46	0.13	0.44	-0.04	-0.02	-0.10	-0.17	-0.02	-0.01	0.33	0.18	0.35	0.37	0.09	0.29	-0.15
Q97) often see people exercising	0.29	0.28	0.16	0.42	-0.08	-0.03	-0.14	-0.21	0.00	0.10	0.38	0.33	0.58	0.29	-0.03	0.08	0.00
Q99) feel part of neighbourhood	0.59	0.68	0.37	0.65	-0.27	-0.44	-0.17	-0.43	-0.41	-0.33	0.38	0.16	0.48	0.16	-0.20	0.12	-0.21
Q100) people are friendly	0.46	0.60	0.45	0.69	-0.37	-0.27	-0.26	-0.39	-0.30	-0.29	0.43	0.17	0.45	0.23	-0.05	0.01	-0.27
Q101) People are willing to help their neighbours	0.40	0.43	0.30	0.57	-0.25	0.01	-0.05	-0.27	-0.08	-0.07	0.49	0.32	0.45	0.31	0.01	-0.09	-0.12
Q102) People can be trusted	0.51	0.58	0.35	0.63	-0.35	-0.34	-0.28	-0.40	-0.48	-0.29	0.24	0.06	0.40	0.26	-0.19	-0.04	-0.07
Q103) People share the same values	0.56	0.38	0.38	0.52	-0.31	-0.11	-0.23	-0.33	-0.39	-0.19	0.40	0.04	0.42	0.18	-0.25	-0.15	-0.20
Q104) neighbourhood is safe	0.59	0.64	0.28	0.61	-0.32	-0.48	-0.29	-0.25	-0.53	-0.38	0.34	0.11	0.40	0.11	-0.20	-0.07	-0.27
Q105A) Violence is not a problem	0.56	0.56	0.11	0.40	-0.32	-0.35	-0.32	-0.22	-0.50	-0.42	0.12	0.08	0.28	0.11	-0.36	0.00	-0.28
Q105B) too many people hanging around on the streets near my home	-0.24	-0.30	-0.15	-0.19	0.42	0.26	0.37	0.32	0.40	0.24	0.02	0.12	-0.05	0.26	0.19	0.24	0.46

ii. Neighbourhood questionnaire items Q90 to Q105B

	Q90	Q91	Q92	Q93	Q94	Q95	Q96	Q97	Q99	Q100	Q101	Q102	Q103	Q104	Q105A	Q105B
Q73) neighbourhood is well maintained	0.18	0.36	0.48	0.37	0.47	0.09	0.29	0.29	0.59	0.46	0.40	0.51	0.56	0.59	0.56	-0.24
Q74) pleasant to walk in neighbourhood.	0.30	0.35	0.57	0.30	0.32	0.22	0.46	0.28	0.68	0.60	0.43	0.58	0.38	0.64	0.56	-0.30
Q75) many trees along the streets	-0.02	0.22	0.33	0.26	0.21	0.03	0.13	0.16	0.37	0.45	0.30	0.35	0.38	0.28	0.11	-0.15
Q76) buildings and houses are interesting.	0.20	0.36	0.45	0.33	0.38	0.19	0.44	0.42	0.65	0.69	0.57	0.63	0.52	0.61	0.40	-0.19
Q77) a lot of noise	0.01	0.02	-0.36	-0.12	-0.12	0.05	-0.04	-0.08	-0.27	-0.37	-0.25	-0.35	-0.31	-0.32	-0.32	0.42
Q78) a lot of unpleasant smells.	-0.10	-0.09	-0.40	-0.08	-0.07	0.01	-0.02	-0.03	-0.44	-0.27	0.01	-0.34	-0.11	-0.48	-0.35	0.26
Q79) has heavy traffic.	0.05	0.04	-0.22	-0.10	-0.05	0.06	-0.10	-0.14	-0.17	-0.26	-0.05	-0.28	-0.23	-0.29	-0.32	0.37
Q80) a lot of trash and litter on the street	-0.19	-0.20	-0.48	-0.12	-0.22	-0.05	-0.17	-0.21	-0.43	-0.39	-0.27	-0.40	-0.33	-0.25	-0.22	0.32
Q81) vandalism	0.16	-0.06	-0.46	-0.15	-0.05	-0.02	-0.02	0.00	-0.41	-0.30	-0.08	-0.48	-0.39	-0.53	-0.50	0.40
Q82) a lot of graffiti	0.08	0.01	-0.37	0.10	0.06	-0.03	-0.01	0.10	-0.33	-0.29	-0.07	-0.29	-0.19	-0.38	-0.42	0.24
Q83) interesting things to do	0.37	0.37	0.25	0.39	0.38	0.21	0.33	0.38	0.38	0.43	0.49	0.24	0.40	0.34	0.12	0.02
Q84) many places to go within walking distance from my home	0.50	0.27	0.10	0.42	0.47	0.30	0.18	0.33	0.16	0.17	0.32	0.06	0.04	0.11	0.08	0.12
Q85) many places to be physically active	0.42	0.31	0.21	0.43	0.52	0.35	0.35	0.58	0.48	0.45	0.45	0.40	0.42	0.40	0.28	-0.05
Q86) park or walking trail within a short walk from my home	0.27	0.27	-0.05	0.38	0.40	0.24	0.37	0.29	0.16	0.23	0.31	0.26	0.18	0.11	0.11	0.26
Q87) sidewalks on most streets	0.36	0.35	0.06	0.05	0.21	0.15	0.09	-0.03	-0.20	-0.05	0.01	-0.19	-0.25	-0.20	-0.36	0.19
Q88) easy to walk to a bus stop, train, or subway station from my home	0.30	0.33	0.09	0.21	0.27	0.21	0.29	0.08	0.12	0.01	-0.09	-0.04	-0.15	-0.07	0.00	0.24
Q89) busy roads to cross when out for walks	0.11	0.02	-0.20	0.02	0.04	0.17	-0.15	0.00	-0.21	-0.27	-0.12	-0.07	-0.20	-0.27	-0.28	0.46

Q90) access to shopping	1.00	0.59	0.35	0.55	0.62	0.49	0.17	0.27	0.31	0.28	0.29	0.12	-0.02	0.20	0.17	-0.02
Q91) access to medical care	0.59	1.00	0.52	0.33	0.44	0.34	0.13	0.14	0.32	0.47	0.39	0.33	0.36	0.36	0.18	-0.07
Q92) policing	0.35	0.52	1.00	0.20	0.22	0.08	0.17	0.05	0.59	0.50	0.32	0.47	0.32	0.64	0.53	-0.39
Q93) access to a large selection of fresh fruits and vegetables	0.55	0.33	0.20	1.00	0.86	0.55	0.33	0.33	0.32	0.25	0.24	0.23	0.27	0.33	0.24	-0.02
Q94) access to large selection of healthy foods	0.62	0.44	0.22	0.86	1.00	0.55	0.30	0.41	0.42	0.40	0.36	0.34	0.35	0.32	0.25	-0.05
Q95) access to many fast food restaurants	0.49	0.34	0.08	0.55	0.55	1.00	0.12	0.08	0.30	0.25	0.13	0.05	-0.07	0.23	0.11	0.06
Q96) often see people walking	0.17	0.13	0.17	0.33	0.30	0.12	1.00	0.60	0.47	0.41	0.44	0.51	0.29	0.33	0.22	-0.07
Q97) often see people exercising	0.27	0.14	0.05	0.33	0.41	0.08	0.60	1.00	0.48	0.44	0.47	0.46	0.42	0.29	0.23	0.03
Q99) feel part of neighbourhood	0.31	0.32	0.59	0.32	0.42	0.30	0.47	0.48	1.00	0.76	0.60	0.71	0.61	0.75	0.69	-0.40
Q100) people are friendly	0.28	0.47	0.50	0.25	0.40	0.25	0.41	0.44	0.76	1.00	0.84	0.78	0.74	0.69	0.43	-0.20
Q101) People are willing to help their neighbours	0.29	0.39	0.32	0.24	0.36	0.13	0.44	0.47	0.60	0.84	1.00	0.69	0.76	0.49	0.23	-0.03
Q102) People can be trusted	0.12	0.33	0.47	0.23	0.34	0.05	0.51	0.46	0.71	0.78	0.69	1.00	0.75	0.71	0.50	-0.27
Q103) People share the same values	-0.02	0.36	0.32	0.27	0.35	-0.07	0.29	0.42	0.61	0.74	0.76	0.75	1.00	0.55	0.33	-0.26
Q104) neighbourhood is safe	0.20	0.36	0.64	0.33	0.32	0.23	0.33	0.29	0.75	0.69	0.49	0.71	0.55	1.00	0.77	-0.44
Q105A) Violence is not a problem	0.17	0.18	0.53	0.24	0.25	0.11	0.22	0.23	0.69	0.43	0.23	0.50	0.33	0.77	1.00	-0.41
Q105B) too many people hanging around on the streets near my home	-0.02	-0.07	-0.39	-0.02	-0.05	0.06	-0.07	0.03	-0.40	-0.20	-0.03	-0.27	-0.26	-0.44	-0.41	1.00

APPENDIX E. SCREE PLOT OF PRINCIPAL COMPONENT ANALYSIS OF NEIGHBOURHOOD QUESTIONNAIRE ITEMS USING TETRACHORIC CORRELATION MATRIX.



APPENDIX F. ROTATED FACTOR LOADINGS OF 3-FACTOR PRINCIPLE COMPONENT ANALYSIS OF NEIGHBOURHOOD ITEMS IN THE DHS SUB-STUDY 2011

	Factor 1 "Order"	Factor 2 "Society and culture"	Factor 3 "Access"
Neighbourhood is well maintained	**-0.67548**	0.36132	0.26288
Pleasant to walk in neighbourhood.	**-0.56958**	0.40894	0.29834
Busy roads to cross when out for walks	**0.52442**	-0.08593	0.21122
A lot of noise	**0.64163**	-0.15532	0.12228
A lot of unpleasant smells.	**0.59698**	0.07438	-0.18137
Presence of heavy traffic.	**0.60777**	-0.12077	0.11379
A lot of trash and litter on the street	**0.69151**	-0.16789	-0.01850
Vandalism	**0.76996**	-0.07816	0.13299
A lot of graffiti	**0.75637**	0.11848	0.19446
Adequate policing	**-0.66613**	0.17395	0.32445
Neighbourhood is safe	**-0.68115**	0.47919	0.19322
Violence is not a problem	**-0.67125**	0.23681	0.15000
Too many people hang around on the streets near my home	**0.60840**	-0.01116	0.09267
Many trees along the streets	-0.13925	**0.45389**	0.09944
Buildings and houses are interesting.	-0.42107	**0.65917**	0.18724
Interesting things to do in neighbourhood	0.02377	**0.62746**	0.30843
Often see people walking in neighbourhood	-0.05708	**0.59719**	0.17699
Often see people exercising in neighbourhood	0.02636	**0.70342**	0.12812
Many places to be physically active in neighbourhood	0.03010	**0.65808**	0.39672
People are friendly in neighbourhood	-0.44647	**0.76670**	0.13944
People are willing to help their neighbours	-0.13424	**0.86558**	0.06846
People can be trusted in neighbourhood	-0.48814	**0.72779**	0.00810
People share the same values in neighbourhood	-0.34655	**0.80118**	-0.13354

Park or walking trail within a short walk from my home	0.20706	0.45841	**0.46516**
Sidewalks on most streets	0.44554	-0.04523	**0.55924**
Easy to walk to a bus stop, train, or subway station from my home	0.14899	-0.03630	**0.59662**
Many places to go within walking distance from my home	0.16654	0.32548	**0.56034**
Access to shopping	-0.05643	0.12780	**0.81494**
Access to medical care	-0.17530	0.28253	**0.60335**
Access to a large selection of fresh fruits and vegetables	-0.13552	0.31041	**0.66869**
Access to large selection of healthy foods	-0.13281	0.38636	**0.72178**
Access to many fast food restaurants	-0.04630	0.04079	**0.66209**

APPENDIX G. ROTATED FACTOR LOADINGS OF 3-FACTOR PRINCIPLE COMPONENT ANALYSIS OF NEIGHBOURHOOD ITEMS IN THE DHS SUB-STUDY 2012

	Factor 1 "Order"	Factor 2 "Society and culture"	Factor 3 "Access"
Neighbourhood is well maintained	-0.47018	**0.62504**	0.06100
Pleasant to walk in neighbourhood.	-0.18519	**0.66339**	0.00579
Busy roads to cross when out for walks	**0.68836**	-0.00458	0.10673
A lot of noise	**0.63248**	-0.09301	0.00061
A lot of unpleasant smells.	**0.69428**	-0.03100	-0.13730
Presence of heavy traffic.	**0.67667**	-0.11485	0.07708
A lot of trash and litter on the street	**0.69561**	-0.29054	-0.04615
Vandalism	**0.66965**	-0.26090	-0.05637
A lot of graffiti	**0.71652**	-0.12287	0.18927
Adequate policing	**-0.52393**	0.18372	0.51039
Neighbourhood is safe	**-0.63958**	0.64988	0.23085
Violence is not a problem	**-0.51545**	0.56471	0.02879
Too many people hang around on the streets near my home	**0.58262**	-0.15387	0.08558
Many trees along the streets	-0.06982	**0.54975**	0.24271
Buildings and houses are interesting.	-0.30274	**0.70918**	0.25387
Interesting things to do in neighbourhood	0.04371	**0.47544**	0.49696
Often see people walking in neighbourhood	0.01893	**0.56606**	0.35750
Often see people exercising in neighbourhood	0.08581	**0.46564**	0.42267
Many places to be physically active in neighbourhood	0.01509	0.30888	**0.52584**
People are friendly in neighbourhood	-0.17325	**0.87305**	0.03101
People are willing to help their neighbours	-0.17242	**0.71893**	0.14340
People can be trusted in neighbourhood	-0.47918	**0.78346**	0.06485
People share the same values in neighbourhood	-0.12295	**0.83684**	0.03361

Park or walking trail within a short walk from my home	0.28440	0.06047	**0.49862**
Sidewalks on most streets	0.46824	-0.09884	**0.52173**
Easy to walk to a bus stop, train, or subway station from my home	0.26349	-0.18704	**0.49445**
Many places to go within walking distance from my home	0.16338	0.34108	**0.52966**
Access to shopping	-0.04744	-0.01901	**0.82599**
Access to medical care	-0.10919	0.14004	**0.65163**
Access to a large selection of fresh fruits and vegetables	-0.19788	0.16454	**0.77076**
Access to large selection of healthy foods	-0.18643	0.18898	**0.78051**
Access to many fast food restaurants	0.05783	0.14404	**0.64393**

APPENDIX H. ROTATED FACTOR LOADINGS OF 3-FACTOR PRINCIPLE COMPONENT ANALYSIS OF NEIGHBOURHOOD ITEMS IN THE DHS SUB-STUDY 2013

	Factor 1 "Order"	Factor 2 "Society and culture"	Factor 3 "Access"
Neighbourhood is well maintained	0.49751	**0.70396**	0.19748
Pleasant to walk in neighbourhood.	0.19886	**0.64460**	0.32882
Busy roads to cross when out for walks	**0.60276**	0.10712	-0.10636
A lot of noise	**0.79718**	0.10231	0.06905
A lot of unpleasant smells.	**0.66885**	0.00732	0.17545
Presence of heavy traffic.	**0.79222**	0.05849	0.07385
A lot of trash and litter on the street	**0.62066**	0.35709	-0.10170
Vandalism	**0.59488**	0.45984	-0.19127
A lot of graffiti	**0.71670**	0.30567	-0.28048
Adequate policing	0.22134	**0.52259**	0.46283
Neighbourhood is safe	0.36764	**0.68726**	0.32026
Violence is not a problem	0.38399	**0.66977**	0.12230
Too many people hang around on the streets near my home	**0.66288**	0.08157	0.03299
Many trees along the streets	0.35892	0.14641	**0.49778**
Buildings and houses are interesting.	0.39552	**0.61152**	0.25431
Interesting things to do in neighbourhood	0.03347	0.42931	**0.55591**
Often see people walking in neighbourhood	-0.07951	**0.49288**	0.43410
Often see people exercising in neighbourhood	-0.08193	**0.65039**	0.29430
Many places to be physically active in neighbourhood	0.01120	0.20566	**0.71976**
People are friendly in neighbourhood	0.16376	**0.82857**	0.25808
People are willing to help their neighbours	0.14677	**0.86507**	0.13389
People can be trusted in neighbourhood	0.26105	**0.86857**	0.06202
People share the same values in neighbourhood	0.04392	**0.84013**	0.19027

Park or walking trail within a short walk from my home	-0.14005	0.23920	**0.62659**
Sidewalks on most streets	-0.44454	-0.10122	**0.46453**
Easy to walk to a bus stop, train, or subway station from my home	-0.33283	-0.19797	**0.34784**
Many places to go within walking distance from my home	-0.14632	0.34425	**0.55734**
Access to shopping	0.04156	0.26683	**0.72337**
Access to medical care	-0.01915	0.25118	**0.55492**
Access to a large selection of fresh fruits and vegetables	0.15282	0.11249	**0.82961**
Access to large selection of healthy foods	0.13933	0.18745	**0.79555**
Access to many fast food restaurants	-0.27018	0.03832	**0.58933**

APPENDIX I. LIST OF QUESTIONNAIRE ITEMS BY NEIGHBOURHOOD FACTORS FROM 3-FACTOR PRINCIPLE COMPONENT ANALYSIS

Neighbourhood factor	Items
Physical and social order (13 items)	Q73) neighbourhood is well maintained Q74) pleasant to walk in neighbourhood. Q77) a lot of noise Q78) a lot of unpleasant smells. Q79) has heavy traffic. Q80) a lot of trash and litter on the street Q81) vandalism Q82) a lot of graffiti Q89) busy roads to cross when out for walks Q92) policing Q104) neighbourhood is safe Q105A) Violence is not a problem Q105B) too many people hanging around on the streets near my home
Social and cultural environment (10 items)	Q75) many trees along the streets Q76) buildings and houses are interesting. Q83) interesting things to do Q85) many places to be physically active Q96) often see people walking Q97) often see people exercising Q100) people are friendly Q101) People are willing to help their neighbours Q102) People can be trusted Q103) People share the same values
Access (9 items)	Q84) many places to go within walking distance from my home Q86) park or walking trail within a short walk from my home Q87) sidewalks on most streets Q88) easy to walk to a bus stop, train, or subway station from my home Q90) access to shopping Q91) access to medical care Q93) access to a large selection of fresh fruits and vegetables Q94) access to large selection of healthy foods Q95) access to many fast food restaurants

APPENDIX J. CORRELATION MATRIX BETWEEN NEIGHBOURHOOD FACTORS AND PAMPALON INDEX

Kendall Tau b Correlation Coefficients
Prob > |tau| under H0: Tau=0
Number of Observations

	Order	*Culture*	*Access*	Material Deprivation	Social Deprivation
Order	1.00000	0.15034	-0.08055	-0.16414	-0.18676
		<.0001	0.0195	<.0001	<.0001
	564	497	546	546	546
Culture	0.15034	1.00000	0.27655	-0.18434	-0.12335
	<.0001		<.0001	<.0001	0.0008
	497	518	505	503	503
Access	-0.08055	0.27655	1.00000	-0.03017	0.17959
	0.0195	<.0001		0.3790	<.0001
	546	505	572	555	555
Material Deprivation Score (Pampalon 2006)	-0.16414	-0.18434	-0.03017	1.00000	0.07692
	<.0001	<.0001	0.3790		0.0212
	546	503	555	581	581
Social Deprivation Score (Pampalon 2006)	-0.18676	-0.12335	0.17959	0.07692	1.00000
	<.0001	0.0008	<.0001	0.0212	
	546	503	555	581	581

APPENDIX K. NEIGHBOURHOOD FACTOR SCORE BY SOCIOECONOMIC VARIABLES IN THE DHS SUB-STUDY 2011

		Order mean (SD)	**Culture** mean (SD)	**Access** mean (SD)
Sex				
	Female	11.0 (2.2)	8.5 (2.0)	7.4 (1.9)
	Male	11.4 (1.9)	9.0 (1.7)	7.5 (1.8)
	p-value	0.0705	**0.0141**	0.494
Marital status				
	Married/Partner	11.5 (1.9)	9.0 (1.6)	7.4 (1.8)
	widowed/divorced/separated	10.8 (2.2)	8.4 (2.1)	7.4 (2)
	Single	10.6 (2.3)	8.2 (2.4)	7.7 (1.6)
	p-value	**0.0005**	**0.0007**	**0.0154**
Education				
	Less than secondary school	10.9 (2.3)	8.6 (2)	7.3 (1.8)
	Secondary school graduation	11.4 (1.9)	8.8 (1.8)	7.5 (2)
	Post-secondary education	11.5 (1.8)	9 (1.6)	7.5 (1.7)
	p-value	**0.0074**	0.1086	0.3254
Household Income				
	<15K$	10.3 (2.7)	8 (2.3)	7.3 (1.8)
	15K$-50K$	11.1 (2.1)	8.6 (2)	7.4 (1.9)
	>50K$	11.7 (1.6)	9.2 (1.3)	7.6 (1.7)
	p-value	**<.0001**	**0.0004**	0.4922
Work Status				
	Working full-time	11.4 (1.8)	9 (1.7)	7.5 (1.8)
	Not working	10.2 (2.7)	7.9 (2.4)	7.2 (2)
	Retired	11.4 (1.9)	8.9 (1.7)	7.5 (1.8)
	p-value	**0.0003**	**<.0001**	0.5351
Number of Chronic Conditions				
	0	11.4 (1.9)	9 (1.7)	7.3 (1.9)
	1	11.4 (1.7)	8.9 (1.8)	7.6 (1.7)
	2+	11.1 (2.2)	8.6 (1.9)	7.4 (1.8)
	p-value	0.3792	**0.0091**	0.3235

P-values are derived from Kurskal-Wallis test.

APPENDIX L. RESULTS OF MODERATOR ANALYSIS BY HOUSEHOLD CHARACTERISTICS AND BETWEEN NEIGHBOURHOOD CHARACTERISTICS IN THE DHS

Analyses of effect modification by neighbourhood characteristics showed significant interactions between land-use mix and social deprivation (p=0.001), number of fast food restaurants (p=0.028) and physical activity facilities (p=0.034), as well as significant interactions between material deprivation and number of cultural services (p=0.033). These results suggest that greater land-use diversity protected against depression particularly for those living in socially deprived areas, but that greater land-use diversity in neighbourhoods that also had a high number of fast food restaurants increased the risk of depression. Greater number of physical activity facilities protected against depression particularly for those living in low land-use mix neighbourhoods. Finally, living in an area with a greater number of cultural services protected against depression particularly in those residing in materially deprived neighbourhoods. Analyses of effect modification by housing characteristics in the DHS sub-study showed a significant interaction between material deprivation and household crowding index (p=0.017) and being able to hear neighbours from dwelling (p=0.032).

APPENDIX M. INFORMATION FOR MODEL SELECTION OF PROBABILITY OF CENSORING WEIGHTS IN THE DHS

Model	Description	Mean	SD	Min	Max	AIC	BIC
Model 1	Numerator includes linear terms for age, sex, duration of diabetes education categories. Denominator includes linear terms for age, sex, duration of diabetes education categories, and one-year lagged marital status, work status, SRH, disability score, number of diabetes complications, number of chronic conditions and smoking status	1.00	0.10	0.58	1.90	3045.19	3142.37
Model 2	Numerator and denominator are as in step 1, and added BMI (continuous), perceived diabetes control, binary household income, age square term.	0.99	0.18	0.35	3.43	2491.97	2610.08
Model 3	Numerator and denominator are as in step 2, but used log(1+value) for diabetes duration, disability score and number of chronic conditions, because these variables were not normally distributed.	0.99	0.18	0.35	3.34	2492.99	2611.1
Model 4	Numerator and denominator are as in step 2, and added time (cycle) in denominator.	1.02	0.22	0.31	3.33	2448.78	2572.8
Model 5	Numerator and denominator are as in step 4, and added diabetes type in numerator and denominator.	1.02	0.22	0.31	3.33	2448.78	2572.8
Model 6	Included 1-year lagged depression score in denominator in model 5.	1.02	0.22	0.31	3.37	2450.65	2580.57
Model 7	Numerator and denominator are as in step 5, and added interactions between age and sex, diabetes duration, disability score and number of chronic conditions, and sex and diabetes duration in denominator..	1.02	0.23	0.29	2.94	2456.22	2609.76
Model 8	Added physical inactivity as numerator to model 5. FINAL MODEL	1.03	0.23	0.28	3.38	2390.63	2520.04

APPENDIX N. INFORMATION FOR MODEL SELECTION OF PROBABILITY OF DEPRESSION AT BASELINE IN THE DHS

Model	Description	Mean	SD	Min	Max	AIC	BIC
Model 1	Numerator includes constant of logistic regression for depression. Denominator includes linear terms for age, sex, duration of diabetes education categories, marital status, work status, SRH, disability score, number of diabetes complications, number of chronic conditions and smoking status	0.99	0.56	0.20	6.88	1298.15	1385.5
Model 2	Numerator and denominator are as in step 1, and added BMI (continuous), and binary household income variable (< vs > 50K$)	0.99	0.59	0.21	10.55	1150.15	1246.2
Model 3	Numerator and denominator are as in step 1, and added binary household income variable (< vs > 50K$) only	1.00	0.55	0.20	6.98	1076.18	1165.32
Model 4	Numerator and denominator are as in step 1, and added binary household income variable (< vs > 50K$) and social support	1.00	0.58	0.20	8.25	1023.83	1117.22
Model 5	Numerator and denominator are as in step 4, and added depression status at follow-up 1. FINAL MODEL	1.00	0.69	0.21	9.32	659.22	750.25

APPENDIX O. SUMMARY TABLE OF COEFFICIENTS FOR THE ASSOCIATION BETWEEN NEIGHBOURHOOD CHARACTERISTICS AND MEASURES OF DEPRESSION FOUND IN MANUSCRIPTS I, III AND IV

	Manuscript I	**Manuscript I**	**Manuscript III**	**Manuscript IV**
	NPHS	**NPHS**	**DHS**	**NPHS**
	General sample	With diabetes	With type II diabetes	General sample
	Depression (minor/major)	Depression (minor/major)	Depression (minor/major)	Trajectory of high persistent major depression prevalence
	N=9026	N=451	N=1198	N=13,618
	HR [95% CI]	HR [95% CI]	HR [95% CI]	OR [95% CI]
Material deprivation	1.01	0.98	1.12	--
	[0.94,1.08]	[0.57,1.69]	[0.99,1.27]	
Social deprivation	0.96	0.87	1.00	--
	[0.89,1.04]	[0.50,1.49]	[0.88,1.14]	
Park and recreation	0.86	1.22	1.38	0.05
	[0.69,1.07]	[0.00,2.5e+214]	[0.17,10.95]	[0.00, 0.67]
Land-use mix	1.22	4.57	1.63	--
	[0.68,2.19]	[0.00,3.3e+173]	[0.72,3.70]	
Fast food restaurants	1.00	1.81	0.98	0.90
	[0.80,1.26]	[0.09,36.10]	[0.91,1.06]	[0.33, 2.71]
Health services	0.85	1.72	0.98	1.00
	[0.66,1.09]	[0.01,476.5]	[0.92,1.04]	[0.27, 3.67]
Healthy food stores	0.87	0.60	0.98	0.12
	[0.67,1.11]	[0.00,2.10e+07]	[0.88,1.09]	[0.00, 11.02]
Physical activity facilities	0.95	1.07	0.71	--
	[0.72,1.24]	[0.00,155985]	[0.55,0.91]	
Cultural services	0.89	0.47	0.75	0.07
	[0.65,1.21]	[0.00,5.58e+10]	[0.57,0.99]	[0.01, 0.60]
Greenness	0.79	0.05	0.94	--
	[0.27,2.33]	[0.00,>9e+99]	[0.88,1.01]	