INDIGENOUS HEALTH COUNTS: ADVANCING META-ANALYSIS METHODS FOR RESPONDENT-DRIVEN SAMPLING AND FIRST NATIONS, INUIT, AND MÉTIS PEOPLES LIVING IN URBAN AREAS IN ONTARIO

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Abstract

Introduction: There is a lack of accurate and valid health information for First Nations, Inuit, and Métis (FNIM) peoples living in urban areas in Canada. Respondent-driven sampling (RDS) is a statistical and sampling technique that allows the health of Indigenous peoples living in urban areas to be examined through the use of their social networks. There are currently no techniques available to pool the results of RDS studies to obtain overall summary-level information across RDS samples. The objective of this dissertation was to develop a meta-analysis technique for RDS data and examine the combined, overall prevalence of key outcomes identified by local Indigenous health service organizations. Data were obtained from the community-led Our Health Counts (OHC) projects – five Indigenous health studies which successfully applied RDS in the cities of Hamilton, Toronto, London, Kenora, and Thunder Bay. Primary outcomes include diabetes mellitus (DM), prescription opioid (PO) use without a prescription or in unprescribed ways, experiences of discrimination in the healthcare system, and use of traditional medicines.

Methods: Four manuscripts were completed, including one simulation study and three applications of the results of the simulation study. The first study developed and validated preliminary meta-analysis methods for random effects (RE) and fixed effects (FE) models for RDS data. The subsequent three manuscripts examine the prevalence of (1) DM, (2) PO use without a prescription or out of keeping with the prescription, and (3) experiences of anti-Indigenous discrimination in the healthcare system and use of traditional medicines in FNIM peoples living in urban areas through RE meta-analysis.

Results: Using the average variance calculated from RDS-II bootstrap confidence intervals as the estimate of within-study variance for RE and FE models was the only valid meta-analysis method for RDS data. For younger adults, the prevalence of DM was higher among FNIM peoples living in Ontario cities compared to the general population. FNIM peoples living in cities also had a higher prevalence of PO use without a prescription or in unintended ways than the general population. Age differences were found in the prevalence of experiences of anti-Indigenous discrimination in the healthcare system by FNIM peoples living in cities, with younger people reporting more discrimination.

Conclusion: RDS is a valuable sampling and statistical technique for examining the health of FNIM peoples living in urban areas in Ontario. Pooling data across OHC sites allows us to obtain a more precise, overall understanding of priority outcomes identified by the Indigenous community partners. Improved understanding allows community partners and decision makers actionable information to tailor programs and interventions to support the needs of Indigenous peoples and to be more effective in improving equity in the healthcare system.

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Most importantly, I am grateful for my parents who have been by my side encouraging me and being a sounding board for various drafts of this work.

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List of Acronyms

AD aggregate data

APS Aboriginal Peoples Survey

CI confidence interval

DM diabetes mellitus

FE fixed effects

FNIM First Nations, Inuit, and Métis

FNRHS First Nations Regional Longitudinal Health Survey

HCG Homophily Configuration Graph

HH Hansen-Hurwitz

HT Horvitz-Thompson

IDF International Diabetes Federation

IPD individual patient data

IPS Indigenous Peoples Survey

MP Markov process

NHS National Household Survey

OHC Our Health Counts

PHAC Public Health Agency of Canada

PO prescription opioid

RCAP Royal Commission on Aboriginal Peoples

RDS respondent-driven sampling

RE random effects

SD standard deviation

SH Salganik-Heckathorn

SS Successive Sampling

SUD substance use disorder

TRC Truth and Reconciliation Commission of Canada

1 Introduction

First Nations, Inuit, and Métis (FNIM) peoples in Canada live in a variety of geographic locations, including urban, rural, and remote areas [1]. However, the majority of Indigenous peoples in Canada now live in cities, and the number of Indigenous peoples living in urban areas continues to increase rapidly [2]. The continued effects of colonialism contribute to health disparities in Indigenous populations, including elevated rates of diabetes mellitus (DM), hypertension, substance abuse, mental health concerns, and overall morbidity and mortality in addition to having significantly reduced life expectancy [3]. However, gaps in data availability continue to persist, and there is a pressing need for valid health information for Indigenous peoples living in urban and related homelands. Accurate information must be provided to Indigenous peoples, the health sector, and policy makers in order to improve health outcomes. The need for improvement in Indigenous healthcare has been recognized in Article 19 of the Truth and Reconciliation Commission of Canada (TRC) Calls to Action [4], which demands that the Government of Canada "establish measurable goals to identify and close the gaps in health outcomes between Aboriginal and non-Aboriginal communities" on indicators such as chronic disease, mental health and illness, injury, among others.

While Indigenous peoples living in urban areas are the fastest growing segment of Indigenous populations in Canada [5], the availability of relevant data remains limited. Valid measurements of the health of FNIM peoples across geographies requires that all FNIM peoples have an opportunity to be included. It is discriminatory to restrict health assessment and response to "status Indians" as defined by federal Indian Act legislation or to First Nations living in on-reserve First Nations communities. It is thus essential to obtain a representative sample of Indigenous populations who are living in urban and related homelands in order to provide community leaders with accurate data that are needed to assess health and measure improvement in healthcare. Given the absence of a population-based sampling frame for Indigenous peoples living in urban areas, the six Our Health Counts (OHC) projects use respondent-driven sampling (RDS) to recruit participants to ensure a representative and valid study. RDS is an effective sampling method for Indigenous populations living in urban areas because it uses strong, existing social networks to sample population members [6].

The OHC data sets are the largest sources of valid, representative health information for FNIM peoples living in urban areas in Ontario, but they are currently not being used to their fullest capacity due to a lack of appropriate statistical techniques. The OHC Indigenous community health service partners identified the prevalence of DM, prescription opioid (PO) use without a prescription or out of keeping with the prescription, discrimination in the healthcare system and traditional medicines use as four indicators of high relevance. Preliminary results from these data sets suggest a potentially elevated prevalence of DM, PO use, and experiences of anti-Indigenous discrimination in the healthcare system. More positively, there appears to be a high rate of traditional medicines use across these studies. However, due to statistical uncertainty, each individual study is not precise enough alone to make strong conclusions for some variables.

Since the required statistical approaches are not available for RDS-based studies, we developed and validated our proposed meta-analysis technique to summarize data across OHC studies. This proposed technique will allow us to determine whether observed health disparities are in fact statistically meaningful by providing a more precise, pooled, province-wide understanding of the measures of interest. This information is essential for improving the health and wellbeing of FNIM peoples living in urban areas.

The dissertation is organized as four related manuscripts. Chapters 1 and 2 provide an introduction and overview of Indigenous health databases, RDS, and meta-analysis. Chapter 3 focuses on developing and validating a meta-analysis technique for the combination of studies using RDS. Chapters 4 to 6 focus on applying these novel methodological approaches to examine the health of Indigenous adults living in urban areas in Ontario across five OHC data sets (Hamilton, Toronto, London, Kenora, and Thunder Bay). Specifically, these chapters examine DM, PO use without a prescription or in unprescribed ways, and both experiences of anti-Indigenous discrimination in the healthcare system and use of traditional medicines, respectively. Chapter 7 provides an overall summary of our findings and conclusions.

2 Background

This chapter contains preliminary background information and provides context for the subsequent manuscripts. The first section provides an overview of the Indigenous health data currently available in Canada, as well as its limitations. The second section reviews respondent-driven sampling (RDS) as both a sampling technique and an analytic method.

2.1 Indigenous health data in Canada

We have an obligation to meet the TRC guideline to "assess progress on closing the gaps between Aboriginal and non-Aboriginal communities in a number of health indicators" [4]. However, meeting this guideline is challenging given the difficulties collecting Indigenous health data [7]. Not only is it still common to use deficit-based health indicators rather than positive, holistic health indicators, there is also a lack of inclusive Indigenous identifiers in most databases. When Indigenous identifiers do exist, they are commonly restricted to Indigenous subpopulations (e.g., Indian status). The following section explores Indigenous health data sets in Canada as well as aspects that are unique to Indigenous health research.

2.1.1 Sources of Indigenous health data

While there are various sources of First Nations, Inuit, and Métis (FNIM) health data available, their limitations make it challenging to obtain representative health estimates. Smylie and Firestone [8] note that the core problem with Indigenous health information infrastructure in Canada is the absence of relevant, consistent, inclusive and reliable Indigenous identifiers in the primary population-level health data sources. Some of the national health surveys (e.g., the Canadian Community Health Survey and the Canadian Health Measures Survey) exclude Indigenous peoples living on reserve, so their ability to provide high quality representative data is limited. Statistics Canada also has various sources of data for Indigenous adults from the Census program, including the National Household Survey (NHS) and the Indigenous Peoples Survey (IPS) which was formerly known as the Aboriginal Peoples Survey (APS), and the Census itself.

There were quality issues with the 2001 and 2006 Census as there was significant non-participation by both on-reserve and off-reserve Indigenous populations, including substantial undercounting of Indigenous peoples living in urban areas [8]. When Indigenous identity and ancestry questions from the mandatory long form Census were transferred to the voluntary NHS in 2011, it was found that the Indigenous response rate to the NHS was even lower than the 2006 Census [8]. Data dissemination is significantly hampered as Indigenous data are no longer available for most Census subdivisions, some Census divisions and metropolitan areas, and at the regional level. Data suppression has contributed to the limited data release, with Statistics Canada citing an Aboriginal profile not being available as the reason. This means that data are suppressed because a population of self-identified Aboriginal peoples is made up of less than 250 people, data quality or confidentiality issues, or the area is comprised of or contains reserves or settlements with an incomplete population count [9]. In addition to violating the principle of Indigenous ownership of Indigenous data, this has been damaging to the foundation of Indigenous health statistics as the undercoverage of FNIM populations and lack of sufficient data for analyses is unable to inform healthcare decisions at the regional, provincial, and national levels.

The IPS is a national survey conducted by Statistics Canada of First Nations peoples living off reserve, Métis, and Inuit living in Canada [10]. While it was still called the APS, the survey had 5 cycles: 1991, 2001, 2006, 2012, and 2017. Most recently, the IPS had two data collection periods: from May 11 to November 30, 2022 and from January 16 to March 31, 2023. It was a voluntary response survey where participants were selected based on someone from their household completing the 2021 Census and identifying as at least one of the Indigenous groups. General topics covered by the survey include access to services, child care, family stability, trauma and discrimination, economic well-being, physical and mental health, education, and sense of belonging and Indigenous languages and culture [10]. However, limitations include inadequate depth in examining each topic due to the size of the survey, access to data for Indigenous peoples being restricted by Statistics Canada, inadequate analysis of variables as only a small number of them are analyzed by Statistics Canada, and inadequate dissemination of results as Statistics Canada does not release all available information [11]. These limitations make it difficult for the IPS to be used for Indigenous health research. Moreover, this process contradicts the OCAP® principles and Indigenous data governance policies, which ensure Indigenous peoples' right to own, access, and control data from and about Indigenous populations and lands [12, 13].

The First Nations Information Governance Centre conducts several Indigenous-led surveys, including the First Nations Regional Longitudinal Health Survey (FNRHS). The FNRHS is the first national survey for First Nations peoples, beginning in 1997 as the First Nations and Inuit Regional Longitudinal Health Survey (now known as the FNRHS pilot). The FNRHS Phase 1 was implemented in 2002/03 and added in Yukon and Northwest Territories. This was when Inuit peoples withdrew from the FNRHS process. Phase 2 data collection occurred from 2008 to 2010, phase 3 data collection occurred from 2015-2017, and phase 4 data collection will be conducted from 2023 to 2024. The FNRHS focuses on First Nations peoples living on reserve and in northern populations, using the INAC Indian Registry counts to weight individual responses in order to more accurately represent the First Nations population [14]. Considering the majority of FNIM peoples live in urban areas in Canada [5], the focus on the on-reserve and northern First Nations peoples limits the generalizability of the FNRHS.

Representative health data is imperative for accurately evaluating Indigenous health in order to appropriately address health inequities. For example, the 2011 Canadian Census severely underestimated the number of FNIM peoples living in Toronto, reporting about one-third of the true population size [2]. Given that Statistics Canada produces several primary national health surveys, many of which are linked to the Census, it is concerning that the health information disseminated from the Census is not representative of the majority of FNIM peoples living in Canada. Moreover, as highlighted, the majority of studies examining Indigenous peoples in Canada are conducted with First Nations peoples living on reserve, despite more Indigenous peoples in Canada living in urban areas [15]. As such, there is a need for comprehensive, representative, population-level health data for Indigenous peoples living in urban areas. To address these deficiencies, the Our Health Counts (OHC) project was created to collect representative and culturally relevant health information for FNIM peoples living in Ontario cities.

2.1.1.1 The continued effects of colonialism

Colonialism in Canada is the forced disconnection of Indigenous peoples from their land, culture, and community by settlers [16]. It continues to this day through government policies attempting to assimilate Indigenous peoples into the Euro-Canadian ways of life, forming the foundation on which health determinants within Indigenous populations and the health disparities they experience are constructed [17–19]. Residential schools are a particularly infamous aspect of colonialism that were, and continue to be, severely damaging for Indigenous peoples. The residential school system was put in place in order to civilize and Christianize Indigenous children, intending to eradicate their language, cultural traditions, and spiritual beliefs [20, 21]. While this attempt at forced assimilation failed, in part due to the resilience and strength of Indigenous peoples, there are continued effects. In particular, Dr. Janet Smylie notes that "Lists of Indigenous people were used to make sure that children weren't hidden when they were forced to go to residential schools" [22], contributing to the distrust and non-participation in government-run, non-Indigenous-led surveys that continue to this day.

In comparison, Indigenous-led health surveys have higher participation rates as these studies are run by the community for the community with content that is culturally relevant and respectful. For example, the OHC projects are a series of

Indigenous-led health surveys that have amassed one of the largest health information databases for FNIM peoples living in Ontario cities. Knowing that local Indigenous health service providers and partners own all data and lead all aspects of data collection, analyses, and results is key to Indigenous peoples' desire to participate in the research.

2.1.2 OHC studies

The OHC projects were created to address the shortcomings of the existing Indigenous health databases, including the low Indigenous response rates and lack of culturally relevant variables. These projects began in 2008 with an initial community partnership with *De dwa da dehs nye>s* Aboriginal Health Centre in Hamilton, Ontario. This study focused on developing a culturally relevant baseline population health database for First Nations peoples living in Hamilton, Ontario under the fundamental premise of community ownership and self-determination [23]. Under the leadership of Dr. Janet Smylie and five other Indigenous community organizations (Tungasuvvingat Inuit, Seventh Generation Midwives Toronto, Southwest Ontario Aboriginal Health Access Centre, Waasegiizhig Nanaandawe'iyewigamig Health Access Centre, and Anishnawbe Mushkiki Health Access Centre), five additional OHC projects were completed in Ottawa, Toronto, London, Kenora, and Thunder Bay. The OHC survey was designed as a respectful health assessment rather than a rapid health assessment, with participants being interviewed in-person. The survey incorporates indicators specific to Indigenous health based on local and cultural understandings of health and wellbeing as well as health and social issues prioritized by Indigenous partners and community members through concept mapping. To date, the six OHC studies make up the largest and most reliable database available for FNIM peoples living in urban and related homelands. We have been given permission by five of the six community organizations to analyze adult Indigenous data from their sites, specifically Hamilton, Toronto, London, Thunder Bay, and Kenora. While Ottawa was supportive of the project, they did not want to participate at this time. Due to FNIM peoples living in urban areas being hidden populations, RDS was used as an appropriate sampling technique as it leverages social networks to recruit study participants. Table 1 contains the number of initial participants from whom recruitment began (i.e., seeds), adult sample sizes and study dates for these five studies.

Table 1. OHC study details

Study location	Study dates	Seeds	Adult sample size
Hamilton	2008-2010	8	555
Toronto	2015-2016	20	917
London	2015-2017	6	508
Thunder Bay	2016-2018	12	601
Kenora	2016-2021	20	319

Note that for Hamilton, RDS recruitment began with six seeds and two seeds that specifically targeted participants with children were later added. As well, recruitment in Toronto began with ten seeds, and ten additional seeds were recruited to increase recruitment speed. For all sites, three recruitment coupons were given to each participant. To speed up recruitment, the number of coupons was increased to five per participant partway through recruitment in Hamilton and after adding in the extra ten seeds for Toronto. Participant eligibility criteria were:

1. Residing, working, or receiving healthcare in their respective city
2. Self-identifying as an Indigenous person
3. Being at least 15 years of age

Participants were only permitted to participate once, with duplicates being identified through provincial health card numbers. Participants were given $20 for participating and $10 for each person they recruited. Participants handed in their recruiter's coupon number, so recruitment chains could be traced using these unique coupon numbers. To measure network size (i.e., degree), participants were asked the number of Indigenous peoples they knew by name (and that knew them by name) that currently lived, worked or used health and social services in their respective city. Additional details of the RDS recruitment process are discussed in Section 2.3.

2.2 Community partnerships and data ownership

The project's community-based research, publication, and data governance agreements ensure Indigenous community leadership in all aspects of study design, data collection, recruitment, analyses, and data interpretation [24, 25]. All priority variables for analyses (including the ones that are examined in this project) are determined by community partners, and they lead all dissemination of results to their respective practices and Indigenous peoples more broadly. This ensures that the analyses and interpretation of results are representative and culturally relevant. In alignment with the ethical guidelines used for research by the Royal Commission on Aboriginal Peoples (RCAP) and the OCAP® principles [12], and in accordance with the project's academic-community partnership agreements, the community partners retain full ownership and control over all data. This ensures Indigenous control over Indigenous research data. Permission to access the databases of OHC Hamilton, Toronto, London, Thunder Bay, and Kenora have been granted by their respective data custodians in accordance with OHC's community-based framework [23]. In addition, over 20 local and regional Indigenous and allied health and social service organizations comprised the OHC project's reference group, meeting quarterly to support the research process. These organizations were involved in the entire study process, including survey design, question development, and data analyses to facilitate careful consideration of underlying local Indigenous ways of being and doing.

2.3 Overview of RDS

RDS is a data collection and analysis technique developed by Heckathorn [26] to improve upon snowball sampling. It uses a link-tracing network sampling strategy to gain access to hidden populations, including Indigenous peoples [26–28], survivors of sex trafficking [29], migrant populations [30], people who inject drugs [29], and people who experience homelessness [29]. RDS has two important characteristics [26].

1. There are a limited number of states (e.g., gender) that participants can take.
2. Any recruiter's recruits are a function of the recruiter's type and not of previous events (e.g., who recruited the recruiter).

Since RDS recruitment is a stochastic process that satisfies the Markov property (i.e., a memoryless process), it can therefore be described as a first-order Markov process (MP). For example, conditional on the gender of the present recruiter, the gender of the recruiter's recruiter and the gender of the recruiter's recruits are independent. Based on theorems regarding regular MPs, Heckathorn [26] gives two theorems for RDS:

1. As the recruitment process continues from wave to wave, an equilibrium mix of recruits will eventually be obtained that is independent of the characteristics of the seed(s).
2. The participant pool generated by an RDS process rapidly approaches equilibrium.

Essentially, as recruitment chains lengthen and sample size increases, the sample composition quickly becomes representative of the target population, negating the initial bias from seed participant selection [31]. Thus, RDS provides asymptotically unbiased estimates when the recruitment chains are long enough.

Figure 1 is an example of an RDS recruitment diagram. Recruitment begins with seeds who are selected from the target population. Each seed is then given k coupons to recruit up to k members of the population who, in turn, recruit up to k participants, and so on. The sampling continues until a pre-specified condition is met, which is either reaching a pre-specified target sample size or achieving stable estimates [32]. Incentives are used to help increase participation. Snowball sampling only provides incentive for participating as participant networks are not tracked, but since RDS does keep track of networks, participants are rewarded for being a part of the study as well as recruiting individuals. Due to the dual incentive system, individuals are also incentivized by social pressure from friends or family members to participate in the study so that the recruiters can receive the full participation incentive.

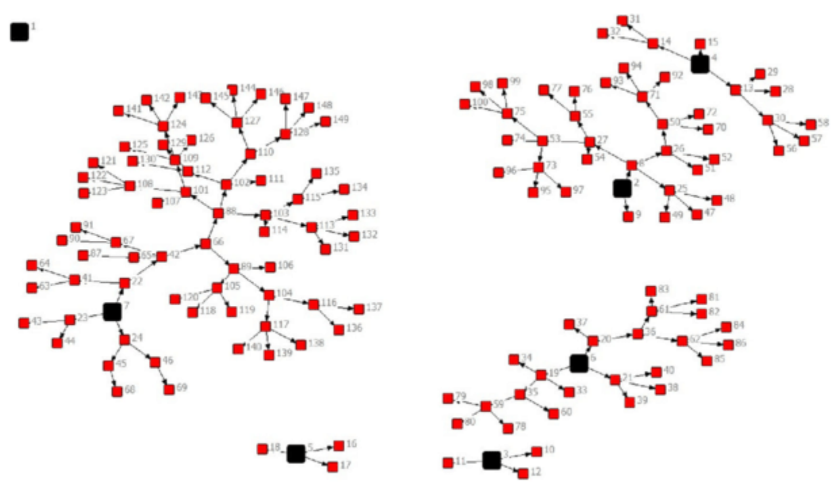

Figure 1. Sample RDS recruitment network diagram [33]. Black represent seeds and red represent recruits.

2.3.1 A review of snowball sampling

The term "snowball sampling" has been used to define two types of network sampling procedures [34, 35]. Goodman [36] introduced a specific form of snowballing called "s stage k name snowball sampling" that draws an initial sample using a probability method on a known sampling frame with fixed sampling process parameters (i.e., the number of connections to each participant k and the number of waves of the sample s). He used snowball sampling to examine social network structures by estimating the number of mutual relationships in the target population.

With the intention of exploring the process and problems of snowball sampling, Biernacki and Waldorf [37] examined a study where a population of ex-heroin addicts was sampled using snowball sampling. They defined snowball sampling as a convenience sampling mechanism used when a standard sampling approach is not feasible. This is often the case when trying to sample from hidden populations, which are characterized by the absence of a useable sampling frame (i.e., a "list" of all those within the population that could be sampled). As an initial probability sample is not feasible, the initial sample must be drawn using a convenience mechanism. However, the convenience mechanism renders the sample a non-probability sample. Thus, snowball sampling is used to obtain a non-probability sample or to construct a sampling frame. This definition of snowball sampling is more commonly used in practice while Goodman's [36] probabilistic approach is more common in statistical literature.

RDS pairs these two definitions of snowball sampling together. It starts with a convenience sample (i.e., seeds), relies on social networks to sample from hidden populations, and aims to approximate a probability sample as recruitment chains lengthen [38]. As such, RDS is a more practical and statistically valid method for hidden populations.

2.3.2 Comparison of RDS to snowball sampling

There are a few differences between RDS and snowball sampling (by Biernacki and Waldorf's [37] definition). Firstly, unlike snowball sampling, RDS is able to restrict the number of recruits per participant using coupons so that no one single-handedly drastically influences the sample. Moreover, coupons allow participants to be traced along RDS recruitment chains while snowball sampling does not keep track of recruitment. In RDS, participants give their coupons to others to recruit them to the study while in snowball sampling, participants give the contact information of their friends, family, etc. to the researcher who then uses that information to try to recruit those individuals into the study. Finally, RDS survey participants are asked about the size of their personal network with respect to the target population, also known as their degree, which is not done in snowball sampling. The resulting RDS data are thus not random as some participants are more likely to be selected than others, and the observations are not independent as the data are naturally clustered within recruiters and seeds.

Snowball sampling is affected by various biases due to limitations like recruitment strategies, location, and choice of seed participants [39]. RDS is able to reduce some of these biases but is particularly effective in reducing selection bias due to the equilibrium of states that is achieved when recruitment chains are long enough. It is an effective sampling method for Indigenous populations living in urban areas because it uses the strong, existing social networks to recruit community members [6]. However, note that responses are dependent due to multiple sources of correlation, and weighting must be applied to individual responses to account for the unequal probability of recruiting participants with varying social network sizes as well as homophily.

2.3.3 Statistical aspects of RDS data

2.3.3.1 Non-random sampling

There is a higher probability of individuals with more social connections to be recruited, thus leading to non-random sampling in RDS data. Weighting must be applied to account for the increased probability of individuals with larger social networks being sampled. For example, in Figure 2, participant B has more connections than participant A, so participant B will be easier to recruit into the study and will thus have lower weighting than participant A.

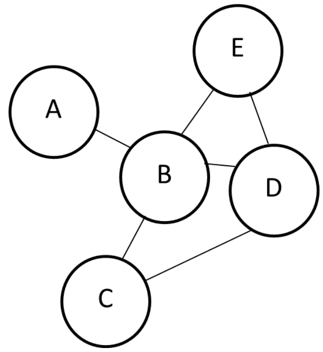

Figure 2. Sample network degree diagram in a small population.

2.3.3.2 Clustering

RDS produces branched recruitment chains where participants are clustered within their recruiters who are, in turn, clustered within their recruiters, and so on. Thus, the data are not independent due to this clustering of participants. There are different ways of clustering the data [40], but it is still unclear as to which method is the best choice for RDS, given the unique, nested sources of correlation. One method would be to consider all participants descended from the same seed as a cluster. However, this disregards the possibility that some recruiters may have a tendency to recruit individuals similar to them while others may not, which would result in sub-clusters. The other method would be to only treat recruits from the same immediate recruiter as a cluster, but this disregards the possibility that similar participant traits may continue for several waves in a recruitment chain.

2.3.3.3 Homophily

When network modeling, homophily is defined as "the correlation between trait values of nodes connected by an edge" [40]. Essentially, homophily refers to the tendency of people to know and recruit those who are similar to them [41], meaning there is an increased probability of within-group connections in the target population. Statistically, homophily (H_x) is defined as

$$H_x = 2\pi(1-\pi)R - 1,\ R = \frac{T_{ii}}{T_{ij}}$$

where T_{ii} is the number of within-group connections, T_{ij} is the number of between-group connections, and π is the outcome prevalence in the population. Thus, $H_x = 1$ indicates that links in the target population are independent of group status while $H_x = 2$ indicates that individuals have twice the probability of being linked to another member in their group as compared to an individual outside their group.

2.3.4 Analysis of RDS data

2.3.4.1 A review of RDS prevalence estimators

Consider a population where members belong to two groups: A and B. We are interested in the proportion of the population that belongs to group A. Relevant notation is as follows.

N	Total number of respondents
N_A	Number of respondents in group A
N_B	Number of respondents in group B
P_A	Proportion of population belonging to group A
P_B	Proportion of population belonging to group B
S_{AB}	Proportion of group A selected by group B
S_{BA}	Proportion of group B selected by group A
T_{AB}	Number of ties between a person in group A and a person in group B
D_i	Network size (degree) for the i^{th} individual
D_A	Network size (degree) of a person in group A
D_B	Network size (degree) of a person in group B

While there have been four iterations of RDS estimators, we will focus on discussing the RDS-I and RDS-II estimators as they are the basis for the other two estimators. The other two estimators are the Gile Successive Sampling (SS) estimator [42] and the Homophily Configuration Graph (HCG) estimator [41]. Briefly, they are modifications of the RDS-II and RDS-I estimators, respectively. The Gile SS estimator assumes that RDS recruitment occurs over a configuration graph and weights the estimate accordingly. The HCG estimator extends the configuration graph used by Gile [42] to allow for homophily and applies the weights of the Gile SS estimator to the RDS-I estimator. A limitation of both the Gile SS and HCG estimators is they require knowledge of the total population size N. While the Gile SS and HCG estimators perform well when the sample is a substantial proportion of the target population, they become biased when the population size is unknown [43]. Thus, the Gile SS and HCG estimators are not ideal for analyzing the data obtained from Indigenous peoples living in urban Ontario due to the unavailability and uncertainty of reliable, accurate estimates of the size of these populations.

2.3.4.2 Naïve estimator

The naïve estimator of the population prevalence is simply the observed sample proportion, calculated as

$$\hat{P}_A = \frac{N_A}{N}.$$

2.3.4.3 Salganik-Heckathorn estimator (2004)

Salganik and Heckathorn [31] proposed the first RDS estimator called the Salganik-Heckathorn (SH) estimator, also known as the RDS-I estimator. This estimator uses sample data to estimate the underlying social network first and then estimates the population prevalence using the estimated social network model. The RDS-I estimator makes use of the number of between-group recruitments (i.e., a member of group A recruits a member of group B or vice versa). This estimator assumes that sampling from a participant's network connections is random and that all connections are reciprocal. Thus, the RDS-I estimator of the proportion of the population that belongs to group A is

$$\hat{P}_A = \frac{S_{BA}\bar{D}_B}{S_{BA}\bar{D}_B + S_{AB}\bar{D}_A}$$

where

$$\begin{array}{ll} \bar{D}_A = \sum_{i \in A} \frac{D_i}{N_A}, & \bar{D}_B = \sum_{i \in B} \frac{D_i}{N_B} \\ S_{BA} = \frac{T_{AB}}{\sum_{i \in A} D_i}, & S_{AB} = \frac{T_{AB}}{\sum_{i \in B} D_i} \end{array}$$

It should be noted that the degrees of the seeds are excluded from the average degree estimates $\bar{D}_A$ and $\bar{D}_B$, removing seed selection bias [27, 44, 45].

2.3.4.4 Volz-Heckathorn estimator (2008)

Volz and Heckathorn [46] proposed an estimator for the proportion of the population in each disjoint set $A,\ B, \ldots$, which they called the RDS-II estimator (also known as the Volz-Heckathorn or V-H estimator). The RDS-II estimator is based on the idea that the probability of an individual being recruited into an RDS study is proportional to their degree. Volz and Heckathorn [46] state that it is a Hansen-Hurwitz (HH) type estimator, but an HH estimator is used when sampling with replacement [47] and the RDS recruitment process samples without replacement. Thus, the RDS-II estimator is closer to a Horvitz-Thompson (HT) type estimator, which is used when sampling without replacement [27]. Given that the MP model of RDS recruitment violates the assumption of independence, their proposed estimator is only similar to an HT estimator. The HT estimator applies inverse probability weighting to account for the differences in participants' probability of study inclusion [48]. In the context of RDS, the inverse probability weighting is the inverse of the participant's reported degree. Thus, the RDS-II estimator of the proportion of the population that belongs to group A is

$$\hat{P}_A = \left(\frac{N_A}{N}\right)\left(\frac{D}{D_A}\right)$$

where $\frac{D}{D_A}$ is the inverse probability weighting that is applied. Essentially, a sampling weight is applied to the naïve estimator in order to correct for network effects. For example, if $D > D_A$, we know that members of group A are being undersampled and the estimate $\hat{P}_A$ is inflated to account for that.

2.3.5 Overview of meta-analyses

There are two general approaches for performing meta-analyses: fixed effects (FE) and random effects (RE) models. An FE model assumes that the true effect of interest is the same in all studies, and sampling error is the only reason for the effect size varying between studies [49]. Studies are then combined using inverse-variance weighting such that larger, more precise studies are given more weight in the pooled analysis. That is, given that the variance of a study is v_i, the weight of each study w_i is calculated as

$$w_i = \frac{1}{v_i}.$$

In comparison, an RE model assumes that the true effect of interest can vary from study to study due to factors such as differing inclusion criteria, different participant populations, and sampling variability. This assumption adds another parameter into the model that is not present in an FE model, which is the between-study heterogeneity (τ^2) [50]. Thus, while larger studies still have heavier weighting than smaller studies, the weighting is moderated by the addition of τ^2 such that

$$w_i = \frac{1}{v_i + \tau^2}.$$

I^2 is a measure of the percentage of variability in effect estimates that is due to between-study heterogeneity rather than chance, where $I^2 = 0$ corresponds to no heterogeneity with increasing heterogeneity as I^2 approaches 1 [51]. The Cochrane Handbook provides a rough guideline on the thresholds for I^2, stating that 0% to 40% might not be important, 30% to 60% may represent moderate heterogeneity, 50% to 90% may represent substantial heterogeneity, and 75% to 100% represents considerable heterogeneity [51]. A high level of heterogeneity indicates that there is considerable variation in the effect sizes, which may make a pooled estimate inaccurate, particularly if the effect sizes vary in direction. Note that there is intentional overlap in the thresholds for substantial and considerable heterogeneity, and determing whether heterogeneity is substantial versus considerate largely depends on the magnitude and direction of effects as well as the strength of evidence for heterogeneity in the literature.

2.3.5.1 Meta-analysis of RDS data

There is currently no framework for the meta-analysis of RDS data available in the literature. There are multiple OHC studies that occur across Ontario, but they are not precise enough alone to allow us to make strong conclusions about FNIM peoples living in urban areas. Beyond OHC, there is an increasing interest in using RDS as a sampling technique for other hidden populations in existing literature. Thus, there is also an increasing need for a valid meta-analysis technique for RDS data. As such, simulation studies will be performed in Chapter 3 to determine the most appropriate method for meta-analyzing RDS data.

2.4 Summary

Current Canadian databases that contain regional, provincial, and national Indigenous health data are not representative of FNIM peoples living in urban areas. Due to low participation rates, some of the data are suppressed by the government, further limiting Indigenous peoples' access to the data and analysis results. The OHC projects are a response to the need for more representative, better quality health data for Indigenous peoples living in urban areas. Since there is a lack of a sampling frame for Indigenous peoples living in Ontario cities, RDS was successfully applied to the OHC projects to obtain the largest, representative samples of FNIM peoples living in urban areas in Ontario. Each OHC site alone is not precise enough to make strong conclusions for some variables, but pooling the OHC sites will allow us to have more precise, province-wide information about the outcomes of interest. However, since RDS data are non-random and clustered along recruitment chains, appropriate meta-analysis techniques require development.

3 Statistical basis for the meta-analysis of RDS data

3.1 Introduction

Heckathorn [26] developed respondent-driven sampling (RDS) as an improved method to measure disease prevalence in hidden populations, including Indigenous peoples, HIV positive individuals, sex workers, and men who have sex with other men [26, 27, 52, 53]. RDS is a statistical and sampling technique that leverages existing social networks to sample participants. Recruitment starts with a convenience sample of an initial group of participants in the target population called "seeds" that are selected from the target population. The seeds are given k coupons to recruit up to k members of the population who are then given k coupons and so on and so forth. Recruitment continues until a pre-specified condition (typically a target sample size) is met. A dual incentive system is used to increase participation where participants are rewarded for participating and then further rewarded every time they recruit another participant to the study.

There are three aspects of RDS that need to be considered when analyzing the data: non-random sampling, clustering, and homophily. Non-random sampling occurs because RDS makes use of social networks to sample participants, so there is a higher probability of individuals with more social connections to be recruited. Weighting needs to be applied to account for this unequal sampling probability, with participants that have larger social networks being given a lower weighting compared to those with smaller social networks. With regards to clustering, if there is homophily in the population, the data will be clustered as participants tend to recruit those who are likely similar to themselves..

There are two general approaches for performing meta-analyses: fixed effects (FE) and random effects (RE) models. An FE model assumes that the true effect of interest is the same in all studies while an RE model assumes that the true effect of interest can vary from study to study. The only source of between-study heterogeneity in an FE model is sampling error [54] while an RE model may have between-study heterogeneity due to differing inclusion criteria, different participant populations, and sampling variability. Both approaches were evaluated for application with RDS data using data collected from Our Health Counts (OHC) sites. In order to meta-analyze data, an estimate of the within-study variance is required, but RDS has no parametric estimate of the variance. Thus, we tested the validity of four different methods of estimating the within-study variance to determine the best method of meta-analyzing RDS data.

3.2 Methods

Statistical simulation was used to evaluate the validity and appropriateness of our proposed meta-analysis. RDS samples were drawn from simulated networked populations and analyzed to evaluate the performance of the FE and RE meta-analysis methods when they are used to pool RDS estimates. The statistical software *R* version 4.3.1 [55] was used to simulate the data as well as to perform the meta-analyses. Specifically, the packages *RDS* and *metafor* were used for analyses.

3.2.1 Meta-analysis preliminaries

There are two types of meta-analysis: aggregate data (AD) and individual patient data (IPD) meta-analyses. An AD meta-analysis is the conventional method used for obtaining a pooled effect measure based on study summary data. In comparison, in an IPD meta-analysis, line-by-line patient data are collected and pooled into one data set to analyze, allowing for greater power than an AD meta-analysis [56]. While the IPD method is considered to be the gold standard for performing a meta-analysis, obtaining the data is relatively complex and costly [57, 58]. Moreover, data sharing can pose two ethical concerns that may make IPD difficult to obtain: (1) the participant's data may be associated with their identity by someone they did not choose to share their identified data with, leading to a potential loss of privacy and possible stigmatization and discrimination and (2) even if the data are not associated with the participant's identity, it may be used for research purposes for which they have not consented [59]. While we have access to raw data for the OHC studies, in practice, meta-analysis typically relies on available summary statistics from published manuscripts. To ensure our statistical approaches are applicable and relevant for other RDS studies, we consider only an AD meta-analysis approach at this time.

3.2.2 Data simulation

3.2.2.1 Population generation

We simulated independent networked populations with the same population size as the respective OHC site they were based upon. Each individual was assigned a binary outcome status where $Y = 0$ indicated not having the outcome of interest and $Y = 1$ indicated having the outcome of interest. Each individual was also assigned a degree D_i that specified the individual's number of connections with other individuals in the population. Like the OHC study degrees, the simulated degrees were distributed lognormally, with the mean and standard deviation (SD) of each simulated population's degrees being equivalent to the OHC site they represented. Table 2 contains a summary of population size and degrees per OHC site. Note that the large degrees are due to some extreme network sizes.

Table 2. Summary of population size and degrees per OHC site

OHC site	Population size	Degrees (mean $\pm$ SD)
Hamilton	11,000	46.93 $\pm$ 107.78
Toronto	37,000	163.41 $\pm$ 391.47
London	17,000	156.67 $\pm$ 388.19
Thunder Bay	6,500	209.05 $\pm$ 438.01
Kenora	14,000	239.29 $\pm$ 545.26

The proportion of the population with the outcome of interest P (i.e., the outcome prevalence) was varied at 10%, 30%, and 50%. Relative activity (ω) is calculated as the ratio of the average reported degree for individuals with $Y = 1$ (i.e., having the outcome of interest) relative to their counterparts, and it was fixed at $\omega = 1$ for all simulated populations. Homophily (H_x) is the proportion of within-group to between-group connections in a given population. Statistically, homophily is defined as

$$H_x = 2\pi(1 - \pi)R - 1, \; R = \frac{T_{ii}}{T_{ij}}$$

where T_{ii} is the number of within-group connections and T_{ij} is the number of between-group connections. Homophily was varied at 1.1 and 1.5. Each level of homophily was combined with each level of outcome prevalence to produce five sets of five simulated networked populations. Note that a single combination of a level of homophily and a level of outcome prevalence will henceforth be referred to as a "scenario" for brevity. Each set of simulated networked populations is representative of several possible scenarios in an OHC site.

10,000 samples were obtained using RDS from each simulated population in order to evaluate the performance of both the FE and RE approaches using the statistical criteria of validity (coverage), precision (i.e., interval width), and bias. Each RDS sample began with 10 seeds and 3 recruitment coupons per seed. Although the RDS sampling procedure is a random walk Markov chain Monte Carlo and assumes sampling with replacement, in these simulations, we sampled without replacement as repeat recruitment is not permitted in real-world applications. Avery et al. [60] evaluated methods for multivariable analysis of RDS data, and our approach for testing and validating RDS methods builds on their work. The algorithm for the simulation process of a single scenario is summarized below:

1. Five independent networked populations using a common pre-specified proportion of interest (P), degree (D_i), and homophily (H_x) were generated to represent each OHC study site.

2. For each study site, an RDS sample was obtained starting with 10 seeds and 3 coupons per seed. Recruitment was allowed to proceed until the target sample size of 200 to 1,000 participants was reached.

3. Once each RDS sample was obtained, RDS analyses were performed and the results were meta-analyzed.

4. The pooled estimate and its associated confidence interval (CI) were then calculated and compared to the known proportion P.

5. Steps 2 to 4 were repeated 10,000 times to examine coverage, precision, and bias.

The simulations focused on the combination of the five OHC studies. Thus, simulation parameters were chosen based on those of the five OHC studies, incorporating considerations of homophily and degree that are summarized in Avery et al. [60]. The parameters that were evaluated are summarized in Table 3.

Table 3. Key simulation parameters

Meta-analysis parameters	Variations	Simulated values
Variance methods	4	Bootstrap CI: lower bound, upper bound, average; Symmetric CI
Models	2	FE, RE
Proportions	3	0.1, 0.3, 0.5
Homophily	2	1.1, 1.5

3.2.3 Variance estimation

Traditional analyses of RDS data have no parametric estimate of the variance, and thus variability is often measured using bootstrap CIs. However, this makes it difficult to meta-analyze RDS data as we need to approximate within-study variance. Thus, we used several different approaches to estimate the within-study variance, which have been chosen because they do not require any additional assumptions on the data. While some newer approaches to RDS analysis do exist, such as model-based [61] and sequential-sampling [42], these approaches require population size specification. Thus, these are not ideal as even external sources, such as the Canadian Census, fail to accurately estimate the number of FNIM peoples living in urban and related homelands [2].

For the first three approaches, we obtained the variance estimates from bootstrap CIs: a variance estimate of v_1 from the lower bound of the interval (denoted as lb) calculated as

$$v_1 = \left(\frac{P - lb}{1.96}\right)^2,$$

a variance estimate of v_2 from the upper bound of the interval (denoted as ub) calculated as

$$v_2 = \left(\frac{ub - P}{1.96}\right)^2,$$

and a simple average variance of v_3 of v_1 and v_2 (henceforth referred to as the "average variance") calculated as

$$v_3 = \frac{v_1 + v_2}{2}.$$

To illustrate with an example, let us assume a trait of interest produces an RDS prevalence of 0.20 with a 95% bootstrap CI of 0.14 to 0.31. v_1 is calculated as

$$v_1 = \left(\frac{0.2 - 0.14}{1.96}\right)^2 = 0.0009,$$

v_2 is calculated as

$$v_2 = \left(\frac{0.31 - 0.2}{1.96}\right)^2 = 0.0031,$$

and v_3 is calculated as

$$v_3 = \frac{0.0009 + 0.0031}{2} = 0.0020$$

Appropriate transformations were applied to ensure that the variance was not underestimated as the values approached zero or one [62]. We repeated the same methods of estimating the variance using the basic symmetric CI obtained from RDS-II [46]. Due to the symmetry of the CI, v_1, v_2, and v_3 calculated from the basic symmetric CI are all the same values. Thus, the variance estimate obtained from the basic symmetric CI is v_4.

3.2.4 Weighting

Inverse probability weighting for each individual is applied to account for the unequal sampling probability in RDS samples. The weights w_i are calculated based on reported degree D_i such that

$$w_i = \frac{1}{D_i} \frac{N}{\sum_{i=1}^{N} \frac{1}{D_i}}.$$

3.2.5 Primary considerations: Coverage, precision, and bias

For all comparisons, the primary focus was on coverage (i.e., the probability that the 95% CI includes the parameter of interest, P). If appropriate coverage was not achieved, the method is not statistically valid as it fails to maintain the nominal type 1 error rate. Thus, precision and bias need not be considered. If methods had similar coverage, precision and bias were used to determine the optimal approach.

3.3 Results

Six total scenarios were examined that were made up of different combinations of the proportion and homophily levels listed in Table 3. When examining the RE model in Table 4, we found that meta-analyses using the average variance calculated from the RDS-II bootstrap CI to approximate within-study variance provided coverage closest to the nominal levels in all scenarios. The meta-analyses using the variances calculated from the lower bound of the RDS-II bootstrap CI and the upper bound of the RDS-II bootstrap CI provided coverage rates that were well below 95%. The meta-analyses using the variances calculated from the basic RDS-II CI also gave much lower coverage than the nominal coverage. It should be noted that the basic RDS-II CI is symmetric, so the variances calculated from either CI bound will always be the same. Thus, the only statistically valid RE meta-analysis method is the method that estimates within-study variance using the average variance calculated from the RDS-II bootstrap CI.

Table 4. Performance of within-study variance estimation methods for meta-analysis of RDS data based on simulated data

	RE meta-analysis			FE meta-analysis		
Method	Coverage	Relative bias (%)	Average interval width	Coverage	Relative bias (%)	Average interval width
$p = 0.1,\ H_x = 1.5$						
v_1	0.870	0.027	0.049	0.637	0.071	0.033
v_2	0.715	-0.077	0.036	0.336	-0.139	0.017
v_3	0.940	-0.026	0.047	0.915	-0.036	0.041
v_4	0.870	-0.015	0.044	0.692	-0.034	0.026
$p = 0.1,\ H_x = 1.1$						
v_1	0.892	0.044	0.061	0.632	0.086	0.035
v_2	0.763	-0.035	0.039	0.313	-0.107	0.013
v_3	0.966	0.009	0.056	0.936	-0.011	0.041
v_4	0.888	0.006	0.043	0.735	-0.009	0.026
$p = 0.3,\ H_x = 1.5$						
v_1	0.826	0.023	0.081	0.072	0.561	0.049
v_2	0.772	-0.025	0.068	0.395	-0.051	0.028
v_3	0.974	-0.001	0.091	0.961	-0.001	0.072
v_4	0.890	0.001	0.068	0.742	-0.002	0.041
$p = 0.3,\ H_x = 1.1$						
v_1	0.812	0.013	0.074	0.566	0.035	0.043
v_2	0.737	-0.027	0.064	0.371	-0.054	0.027
v_3	0.973	-0.006	0.088	0.962	-0.008	0.069
v_4	0.888	-0.007	0.065	0.755	-0.011	0.040

Table 4. Performance of within-study variance estimation methods for meta-analysis of RDS data based on simulated data

	RE meta-analysis			FE meta-analysis		
Method	Coverage	Relative bias (%)	Average interval width	Coverage	Relative bias (%)	Average interval width
$p = 0.5,\ H_x = 1.5$						
v_1	0.805	0.024	0.084	0.467	0.047	0.044
v_2	0.805	-0.016	0.082	0.493	-0.039	0.044
v_3	0.974	0.004	0.096	0.968	0.002	0.076
v_4	0.882	0.003	0.075	0.727	0.003	0.044
$p = 0.5,\ H_x = 1.1$						
v_1	0.778	0.012	0.079	0.461	0.030	0.040
v_2	0.765	-0.020	0.077	0.472	-0.036	0.039
v_3	0.976	-0.003	0.098	0.968	-0.002	0.077
v_4	0.888	-0.004	0.072	0.756	-0.004	0.452

p = outcome prevalence, H_x = homophily
v_1, v_2, and v_3 are calculated from bootstrap CIs
v_4 is calculated from symmetric CIs

Similarly, for the FE model, meta-analyses using the average variance calculated from the bootstrap CI to approximate within-study variance provided coverage closest to the nominal levels across all scenarios. Again, this was the only statistically valid meta-analysis method out of all the methods we tested. When comparing the RE and FE models' precision and bias, the FE model was more precise than the RE model, with average CI widths that were narrower across all scenarios. Both models had extremely small relative bias, with the FE model for the first scenario ($P = 0.1$, $H_x = 1.5$) having the largest bias (-0.03%). Thus, we can conclude that both RE and FE models provided approximately unbiased estimates when parameter estimates were similar across studies, and researchers can determine their model decision between the RE or FE based on the available context and observed heterogeneity.

3.4 Discussion

The validity of our proposed AD meta-analysis approaches for RDS data were evaluated using simulated data with outcome prevalence, homophily, and degrees modelled based on RDS data collected from five Indigenous populations living in Ontario cities (i.e., Hamilton, Toronto, London, Thunder Bay, and Kenora). The performances of the proposed meta-analysis approaches were examined in six combinations of outcome prevalence levels and homophily levels, which were representative of possible scenarios in our planned analyses of Indigenous health data from the OHC studies.

Results indicated that using the average of the variances calculated from the lower and upper bounds of RDS-II bootstrap CIs as an estimate of within-study variance is statistically valid across all combinations of outcome prevalence and homophily levels. It provides approximately unbiased estimates, with slightly more precision when using the FE model compared to the RE model. Using the variance calculated from the lower bound of RDS-II bootstrap CIs, the upper bound of RDS-II bootstrap CIs, and RDS-II to estimate within-study variance provided coverage that was well below nominal levels across all combinations of outcome prevalence and homophily levels and was thus not valid.

There is an increasing interest in using RDS as a sampling technique for hidden populations in existing literature. These populations often exist in small hidden underground communities [29], so population-level statistics are often unavailable. This paper proposes valid meta-analysis approaches (both FE and RE) for RDS data to combine relevant datasets that will help to fill this knowledge gap.

There were two limitations to this study. The first is that only a relatively small number of populations were considered in the validation process of our proposed meta-analysis technique because we modeled our simulations based on the OHC sites. A small number of pooled studies may cause the estimate of between-study heterogeneity to be inaccurate, potentially resulting in biased pooled estimates and CIs that are too narrow [63]. Secondly, given that the OHC outcome prevalences across all sites are similar for most variables, we only examined consistent outcome prevalences. Thus, an FE model is expected to perform well in this case.

As RDS is used to gain access to hidden populations, there is often a lack of an accurate, population-level understanding of these populations as individual RDS data sets are not precise enough alone to allow for strong conclusions. Using a meta-analysis technique to summarize data across data sets and attempts to remedy this lack of precision. However, we note that in the presence of heterogeneity, the RE model may in fact decrease precision. Nonetheless, providing an improved population-level understanding of the outcomes of interest is often helpful even in these cases. It should also be noted that, in the context of Indigenous health data, FNIM peoples' diverse and rich cultural traditions are rooted in the variety of their local lived environments. The RE model may be more suitable for pooling FNIM peoples' health data across various geographical locations, such as different cities in Ontario. Future expansions of this work include examining the performance of these methods with both fewer and more studies being pooled as well as considering additional sources of heterogeneity. Creating and validating an IPD approach for meta-analyzing RDS data is another expansion of the work in this chapter. While practically, AD meta-analyses are more common as raw individual level data is often not available, IPD meta-analyses are still considered the gold standard. The validity of an IPD approach needs to be examined in order to provide an analytical tool for those who are able to access such data.

3.5 Conclusion

Based on simulation studies, the average of the variances calculated from the lower and upper bounds of RDS-II bootstrap CIs is the most appropriate estimator of the within-study variance estimate and should be used for meta-analyzing RDS data. When multiple data sources are available, applying meta-analysis techniques to RDS data will more accurately inform health sectors and policy makers about the true state of health outcomes in hidden populations.

4 Examining diabetes mellitus in First Nations, Inuit, and Métis peoples living in urban areas in Ontario

4.1 Introduction

Diabetes mellitus (DM) is one of the largest global health challenges of the twenty-first century, and the global prevalence of DM is on the rise. In 2019, the global prevalence of DM was estimated to be approximately 9%, which is predicted to rise to 11% by 2045 [64]. To put this into perspective, 1 in 11 adults aged 20 to 79 years (i.e., 463 million people) were diagnosed with DM in 2019 [65]. The International Diabetes Federation (IDF) predicts that, by 2045, 700 million adults will be diagnosed with DM worldwide. Considering the IDF report further stated that 10% of global health expenditure (USD 760 billion) was due to DM in 2019, the global financial cost of DM will continue to rise in conjunction with the DM incidence rate. However, even more concerning than the cost of DM is its contribution to premature mortality, with DM causing over 4 million deaths per year [65].

DM is a disease where the body is either unable to produce insulin or unable to properly use the insulin it produces [66, 67]. Insulin is a peptide hormone produced by the pancreas that controls how blood glucose is used and stored in the body. Blood glucose cannot be converted to energy without insulin. Without insulin, high levels of glucose accumulate in the blood and, if left untreated, cause damage to organs, blood vessels, and nerves. Complications related to DM are either microvascular (e.g., retinopathy, neuropathy and nephropathy) or macrovascular (e.g., cardiovascular, cerebrovascular, and peripheral vascular disease) in nature [68]. While there are three major types of DM (type 1 diabetes, type 2 diabetes, and gestational diabetes), this study will not distinguish between types, but rather examine DM as a whole.

In 2023, 10% of Canadians were reported as having DM, which is predicted to rise to 17% by 2033 [69]. First Nations peoples in Canada have a higher prevalence of DM than the general population, with the prevalence of DM being four times higher for First Nations adults living on reserve in Ontario compared to their non-First Nations counterparts [70, 71]. DM is also associated with higher morbidity and increased health disparity in First Nations populations in Canada compared to their non-First Nations counterparts [72].

Given the limitations and lack of valid health data for First Nations, Inuit, and Métis (FNIM) peoples living in urban areas, our study aims to accurately determine the prevalence of DM among FNIM peoples living in Ontario cities. Using respondent-driven sampling (RDS) to obtain representative samples, the Our Health Counts (OHC) studies were designed to establish baseline and longitudinal health information for FNIM peoples living in Hamilton, London, Ottawa, Toronto, Thunder Bay, and Kenora. However, individual OHC studies have limits in precision for some variables due to sample size and design effect. Our study aims to apply meta-analysis techniques to increase precision and accurately determine the prevalence of DM among FNIM peoples living in cities, and explore differences by age, gender, and other relevant variables. As meta-analysis techniques are currently unavailable for RDS data, we apply our previously discussed and validated (Chapter 3) statistical technique to the outcome of DM.

4.2 Methods

4.2.1 Community partnerships

Permission to access the health information databases of OHC Hamilton, Toronto, London, Thunder Bay, and Kenora was granted by their respective data custodians (*De dwa da dehs nye>s* Aboriginal Health Centre, Seventh Generation Midwives Toronto, Southwest Ontario Aboriginal Health Access Centre, Anishnawbe Mushkiki Health Access Centre, and Waasegiizhig Nanaandawe'iyewigamig Health Access Centre) in accordance with OHC's community-based framework [23]. Tungasuvvigat Inuit, the data custodians for OHC Ottawa Inuit are supportive, but have chosen not to participate at this time. Moreover, given the observed lower rates of DM in the OHC Ottawa Inuit study and the lower rates of DM among Inuit more generally in comparison to First Nations and Métis [73], it may not be scientifically relevant to combine the Inuit-specific OHC Ottawa study estimate with the other OHC studies. In keeping with RCAP ethical research guidelines and OCAP® principles [12], the community partners retain full ownership and control over all data used in this study. Ethics approval has been obtained for this project from York University (Certificate #: e2021-186).

4.2.2 Study participants

Each OHC site started with a certain number of seeds (see Table 1) which were each given three recruitment coupons. As an incentive, participants received \$20 for participating and \$10 for each person they recruited. In order to participate, participants needed to (1) reside, work, or receive healthcare in their respective city, (2) self-identify as an Indigenous person, and (3) be at least 15 years of age.

This recruitment process continued until stable estimates were reached. Final sample sizes per OHC site are in Table 1. Recruitment chains were traced using the unique recruitment coupon numbers. To measure network size (i.e., degree), participants were asked approximately how many Indigenous peoples they knew by name and that knew them by name who are currently living, working, or using health and social services in their respective city. All participants were asked the question "Do you have diabetes as diagnosed by a healthcare provider?". We used this question to determine whether the participant has DM.

4.2.3 Statistical methods

R version 4.1.3 [55] was used to perform all statistical analyses with a 5% type I error rate. Missing data, ranging from 0.2% to 6% missingness across sites in the analyzed variables, were removed using pairwise deletion [74].

In order to meta-analyze RDS data, we must approximate within-study variance as RDS data has no parametric estimate of the variance. Based on simulation studies (see Chapter 3), the variance estimate obtained by averaging the variance estimates calculated from the upper and lower bounds of RDS bootstrap CIs is the optimal within-study variance estimate for meta-analyses of RDS data.

Given the potential for between-study heterogeneity due to differing study populations and urban social contexts, a random effects (RE) meta-analysis was chosen to examine the pooled DM prevalences of Indigenous peoples living in urban areas in Ontario. Sites were combined using inverse-variance weighting such that larger, more precise studies were weighted more heavily in the pooled analysis. That is, the weight of each study w_i was calculated as

$$w_i = \frac{1}{v_i + \tau^2},$$

where v_i is the within-study variance and τ^2 is the between study heterogeneity.

The *R* package *metafor* [75] was used to perform the meta-analysis determining the overall prevalence of DM among FNIM peoples living in Ontario cities. Subgroup meta-analyses were then performed to determine the prevalence of DM in the community in various age [76], gender [77, 78], and BMI [79] subgroups as these factors are known to be associated with DM in the general population. DM was also explored by use of traditional medicines and whether traditional food are eaten, as these factors were of significant interest to the Indigenous community partners. The MOVER approach was applied to obtain the prevalence difference in DM diagnosis between categories where appropriate. This approach obtains an estimate of the variance of each proportion near its confidence limits, using it to calculate a confidence interval (CI) for the effect measure of interest [80].

Age was calculated based on date of birth and date of survey completion. Gender was determined by asking the participants “What is your gender?”, with the options of “a man”, "a woman”, “trans (e.g., transgender, transsexual, gender queer)”, and “other (you do not have a category that applies to me)”. Use of traditional medicines was identified by the question “Do you use traditional medicines?”. Participants were also asked whether they eat traditional food through the question "In the past 12 months, how often have you eaten traditionally hunted/gathered/grown and/or country food?".

4.3 Results

A total of 2,400 Indigenous peoples were recruited and included in the OHC studies across the five sites. Figures A1 to A5 in Appendix A present the RDS recruitment network diagrams per site, and Tables A1 to A5 in Appendix A contains both the number of recruits and recruitment waves per seed for each OHC site. Baseline demographic characteristics across all sites are presented in Table B1 in Appendix B.

The RE meta-analysis showed that the pooled prevalence of DM across the five OHC sites was 11.3% (95% CI: 7.1% to 15.4%) with substantial heterogeneity [51] between sites ($I^2 = 76.8\%$).

Table 5. Meta-analysis of DM prevalence across OHC sites

OHC site	Prevalence (%) (95% CI)
Hamilton	14.8 (9.4, 20.3)
Kenora	4.6 (0.0, 9.2)
London	14.7 (9.5, 20.0)
Thunder Bay	8.2 (4.8, 11.6)
Toronto	14.7 (10.6, 18.7)
Pooled ($I^2 = 76.8\%$)	11.3 (7.1, 15.4)

Further subgroup analyses were performed to determine whether certain factors were significantly associated with the DM prevalence among FNIM peoples living in urban areas in Ontario.

Table 6. Subgroup analyses of DM prevalence across OHC sites

Subgroups	I^2 (%)	Prevalence (%) (95% CI)	Prevalence difference (95% CI)
Age (years)			
15 - 24	0.0	2.4 (0.9, 3.8)	ref†
25 - 34	28.8	4.0 (1.8, 6.1)	0.02 (-0.01, 0.09)
35 - 44	0.0	8.9 (5.1, 12.6)	0.07 (0.02, 0.14) *
45 - 54	78.3	16.1 (6.4, 25.9)	0.14 (0.04, 0.26) *
55 - 64	72.2	28.6 (13.9, 43.2)	0.26 (0.11, 0.42) *
65+	37.3	22.7 (10.9, 34.6)	0.20 (0.08, 0.34) *
Gender			
Women	53.0	11.9 (8.0, 15.8)	0.011 (-0.05, 0.08)
Men	65.7	10.8 (5.6, 15.9)	ref
BMI (kg/m^2)			
18.5 - 24.9	38.4	4.8 (1.8, 7.8)	-0.06 (-0.10, -0.01) *
25 - 29.9	0.0	10.3 (6.8, 13.8)	ref
30+	45.1	18.8 (12.5, 25.1)	0.09 (0.01, 0.16) *
Use traditional medicines			
No	74.8	12.8 (6.3, 19.2)	ref
Yes	0.0	10.6 (8.3, 12.9)	-0.02 (-0.27, 0.05)
Eat traditional foods‡			
No	66.9	10.3 (3.5, 17.1)	ref
Yes	67.0	10.6 (6.3, 14.9)	0.003 (-0.08, 0.08)

* Significant prevalence difference
† "ref" indicates reference group for prevalence difference
‡ OHC Hamilton survey did not ask about traditional food and was thus not included in this analysis

Participants between the ages of 15 to 24 years had the lowest DM prevalence (2.4%, 95% CI: 0.9% to 3.8%). It should be noted that participants aged 64 years and older were undersampled in the OHC studies and have wide CIs. Thus, there is some imprecision to these prevalence rates. Individuals aged 35 years and older had a significantly higher prevalence of DM than those who were 15 to 24 years of age. Women had a similar DM prevalence (11.9%, 95 CI%: 8.0% to 15.8%) to men (10.3%, 95% CI: 4.3% to 16.3%). BMI categories were chosen based on the CDC suggested categories [81]. Note that only two OHC sites had participants with a BMI of less than 18.5kg/m^2 who also were diagnosed with DM, and the cell sizes for those two sites were too small to present without risking identification. Thus, this BMI category was omitted from the subgroup analyses. Participants who had a BMI between 18.5 to 24.9 kg/m^2 had the lowest DM prevalence (4.8%, 95% CI: 1.8% to 7.8%) while those who had a BMI of 30kg/m^2 or more had the highest DM prevalence (18.8%, 95% CI: 12.5% to 25.1%). Individuals with a BMI between 18.5 and 24.9 kg/m^2 had a significantly lower prevalence of DM than those with a BMI between 25 and 29.9 kg/m^2. Individuals with a BMI of 30 kg/m^2 or higher had a significantly higher prevalence of DM than those with a BMI between 25 and 29.9 kg/m^2. There were no significant prevalence differences in DM found for both using traditional medicines and eating traditional food.

Table 7. DM prevalences in general Ontario population subgroups

PHAC† subgroups [82]	Prevalence (%) (95% CI)
Age (years)	
18 - 34	0.9 (0.6, 1.1)
35 - 49	4.1 (3.6, 4.7)
50 - 64	10.6 (9.7, 11.5)
65 - 79	18.4 (17.3, 19.5)
80+	17.9 (16.0, 19.8)
Gender	
Women	6.0 (5.8, 6.2)
Men	8.5 (8.2, 8.8)

† PHAC = Public Health Agency of Canada

We also compared the OHC prevalences of DM in age and gender subgroups to the general population. While equivalent age categories were not available in the literature for Ontario, Public Health Agency of Canada (PHAC) examined the prevalences of DM in similar age categories. While the categories are not identical, in general, the age-stratified OHC prevalences were higher than the comparable general population prevalences, with those in the 25 to 34 and 35 to 44 years age groups having substantially higher prevalences of DM. The OHC prevalence of DM in women (11.9%, 95% CI: 8.0%, 15.8%) was significantly higher than the DM prevalence in women in the general population of Ontario (6.0%, 95% CI: 5.8%, 6.2%).

4.4 Discussion

We applied our proposed meta-analysis technique to five OHC sites (Hamilton, London, Toronto, Thunder Bay, and Kenora) to determine the prevalence of DM in the Indigenous population living in Ontario cities. The pooled crude population prevalence estimate was 11.3% (95% CI: 7.1% to 15.4%). In comparison, the non-Indigenous population in Ontario has a DM prevalence of 7.2% (95% CI: 7.1%, 7.4%) [82]. While CIs remain wide due to the use of RDS, our findings unmask a compelling health status disparity as Indigenous populations are substantially younger than the general population and DM prevalence increases with age [83, 84]. This is further demonstrated by the subgroup analyses where we showed that Indigenous adults living in cities age 25 to 34 and 35 to 44 years have substantially higher prevalences of DM compared to the general population in the same age category. However, more study is needed to increase precision. The substantial between-study heterogeneity in DM prevalences may be due to different levels of access to healthcare at each OHC site. As DM diagnosis is self-reported in the OHC surveys, difficulty accessing healthcare may lead to less reporting of DM diagnosis. Thus, the true number of individuals diagnosed with DM may be underreported at OHC sites. Continued efforts to reduce the prevalence of DM among Indigenous peoples living in urban areas in Ontario are thus imperative in order to reduce this health disparity.

Health interventions that prioritize groups that have a higher prevalence of DM should also be focused on, allowing for more effective prevention of DM onset and development of appropriate interventions. In particular, subgroup analyses of Indigenous populations in Ontario cities showed that individuals between 55 to 64 years of age, women, and those who had a BMI higher than 30 kg/m^2 had the highest DM prevalence within their respective subgroups.

As studies have shown that Indigenous-led healthcare partnerships improve Indigenous health outcomes [85], more emphasis should be placed on the importance of partnering with Indigenous healthcare practitioners to provide culturally appropriate healthcare (such as incorporating traditional Indigenous medicines) for Indigenous peoples living in Ontario cities. With regards to eating traditional foods, there is evidence that a diet that includes traditional food is associated with a decreased risk of DM in Indigenous peoples [86, 87]. However, we did not find a significant prevalence difference in DM between those who eat traditional foods and those who do not.

4.4.1 Strengths and limitations

Although each dataset from the OHC project was acquired using RDS to ensure a comprehensive and valid study, employing meta-analysis techniques to pool data from various OHC sites enables us to offer a more accurate and comprehensive understanding of DM on a provincial scale.

As the OHC study sites are all within Ontario, the pooled prevalence estimates of DM that are obtained from these Indigenous data sets are Ontario-specific. There are also differences between the northern and southern Indigenous populations that must be kept in mind, with the DM prevalences in the northern populations (Kenora and Thunder Bay) being lower than the southern populations (Hamilton, London, and Toronto). There are likely differences in diet and access to healthcare that play a role in the lowered prevalences of DM in the northern populations. Care must be taken when generalizing these results to other provinces or across Canada as well as generalizing over the distinct populations and nations of Indigenous peoples. Given that the OHC data are self-reported, participant responses may be subject to recall bias. As well, the data are cross-sectional, so we cannot infer causal relationships with DM.

4.5 Conclusion

This work provides some preliminary evidence that the prevalence of DM in Indigenous populations living in urban areas in Ontario are higher than the general population. Indigenous populations are much younger than the general population, and the prevalence of DM in the younger age groups are substantially and statistically significantly, higher than the general population. The DM prevalences among Indigenous women living in Ontario cities are also significantly higher than the general population. Moreover, individuals with a BMI of 30 kg/m^2 or more have a significantly higher prevalence of DM among Indigenous peoples living in urban areas. Tailoring health interventions to be more specific to subgroups that have a higher prevalence of DM may help to decrease the prevalence of DM in FNIM peoples living in urban settings and improve equity in the healthcare system.

5 Examining prescription opioid use in First Nations, Inuit, and Métis peoples living in urban areas in Ontario

5.1 Introduction

The opioid crisis continues to run rampant across the world. Around 60 million people globally use prescription opioids (POs) without a prescription or out of keeping with how they were prescribed, and more than 100,000 people die every year from PO overdose [88]. Major drivers of this crisis include the influence of pharmaceutical companies, inadequate regulation of usage, and overprescription by medical professionals. Canada is no exception, having one of the highest levels of PO use, morbidity, and mortality globally, given that it has the second highest PO dispensing rate per capita [89]. In fact, approximately 3% of Canadians who used POs in 2017 reported using them for non-medical purposes [90]. Moreover, in 2019, PO use was responsible for 6.4 deaths per 100,000 people in Canada [88].

POs are medications primarily used for pain treatment, both acute and chronic [90]. According to the 2018 Canadian Community Health Survey (CCHS), the most commonly used POs in Canada include codeine (76%), hydromorphone or morphine (28%), oxycodone (20%), and fentanyl (5%) [91]. In 2017, 11.8% of the Canadian population used POs, with a greater number of Indigenous peoples living off reserve reporting using POs in the past year than their non-Indigenous counterparts [90]. Reports from British Columbia and Alberta highlight the impact of the opioid crisis on the First Nations populations living in those provinces, with First Nations people being five times more likely than their non-First Nations counterparts to experience an opioid-related overdose and three times more likely to die from an opioid-related overdose [92].

Indigenous populations living in urban areas in Canada are undersampled by national surveys that collect Canadian health data, which leads to a lack of valid health data for this population. The Our Health Counts (OHC) studies were designed to establish baseline and longitudinal health information for First Nations, Inuit, and Métis (FNIM) peoples living in Hamilton, London, Ottawa, Toronto, Thunder Bay, and Kenora. From this framework, our study aims to accurately determine the prevalence of PO use without a prescription or in unprescribed ways among FNIM peoples living in urban areas in Ontario.

Globally, Indigenous peoples experience a disproportionate burden of mental health challenges compared to non-Indigenous peoples [8, 93, 94]. Canada is no different, where these mental health challenges can be linked to experiences of anti-Indigenous racism [94, 95], multi-generational family disruptions, and colonial interference with traditional and contemporary Indigenous economies. Colonialism continues to affect the psychological wellbeing of Indigenous peoples, including increased rates of depressive symptoms and suicidal ideations compared to their non-Indigenous counterparts [95]. Poverty is one of multiple forms of social inequity associated with mental health challenges [3, 96]. The First Nations Financial Management Board [97] notes that the Indian Act has created an "economic desert" for First Nations peoples. The poor investment environment plays a role in the poverty experienced by First Nations peoples. While we cannot generalize First Nations peoples' economic environment to other Indigenous peoples, FNIM peoples experience substantial economic disparities [98].

There is evidence of the comorbidity of substance use disorders (SUDs), such as use of POs without a prescription or in unintended ways, and mental health challenges [99]. Firestone et al.'s [28] initial findings suggest SUDs among First Nations peoples may reflect coping mechanisms for mental health challenges. The authors speak to the importance of cultural-based coping mechanisms and health services, with balance in physical, mental, emotional, and spiritual aspects of self; a strong sense of cultural identity; resilience; and enculturation as protective factors against mental health challenges and SUDs among First Nations peoples. Nonetheless, there are significant gaps in evidence for the co-occurrence of SUDs and mental health challenges as well as treatment for this co-occurrence for Indigenous peoples living in urban areas [28]. The relationship between SUDs and mental health challenges exists across Indigenous populations, and both historical and lived trauma are common drivers within this relationship [99]. Lack of access to culturally appropriate healthcare is another common driver of SUDs and mental health challenges within Indigenous populations [100].

From this framework, we applied our previously discussed and validated statistical technique (Chapter 3) to examine the prevalence of PO use without a prescription (or out of keeping with the prescribed use) among Indigenous peoples living in urban areas in Ontario. While OHC studies have addressed many gaps in health information for FNIM living in cities, design effect can limit the precision of specific descriptive and analytic statistics at the individual study level. Meta-analyses can improve the precision of estimates [101] and allow exploration of prevalences in smaller subgroups. As secondary objectives, we also explore relevant age and gender stratified rates, in addition to potential differences associated with use of traditional medicines and psychological/mental health disorder diagnoses by a healthcare worker.

5.2 Methods

5.2.1 Community partnerships

Permission to access the health information databases of OHC Hamilton, Toronto, London, Thunder Bay, and Kenora (*De dwa da dehs nye>s* Aboriginal Health Centre, Seventh Generation Midwives Toronto, Southwest Ontario Aboriginal Health Access Centre, Anishnawbe Mushkiki Health Access Centre, and Waasegiizhig Nanaandawe'iyewigamig Health Access Centre) was granted by their respective data custodians in accordance with OHC's community-based framework [23]. While OHC Ottawa supports this project, they have chosen not to participate at this time. Upholding RCAP ethnical research guidelines and OCAP® principles [12], the community partners maintain full ownership and control of all data used in this study. Ethics approval was obtained for this project at York University (Certificate #: e2021-186).

5.2.2 Study participants

Respondent-driven sampling (RDS) was used to obtain representative samples of Indigenous populations living in Ontario cities through the OHC studies. Each OHC site started with a certain number of seeds (see Table 1) who received three recruitment coupons each. A dual incentive system was used, where participants received $20 for participating and $10 for each person they recruited. In order to participate, participants needed to (1) reside, work, or receive healthcare in their respective city, (2) self-identify as an Indigenous person, and (3) be at least 15 years of age.

Recruitment continued until stable estimates were reached. Table 1 includes final sample sizes for each OHC site. Recruitment chains were traced using the unique recruitment coupon numbers. To measure network size (i.e., degree), participants were asked approximately how many Indigenous peoples they knew by name and that knew them by name who are currently living, working, or using health and social services in their respective city. All participants were asked the question "Have you used prescription opiates (codeine, morphine, Percodan, Tylenol 3, fentayl, talwin, etc.) in the last 12 months without a prescription or out of keeping with how they were prescribed?" to determine the nature of the participant's PO use.

5.2.3 Statistical methods

R version 4.1.3 [55] was used to perform all statistical analyses with a 5% type I error rate. Pairwise deletion [74] was used to remove missing cases (0.2% to 6% missingness) across OHC sites.

In order to meta-analyze RDS data, the within-study variance must be approximated as RDS has no parametric variance of the estimate. Based on simulation studies (see Chapter 3), averaging the variance estimates calculated from the upper and lower bounds of RDS bootstrap CIs is the most valid method for obtaining an estimate of the within-study variance for meta-analyzing RDS data.

A random effects (RE) meta-analysis was chosen because of the potential for between-study heterogeneity due to differing study populations and urban social contexts. Sites were combined using inverse-variance, weighting larger, more precise studies more heavily in the pooled analysis. The weight of each study w_i was thus calculated as

$$w_i = \frac{1}{v_i + \tau^2},$$

where v_i is the within-study variance and τ^2 is the between study heterogeneity.

A meta-analysis was performed using the *R* package *metafor* [75] to determine the overall prevalence of PO use without a prescription or out of keeping with the prescription among FNIM peoples living in Ontario cities. Subgroup meta-analyses were then performed to determine the prevalence of PO use in the community in various age [102] and gender [103] categories to estimate differences in PO use across these subgroups. Finally, the Indigenous community partners were interested in links between mental health disorders, traditional medicine use and PO use, thus these were also examined. The MOVER [80] approach was used to obtain the difference in prevalence of PO use between categories where appropriate. This approach obtains an estimate of the variance of each proportion near its confidence limits and uses these estimates to obtain a confidence interval (CI) for the effect measure of interest [80].

Age was calculated as the difference between date of birth and date of survey completion. With regards to gender, participants were asked “What is your gender?”, with response options of “a man”, “a woman”, “trans (e.g., transgender, transsexual, gender queer)”, and “other (you do not have a category that applies to me)”. Participants were also asked “Do you use traditional medicines?”, and a mental health disorder diagnosis was determined by the question “Have you ever been told by a health care worker that you have a psychological and/or mental health disorder?”.

5.3 Results

2,400 FNIM peoples living in urban areas in Ontario were recruited and included in the OHC studies across the five sites. The RDS recruitment network diagrams per site as well as the number of recruits and recruitment waves per seed for each OHC site are presented in Appendix A. Table B in Appendix B includes baseline demographic characteristics across all sites.

The RE meta-analysis showed that the pooled prevalence of PO use without a prescription or out of keeping with the prescription across the five OHC sites was 15.8% (95% CI: 12.6% to 19.1%) with substantial heterogeneity [51] between sites ($I^2 = 64.8\%$).

Table 8. Meta-analysis of PO use prevalence across OHC sites

OHC site	Prevalence (%) (95% CI)
Hamilton	18.3 (3.4, 33.2)
Kenora	17.5 (11.9, 23.0)
London	17.4 (13.8, 21.0)
Thunder Bay	10.5 (7.7, 13.6)
Toronto	18.6 (15.4, 21.8)
Pooled ($I^2 = 64.8\%$)	15.8 (12.6, 19.1)

Further subgroup meta-analyses were performed to determine whether certain factors were significantly associated with the PO use prevalence among FNIM peoples living in urban areas in Ontario.

Table 9. Subgroup analyses of PO prevalence across OHC sites

Subgroups	I^2 (%)	Prevalence (%) (95% CI)	Prevalence difference (95% CI)
Age (years)			
15 - 24	76.1	9.0 (2.6, 15.4)	ref†
25 - 34	83.6	23.0 (11.2, 34.9)	0.14 (0.01, 0.30) *

Table 9. Subgroup analyses of PO prevalence across OHC sites

Subgroups	I^2 (%)	Prevalence (%) (95% CI)	Prevalence difference (95% CI)
35 - 44	0.0	24.9 (19.6, 30.3)	0.16 (0.08, 0.24) *
45 - 54	57.5	11.1 (5.7, 16.5)	0.02 (-0.06, 0.10)
55 - 64	75.5	9.1 (3.0, 15.1)	0.00 (-0.09, 0.10)
65+	73.1	13.7 (3.6, 23.9)	0.05 (-0.07, 0.11)
Gender			
Women	78.0	14.8 (9.5, 20.0)	ref
Men	36.0	16.4 (12.4, 20.3)	0.02 (-0.05, 0.11)
Psychological/mental health disorder diagnosis by healthcare worker			
No	0.4	11.8 (9.5, 14.0)	ref
Yes	80.0	21.0 (12.6, 29.3)	0.09 (0.01, 0.12) *
Use traditional medicines			
No	67.3	19.3 (13.4, 25.2)	ref
Yes	51.7	12.2 (8.6, 15.8)	-0.07 (-0.18, 0.00) *

[*] Significant prevalence difference

[†] "ref" indicates reference group for prevalence difference

Participants aged 35 to 44 years had the highest prevalence of PO use (24.9%, 95% CI: 19.6% to 30.3%) while participants aged 15 to 24 years had the lowest prevalence of PO use at 9.0% (95% CI: 2.6% to 15.4%). Individuals aged 25 to 34 and 35 to 44 years of age had a significantly higher prevalence of PO use than individuals aged 15 to 24 years. Prevalence of PO use in women and men was comparable, with women at 14.8% (95% CI: 9.5% to 20.0%) versus men at 16.4% (95% CI: 12.4% to 20.3%). Participants who were not diagnosed with a mental health disorder had a significantly lower prevalence of PO use than those who did were diagnosed with a mental health disorder. More positively, participants who used traditional Indigenous medicine had a significantly lower prevalence of PO use compared to those who did not use them.

5.4 Discussion

Our previously validated meta-analysis technique was applied to five OHC sites (Hamilton, London, Toronto, Thunder Bay, and Kenora) to examine the prevalence of PO use without a prescription or out of keeping with the prescription among Indigenous peoples living in Ontario cities. The pooled prevalence across all OHC sites was 15.8% (95% CI: 12.6% to 19.1%). This is significantly higher than the prevalence of PO use without a prescription or out of keeping with the prescription in the general population. For comparison, in 2018, 9.6% of adults living in Canada reported using POs in unprescribed or in unintended ways [90]. Thunder Bay had a lower prevalence of PO use than the other OHC sites, which may have been due to participants not feeling safe sharing about their PO use given the stigma surrounding use of these drugs in that particular population and also a lower rate of access to regular primary care providers who could provide prescriptions. Higher rates of PO use have been linked to higher rates of mental health challenges among Indigenous populations as PO use without a prescription or in unprescribed ways may be a coping mechanism for mental health challenges [28]. Historical and lived trauma as well as lack of access to culturally appropriate healthcare are drivers for both PO use and mental health challenges [99, 100]. Unstable economic environments and poverty also contribute to higher rates of mental health challenges, which in turn may exacerbate the rate of PO use [3, 96, 97].

Age and gender differences have been found in the prevalence of PO use in the general population, and the subgroup analyses of the OHC data showed similar trends. Participants 25 to 34 and 35 to 44 years of age reported higher prevalences of PO use than those aged 15 to 24 years as anticipated. Previous work has shown that individuals younger than 40 years of age have been found to be at a higher risk of using POs than those older than 40 years of age [104]. Moreover, in 2021, 30 to 40 year olds made up approximately 42% of opioid-related deaths in Canada [105]. This is particularly concerning given the overall younger age profile of Indigenous populations as it translates into a higher relative total population burden. In the general population, men are also more likely to use POs in unintended ways [106, 107], with men being more likely than women to escalate their PO doses and obtain POs through an illegitimate source [108]. We found that men and women in Indigenous populations living in urban areas in Ontario had similar prevalences of PO use.

Any individual that is prescribed opioids is, to some degree, at risk of developing drug dependence. There are exogenic factors such as mental health [109, 110] that may increase the risk of individuals developing opioid dependence and using the drug without a prescription or in ways that were not prescribed. In the general population, poor mental health or lack of support for mental health has been identified as a risk factor of using POs without a prescription or in unintended ways [107]. Our subgroup analyses showed that Indigenous peoples living in urban areas in Ontario who were diagnosed with a mental health disorder had a significantly higher prevalence of PO use than those who did not have such a diagnosis.

On a more positive note, participants who used traditional Indigenous medicine had a significantly lower prevalence of PO use than those who did not use them. This association links traditional medicine use with not using PO in ways that they are not prescribed. This speaks to the importance of continuing to pass on traditional knowledge as well as the need for more Indigenous-led healthcare partnerships to incorporate traditional knowledge and medicine, which has been shown to improve health outcomes in Indigenous populations [85].

5.4.1 Strengths and limitations

Ensuring representativeness and validity, each dataset from the OHC project was obtained using RDS. Combining data across OHC sites using meta-analysis techniques allows us to provide a more precise and cohesive understanding of PO use without a prescription or in unintended ways on a province-wide scale among Indigenous peoples living in Ontario cities. The rate of PO use may be underestimated in this study as there is continued stigma that surrounds using POs without a prescription or in ways they were not prescribed for, potentially causing participants to feel unsafe reporting their PO use. Moreover, POs may be obtained from family members who have a prescription, which may cause reluctance to report use of the drug.

As the OHC study sites are all within Ontario, the pooled prevalence of PO use obtained from this study remains Ontario-specific. Different provinces and territories across Canada have different rates of dispensing opioids [111], which may affect the prevalence of PO use out of keeping with the prescribed use. While the majority of the physiological and behavioral variables may be generalizable to Indigenous populations living in other urban areas, care must be taken when generalizing to other provinces or across Canada as a whole due to the diverse composition of Indigenous populations and geographies. Participant responses may also be subject to recall bias due to the OHC data being self-reported. Moreover, given the cross-sectional nature of the data, we cannot assume causality between PO use and the explanatory variables considered in this study.

5.5 Conclusion

Based on our meta-analysis results, FNIM peoples living in Ontario cities have a significantly higher prevalence of PO use without a prescription or out of keeping with the prescription than the general population. Individuals aged 25 to 44 years had a significantly higher prevalence of using POs than those who are younger. Men were also found to have at higher prevalence of using POs. Our findings that individuals who use traditional Indigenous medicine have a lower prevalence of using POs without a prescription or in unintended ways contribute to the evidence supporting Indigenous-led healthcare that includes access to traditional medicines. Moreover, we must ensure that health interventions prioritize groups that have a higher prevalence of PO use by addressing both immediate service needs such as access to harm reduction and health services and root causes such as underlying concurrent mental health problems and social determinants of health.

6 Examining Indigenous experiences of discrimination in healthcare and traditional medicines use in First Nations, Inuit, and Métis peoples living in urban areas in Ontario

6.1 Introduction

Discrimination in the Canadian healthcare system continues to this day. In particular, health inequities experienced by Indigenous peoples living in Canada can, in part, be attributed to anti-Indigenous discrimination by healthcare providers. Srugo et al. [112] compared the experiences of Indigenous and non-Indigenous women across Canada and found that Indigenous peoples experienced difficulties accessing a regular healthcare provider, resorting to using hospital services for non-urgent care due to longer waits for appointments. They posited that systemic barriers, such as racism leading to distrust of healthcare systems, were some of the main reasons for the lack of primary care access and thus unmet health needs and disparities. The lack of understanding or addressing of relevant social determinants of health for Indigenous patients in the Canadian healthcare system also contributes to the health inequities experienced by Indigenous peoples [113]. In fact, the importance of having access to culturally relevant care is highlighted by Our Health Counts (OHC) Hamilton analysis results, which showed that a lack of culturally relevant care was associated with a self-reported diagnosis of diabetes mellitus (DM) by a healthcare professional [114, 115].

In the absence of a pre-existing population-based sampling frame, OHC studies use respondent-driven sampling (RDS) to obtain representative samples of First Nations, Inuit, and Métis (FNIM) peoples living in several Ontario cities, establishing baseline health information for these populations. In particular, permission was granted by the data custodians for OHC Hamilton, Toronto, London, Thunder Bay, and Kenora to access their health information databases. Individually, the OHC studies are not large enough to allow for precise conclusions for some variables or to perform subgroup analyses, such as accurate age-stratified estimation. This is because RDS has a design effect, which requires larger samples compared to what might be required if a random sample was possible. Applying a meta-analysis technique can thus increase precision [101]. As there are currently no meta-analysis techniques for RDS in the existing literature, we have developed and proposed a meta-analysis technique which we then applied to the OHC studies. Our objective is to examine the prevalence of experiences of anti-Indigenous discrimination in the healthcare system as well as the rate of and desire for access to traditional medicines and ceremonies among FNIM peoples living in Ontario cities. Pooling data across OHC study sites allows us to summarize this information at the provincial level, giving us a better understanding of the extent of anti-Indigenous discrimination in the healthcare system as we continue to work towards addressing the Calls to Action of the TRC [4] and improve the experiences of Indigenous peoples in the healthcare system. Obtaining pooled estimates of the rate of use of traditional medicines is also critical, as this will help advocate for additional resources to ensure a culturally relevant approach to Indigenous health is available and accessible for community members who seek these services.

6.2 Methods

6.2.1 Community partnerships

Access to the health information databases of OHC Hamilton, Toronto, London, Thunder Bay, and Kenora was authorized by their respective data custodians (*De dwa da dehs nye>s* Aboriginal Health Centre, Seventh Generation Midwives Toronto, Southwest Ontario Aboriginal Health Access Centre, Anishnawbe Mushkiki Health Access Centre, and Waasegiizhig Nanaandawe'iyewigamig Health Access Centre), adhering to OHC's community-based framework [23]. Although OHC Ottawa is supportive, they have opted out at this time. In line with RCAP ethnical research guidelines and OCAP® principles [12], the community partners retain full ownership and control over all study data. Ethics approval has been obtained at York University for this project (Certificate #: e2021-186).

6.2.2 Study participants

Seeds (see Table 1) were selected for each OHC site to begin the sampling process. Each seed was given three recruitment coupons. To incentivize study participation, participants received $20 for participating and $10 for each person they recruited. The participation criteria was that participants needed to (1) reside, work, or receive healthcare in their respective city, (2) self-identify as an Indigenous person, and (3) be at least 15 years of age.

Recruitment continued until stable estimates were reached. Table 1 contains the final sample sizes per OHC site. Each recruitment coupon had a unique number that was used to trace recruitment chains. To measure network size (i.e., degree), participants were asked approximately how many Indigenous peoples they knew by name and that knew them by name who are currently living, working, or using health and social services in their respective city. To examine experiences of anti-Indigenous discrimination in healthcare, all participants were asked the question "Have you ever been treated unfairly (e.g. treated differently, kept waiting) by a health professional (e.g. doctor, nurse, etc.) because you are Indigenous?". Note that due to changing terminology over survey years, some sites used "Aboriginal" instead of "Indigenous" in this question. To examine use of traditional medicine, all participants were asked the question "Do you use traditional Indigenous medicine or practices to maintain your health and wellbeing?". Note that OHC Hamilton had different wording for both questions. For experiences of discrimination in the healthcare system, the question was "Have you ever been treated unfairly by a health professional because you are First Nations?", and the question regarding use of traditional medicines was "Do you use traditional medicine?". Indigenous community partners agreed that the OHC Hamilton questions were similar enough to the other OHC studies' questions to justify pooling of results in the meta-analysis framework.

6.2.3 Statistical methods

R version 4.1.3 [55] was used to perform all statistical analyses with a 5% type I error rate. All missing cases were removed using pairwise deletion. Missingness ranged from 0.3% to 0.6% for experiences of discrimination and 0.2% to 3% for use of traditional medicines.

Within-study variance must be approximated in order to meta-analyze RDS data as RDS data has no parametric variance of the estimate. Based on simulation studies (see Chapter 3), averaging the variances calculated from the upper and lower bounds of RDS bootstrap CIs is the most valid method for obtaining a within-study variance estimate for meta-analyzing RDS data. A random effects (RE) meta-analysis was chosen as there was a potential for between-study heterogeneity due to differing study populations and urban social contexts between OHC sites. The weight of each study w_i was thus calculated as

$$w_i = \frac{1}{v_i + \tau^2},$$

where v_i is the within-study variance and τ^2 is the between study heterogeneity.

Meta-analyses were performed to determine the overall prevalence of discrimination and use of traditional medicines among Indigenous peoples living in urban areas in Ontario. Subgroup meta-analyses were then performed to determine the prevalence of these outcomes of interest in the community for various age and gender categories. The MOVER [80] approach was used where appropriate to obtain prevalence differences between categories. This approach uses the estimate of the variance of each proportion obtained near its confidence limits to calculate a confidence interval (CI) for the effect measure of interest [80].

Age was obtained as the difference between date of birth and date of survey completion. Gender was obtained through the question “What is your gender?”, with response options of “a man”, ”a woman”, “trans (e.g., transgender, transgenderual, gender queer)", and "other (you do not have a category that applies to me)".

6.3 Results

Across the five sites, 2,400 FNIM peoples were recruited and included in the OHC studies. The RDS recruitment network diagrams and the number of recruits and recruitment waves per seed for each OHC site are presented in Appendix A. Table B1 in Appendix B includes baseline demographic characteristics across all sites.

6.3.0.1 Experiences of discrimination in the healthcare system

The RE meta-analysis showed that the pooled prevalence of experiences of discrimination in the healthcare system across the five OHC sites was 27.8% (95% CI: 18.0%, 37.7%) with considerable heterogeneity [51] between sites ($I^2 = 93.2\%$).

Table 10. Meta-analysis of the prevalence of experiences of discrimination in the healthcare system across OHC sites

OHC site	Prevalence (%) (95% CI)
Hamilton	11.0 (6.7, 15.4)
Kenora	37.0 (28.5, 45.4)
London	26.0 (19.6, 32.4)
Thunder Bay	39.0 (32.9, 45.1)
Toronto	27.4 (22.5, 32.3)
Pooled ($I^2 = 93.2\%$)	27.8 (18.0, 37.7)

Through consultation with Indigenous community partners, it was raised that OHC Hamilton is an older study as it was completed in 2010 [116]. As such, it was likely still less socially unacceptable to talk about experiences of discrimination at the time. This may have led to underreporting of cases of discrimination, contributing to the considerable between-study heterogeneity. Thus, we also examined the pooled prevalence of experiences of discrimination in the healthcare system across OHC sites without Hamilton.

Table 11. Meta-analysis of the prevalence of experiences of discrimination in the healthcare system across OHC sites

OHC site	Prevalence (%) (95% CI)
Kenora	37.0 (28.5, 45.4)
London	26.0 (19.6, 32.4)
Thunder Bay	39.0 (32.9, 45.1)
Toronto	27.4 (22.5, 32.3)
Pooled ($I^2 = 76.7\%$)	32.1 (25.5, 38.6)

Removing OHC Hamilton reduced the between-study heterogeneity from $I^2 = 93.2\%$ to $I^2 = 76.7\%$ and increased the pooled prevalence of experiences of discrimination in the Canadian healthcare system from 27.8% (95% CI: 18.0%, 37.7%) to 32.1% (95% CI: 25.5%, 38.6%). We also note the increase in precision due to the reduction of heterogeneity.

Further subgroup meta-analyses (removing OHC Hamilton) were performed to determine whether age and gender were significantly associated with the participants' experiences of anti-Indigenous discrimination in the healthcare system.

Table 12. Subgroup analyses of the prevalence of experiences of discrimination in the healthcare system across OHC sites

Subgroups	I^2 (%)	Prevalence (%) (95% CI)	Prevalence difference (95% CI)
Age (years)			
15 - 24	86.1	19.6 (8.2, 30.9)	0.07 (-0.06, 0.15)
25 - 34	76.6	26.6 (16.5, 37.7)	0.14 (0.02, 0.22) *
35 - 44	73.4	27.1 (15.6, 38.6)	0.15 (0.01, 0.28) *
45 - 54	86.2	33.6 (16.8, 50.4)	0.21 (0.03, 0.29) *
55 - 64	72.9	28.6 (13.3, 43.8)	0.16 (-0.01, 0.33)
65+	0.0	12.5 (5.8, 19.2)	ref†

Table 12. Subgroup analyses of the prevalence of experiences of discrimination in the healthcare system across OHC sites

Subgroups	I^2 (%)	Prevalence (%) (95% CI)	Prevalence difference (95% CI)
Gender			
Women	92.3	28.8 (15.4, 42.2)	0.04 (-0.12, 0.17)
Men	79.6	24.9 (16.5, 33.3)	ref

Note that OHC Hamilton is removed from these analyses.
* Significant prevalence difference
† "ref" indicates reference group for prevalence difference

Overall, 33.6% (95% CI: 16.8%, 50.4$) of participants aged 45 to 54 years experienced discrimination in the healthcare system due to their Indigenous identity, which was the highest prevalence out of all the age groups. Participants aged 65 years and older had the lowest reported prevalence of experiences of discrimination at 12.5% (95% CI: 5.8%, 19.2%), with individuals aged 25 to 54 years of age having a significantly higher prevalence of reported experienced discrimination than the oldest age group. Women and men had comparable rates of experiences of discrimination in the healthcare system than men (28.8%, 95% CI: 15.4% to 42.2% vs. 24.9%, 95% CI: 16.5% to 33.3%, respectively).

6.3.0.2 Use of traditional medicine

The RE meta-analysis showed that the pooled prevalence of traditional medicines use across the five OHC sites was 46.4% (95% CI: 36.0%, 56.7%) with considerable heterogeneity ($I^2 = 91.3\%$).

Table 13. Meta-analysis of the prevalence of use of traditional medicines across OHC sites

OHC site	Prevalence (%) (95% CI)
Hamilton	31.0 (24.2, 37.8)
Kenora	51.1 (42.0, 60.1)
London	62.0 (54.5, 69.5)
Thunder Bay	39.4 (33.3, 45.4)
Toronto	49.0 (43.4, 54.7)
Pooled ($I^2 = 91.3\%$)	46.4 (36.0, 56.7)

Further subgroup meta-analyses were performed to determine whether age and gender were significantly associated with the participants' use of traditional medicines.

Table 14. Subgroup analyses of the use of traditional medicines across OHC sites

Subgroups	I^2 (%)	Prevalence (%) (95% CI)	Prevalence difference (95% CI)
Age (years)			
15 - 24	57.9	47.7 (36.1, 59.4)	-0.01 (-0.24, 0.38)
25 - 34	81.8	44.4 (29.7, 59.1)	-0.05 (-0.29, 0.20)
35 - 44	61.7	45.9 (34.4, 57.5)	-0.03 (-0.26, 0.20)
45 - 54	82.5	46.4 (39.2, 62.6)	-0.03 (-0.23, 0.20)
55 - 64	29.1	42.6 (32.0, 53.1)	-0.06 (-0.29, 0.21)
65+	64.3	49.0 (29.6, 68.5)	ref†
Gender			
Women	91.6	49.8 (35.8, 63.8)	0.07 (-0.10, 0.18)
Men	67.9	43.3 (35.1, 51.6)	ref

* Significant prevalence difference
† "ref" indicates reference group for prevalence difference

Prevalences of use of traditional medicines were similar across all age groups. The 65 years and older age group was chosen as the reference group to calculate prevalence differences because First Nations Information Governance Centre's [117] report showed that, among First Nations peoples, older age groups used traditional medicines more often. There were no significant differences in use of traditional medicines between genders.

6.4 Discussion

Through previous statistical simulations, we determined that a meta-analysis model using the average of the variances calculated from the lower and upper bounds of RDS-II bootstrap CIs as the estimate of within-study variance is the most appropriate method for meta-analyzing RDS data. We then applied this technique to four OHC sites (London, Toronto, Thunder Bay, and Kenora) to examine both the prevalence of experiences of anti-Indigenous discrimination in the healthcare system and the prevalence of traditional medicines use among Indigenous populations living in five Ontario cities (Hamilton, London, Toronto, Thunder Bay, and Kenora). As OHC Hamilton was contributing considerable between-study heterogeneity, it was removed from the analyses of anti-Indigenous discrimination in healthcare. The lower reported prevalence of anti-Indigenous discrimination in Hamilton may have been due to underreporting stemming from potential stigma surrounding the discussion of discrimination at the time of the study, which took place six years prior to the next included OHC study. It should be noted that experiences of racial discrimination are almost always underreported in primary survey-based data collection, both inside and outside of Canada [115, 118]. As such, Allan and Smylie [119] state that current research on experiences of racial discrimination in healthcare should be interpreted as an underestimation of the true prevalence of racism in Canada. After removing OHC Hamilton from the meta-analysis, the pooled prevalence of experiences of discrimination in the healthcare system was 32.1% (95% CI: 25.5% to 38.6%). The significantly lower prevalence of experiences of discrimination in the healthcare system found in individuals aged 65 years and older (12.5%, 95% CI: 5.8% to 19.2%) may be due to challenges in reporting discrimination linked to the intensity of historic anti-Indigenous racism and systemic discriminatory abuses such as residential school policies. Individuals in the younger age groups may also be more outspoken about their experiences of discrimination as it is more acceptable to acknowledge and admit to experiences of discrimination in the current social and political climate.

Discrimination is endemic in the Canadian healthcare system, increasing the health disparity that Indigenous peoples are experiencing due to perpetuated mistrust of and difficulty accessing the healthcare system [120]. Disrespect in both tone and body language, overt racism, and being neglected, not taken seriously, clinical practice guideline non-adherence (e.g., not getting recommended tests and/or treatments) are only some of the maltreatment that Indigenous peoples experience [121]. There is extensive evidence of racist stereotyping of Indigenous peoples in healthcare, such as presuming patients are intoxicated, drug-seeking, or non-compliant with medical advice [122]. This often leads to lack of appropriate care or poor quality of care. There is also evidence of differential access to lifesaving medical procedures in healthcare. For example, First Nations peoples in Manitoba and Alberta experienced delays in receiving care, such as coronary angiography for cardiovascular diseases while non-Indigenous people did not [123, 124]. Culturally appropriate, high quality care is needed to improve health outcomes and also ensure health equity. Continuing to bring awareness of Indigenous peoples' experiences of racism in the healthcare system and non-Indigenous healthcare provider self-awareness regarding how they may be contributing to inequitable care is needed to reduce the discrimination that continues to occur and reduce the unmet health needs FNIM peoples continue to experience. A recent randomized controlled trial [125] demonstrated that novel patient-oriented tools and cultural safety training improved patient experience and increased clinician recommendation. Patient experience and recommendation of clinicians to patient networks are important for improving access to and quality of healthcare. Thus, further exploration and development of these tools and training is imperative to continue working towards addressing the Calls to Action of the TRC [4] and improve the health of Indigenous peoples living in urban areas in Ontario.

With regards to traditional medicines use, the prevalence across OHC sites was

46.4% (95% CI: 36.0% to 56.7%). Note that there were variations in the survey question regarding use of traditional medicines between sites. OHC Hamilton asked "Do you use traditional medicine?" while all other sites asked "Do you use traditional Indigenous medicine or practices to maintain your health and wellbeing?". Indigenous peoples have a right to access their traditional medicine, but there are many barriers that prevent them from doing so [126]. Based on the pooled prevalence we obtained from this study, we note that nearly half of the Indigenous peoples living in Ontario cities are using traditional medicines. In previous analyses, we also found that using traditional medicines was associated with improved health outcomes. However, we have also found high rates of gaps in access to traditional medicines across OHC sites [e.g., 127, 128]. Thus, decision makers must continue to work with Indigenous peoples and engage in more Indigenous-led healthcare initiatives to improve the quality of healthcare for Indigenous peoples living in urban areas in Ontario.

6.4.1 Strengths and limitations

Through the use of RDS for each dataset from the OHC studies, we ensured representativeness and validity of our study results. Employing meta-analysis techniques to pool data from OHC sites allows us to present a more accurate and integrated understanding of experiences of anti-Indigenous discrimination in the healthcare system and use of traditional medicines among Indigenous peoples living in urban Ontario. Nonetheless, in some cases with high degrees of variability in estimates, the precision of our estimates in the meta-analysis decreased due to the substantial between study heterogeneity.

As the OHC study sites are all within Ontario, the pooled prevalence estimates of experiences of discrimination in the healthcare system and use of traditional medicines are Ontario-specific. Care must be taken when generalizing to other provinces or across Canada as distinct populations and geographic areas may have different rates of access to healthcare as well as traditional medicines. Given that the OHC data used in this study are self-reported, participant responses may be subject to recall bias. Self-report of experiences of racial discrimination is known to be particularly prone to underreporting. This is likely linked to the fact that individuals who have experienced dense racial discrimination may find it easier in everyday life to ignore and/or deny it. It also may not necessarily be safe or comfortable to speak about experiences of racial discrimination in interviews. Thus, the pooled prevalence of anti-Indigenous discrimination in the healthcare system in Ontario cities found in this study may be underestimated. Moreover, causality cannot be inferred in this study due to the cross-sectional nature of the data.

There is also substantial heterogeneity in the meta-analyses of these outcomes of interest, so caution must be used when interpreting the results. OHC Hamilton contributes to the considerable amount of between-study heterogeneity found in the meta-analysis of experiences of anti-Indigeous discrimination in the healthcare system as the between-study heterogeneity decreased by approximately 17% when removing the site from the analysis. This was potentially due to the Hamilton study being performed much earlier than the other sites. At the time of OHC Hamilton, there may have been higher levels of stigma reporting experiencing anti-Indigenous discrimination in the healthcare system as the study took place six years prior to the next included study. Alternatively, individuals living in Hamilton at the time the study took place may have been those who had experienced dense racial discrimination and found it easier to ignore and/or deny it. This may have, in part, contributed to the amount of between-study heterogeneity in these meta-analyses.

6.5 Conclusion

Indigenous peoples living in Ontario cities continue to experience a high rates of anti-Indigenous discrimination in the healthcare system. This is unacceptable and in tension with commitments that Canada has to equitable and accessible health care for all. More positively, we also found that there is a high prevalence of traditional Indigenous medicine use. Given the strong desire for access to traditional medicine, known gaps in current availability, and the associated improvement in health outcomes when FNIM peoples are able to use traditional medicines, it is important to continue to advocate for additional resources to ensure culturally appropriate health-care for Indigenous peoples living in urban areas in Ontario.

7 Discussion

This dissertation developed, validated, and applied a novel meta-analysis technique for respondent-driven sampling (RDS) data. Due to the nature of RDS, an appropriate estimate of within-study variance is needed in order to combine data in a meta-analytic framework. In the first manuscript chapter, I developed and validated an appropriate method for combining RDS data. Results of the simulation study showed that averaging the variances calculated from the upper and lower bounds of RDS-II bootstrap confidence intervals (CIs) is the optimal method of estimating within-study variance for meta-analyzing RDS data. In the subsequent three chapters, this statistical technique was used to combine prevalences of diabetes mellitus (DM), prescription opioid (PO) use without a prescription or out of keeping with the prescription, experiences of anti-Indigenous discrimination in the healthcare system, and use of traditional medicines among First Nations, Inuit, and Métis (FNIM) peoples living in urban areas in Ontario. In addition to the contribution to statistical methods, this thesis makes a substantial contribution to the health and wellbeing of Indigenous peoples living in urban areas.

7.1 Contributions

Use of RDS as a sampling technique for hidden populations is gaining popularity. However, precise population-level statistics are difficult to obtain due to these populations often existing in separate small communities and the increased variability and linked design effect of RDS samples compared to simple random sampling. As there was no method for the meta-analysis of RDS data in the existing literature, it is important to fill this knowledge gap. The third chapter of this dissertation presented valid fixed effects (FE) and random effects (RE) meta-analysis approaches for RDS data. We examined approaches for estimating within-study variance using RDS bootstrap confidence intervals (CIs) and basic symmetric RDS-II CIs. Averaging the variances calculated from upper and lower bounds of RDS bootstrap CIs was found to be the only valid method of obtaining within-study variance for meta-analyzing RDS data with both FE and RE models.

Given the possibility of between-study variance, only an RE meta-analysis model was applied to the OHC studies in order to examine outcomes prioritized by the Indigenous community partners. Chapters 4 to 6 of this dissertation estimated population-level summaries of DM, PO use without a prescription or out of keeping with the prescription, experiences of anti-Indigenous discrimination in the health-care system, and traditional medicines use among Indigenous peoples living in urban areas in Ontario. Given that Indigenous populations are substantially younger than the general population, the prevalence of DM among FNIM peoples living in Ontario cities (11.3%, 95% CI: 7.1%, 15.4%) is likely substantially higher than the general population (7.2%). Moreover, this is consistent with our findings that younger age groups have substantially higher rates of DM than the general population. Groups that have a higher prevalence of DM within Indigenous populations living in urban areas in Ontario include women and individuals with a BMI higher than 30 kg/m^2. Due to the stigma surrounding having DM, there may also be some reluctance in reporting a diagnosis that is contributing to the lower prevalence of DM found in Indigenous men compared to the general population.

We found that the pooled prevalence of PO use without a prescription or in unintended ways was more than 1.5 times higher among Indigenous peoples living in urban areas in Ontario (15.8%, 95% CI: 12.6%, 19.1%) than in the general population (9.6%). Age and gender differences were found in the prevalence of PO use in Indigenous populations, with individuals 25 to 34 and 35 to 44 years of age and men having the highest prevalences of PO use. Moreover, Indigenous peoples diagnosed with a mental health disorder were found to have a significantly higher prevalence of PO use than those without a diagnosis. More positively, individuals who used traditional medicines had a significantly lower prevalence of PO use than those who did not use it.

Finally, high prevalences of experiences of anti-Indigenous discrimination in the healthcare system and use of traditional medicines were also reported among FNIM peoples living in urban areas in Ontario. We found a significantly lower prevalence of experiences of anti-Indigenous discrimination in individuals 65 years of age and older, which may be due to challenges in reporting discrimination stemming from historical anti-Indigenous racism and systemic discriminatory abuse as well as younger individuals being more outspoken about their experiences of discrimination given current social norms.

7.2 Study implications

Results of this dissertation include (1) a valid method of pooling RDS samples for researchers and (2) more precise, population-level health information for health indicators prioritized by Indigenous community partners for Indigenous peoples, the health sector, and policy makers. As RDS is becoming increasingly popular as a sampling and statistical method for examining hidden populations, the FE and RE meta-analysis techniques developed and validated in this dissertation will allow researchers to pool RDS data across studies and obtain valid statistics. Moreover, the overall prevalences of DM, PO use without a prescription or out of keeping with the prescription, experiences of anti-Indigenous discrimination in the healthcare system, and use of traditional medicines are relevant for the Indigenous community partners to lead healthcare decisions for Indigenous peoples. Subgroup analyses identified higher prevalences of DM in younger community members, which will help with further tailoring healthcare approaches for the community. Moreover, the high prevalence of traditional medicines use as well as the connection between traditional medicines use and low prevalences of DM and PO use is a strong indicator that incorporating traditional Indigenous medicine into Indigenous peoples' healthcare is important for improving their health outcomes. Thus, the need for more Indigenous-led healthcare partnerships to reduce health disparities between Indigenous peoples living in urban areas and the general population is highlighted.

7.3 Strengths

The methodological portion of this dissertation filled a gap in available statistical techniques for analyzing RDS data. Simulation studies included a variety of population and estimator conditions to be analyzed. Through the use of simulated populations, we know the true population parameters and are able to explore the performance of different methods of estimating within-study variance in RDS studies for meta-analysis. The applied portion of this dissertation combined this newly validated meta-analysis approach to data across OHC sites using meta-analysis to provide a more precise province-wide understanding of the outcomes of interest.

7.4 Limitations

As all participants in the OHC studies live in urban areas of Ontario, the pooled prevalences obtained from the OHC data sets are Ontario-specific. Care must be taken when generalizing to other provinces and territories due to factors such as different healthcare systems and differing levels of access to healthcare for Indigenous peoples. The distinct nations, communities, and groups that make up the diverse populations of Indigenous peoples living in Ontario cities may also differ in culture and practices. Thus, we must be wary of overgeneralizing across these populations. Moreover, as all survey responses in this study are self-reported, there is the possibility of recall bias. Finally, the data are cross-sectional, so we cannot assume causality of any outcomes of interest.

7.5 Summary

RDS is a valuable tool for sampling and understanding hidden populations. This dissertation contributes to analytical methods for RDS data and contributes to our knowledge of the prevalence of DM, PO use without a prescription or out of keeping with the prescription, experiences of discrimination in the healthcare system, and use of traditional medicines among FNIM peoples living in Ontario cities. These analyses were prioritized by OHC Indigenous health service provider community research partners to support their goals and improve the health of local FNIM peoples.

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Appendix A RDS recruitment networks

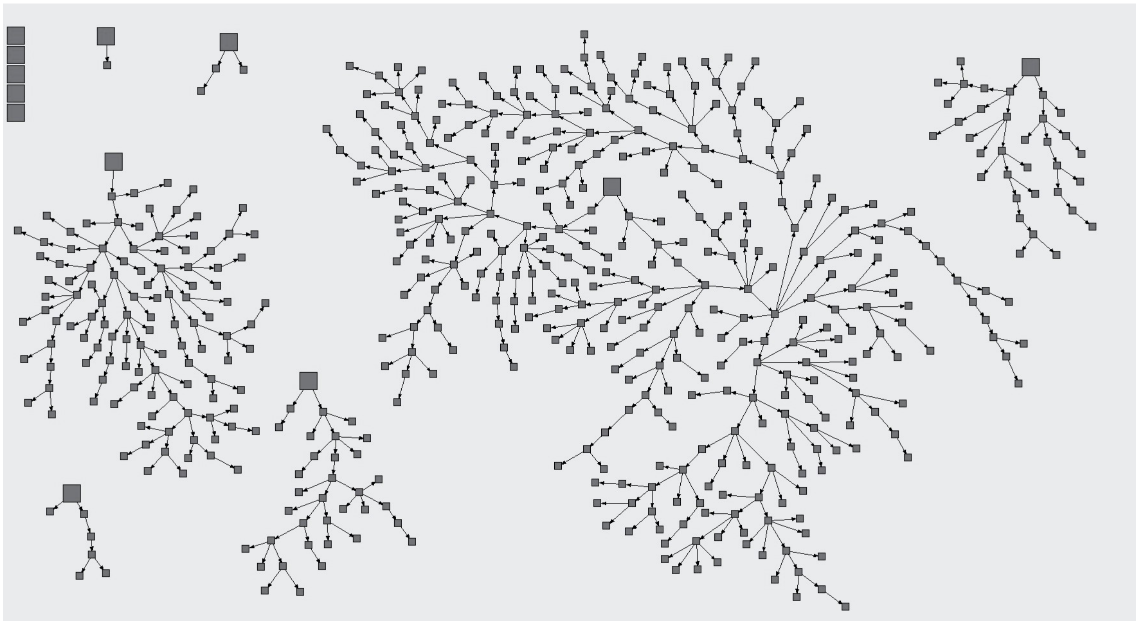

Figure A1. RDS recruitment network diagram for OHC Hamilton. Large squares represent seeds and small squares represent recruits.

Table A1. Number of recruits and recruitment waves per seed for OHC Hamilton

Seed ID	Number of recruits	Number of recruitment waves
107	35	8
140	1	0
154	35	9
162	1	0
175	4	2
182	1	0
260	1	0
377	351	19
472	115	12
496	7	4
53	2	1
550	1	0

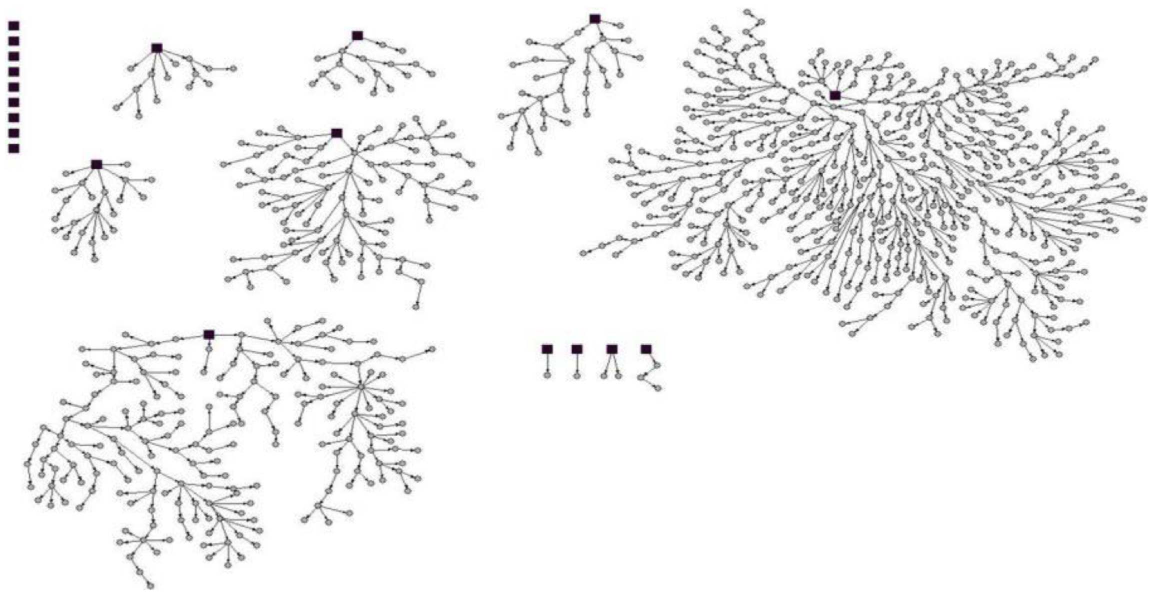

Figure A2. RDS recruitment network diagram for OHC Toronto [2]. Squares represent seeds and circles represent recruits.

Table A2. Number of recruits and recruitment waves per seed for OHC Toronto

Seed ID	Number of recruits	Number of recruitment waves
00-1-001	18	5
00-1-002	34	9
00-1-004	1	0
00-1-013	15	3
00-1-100	1	0
00-1-156	1	0
00-2-001	196	16
00-2-002	509	18
00-2-003	2	1
00-2-022	1	0
00-2-080	2	1
00-2-121	1	0
00-2-167	24	4
00-2-177	3	1
00-2-181	1	0
00-2-366	1	0
00-3-001	102	10
00-3-002	1	0
00-3-003	1	0
00-3-010	4	3

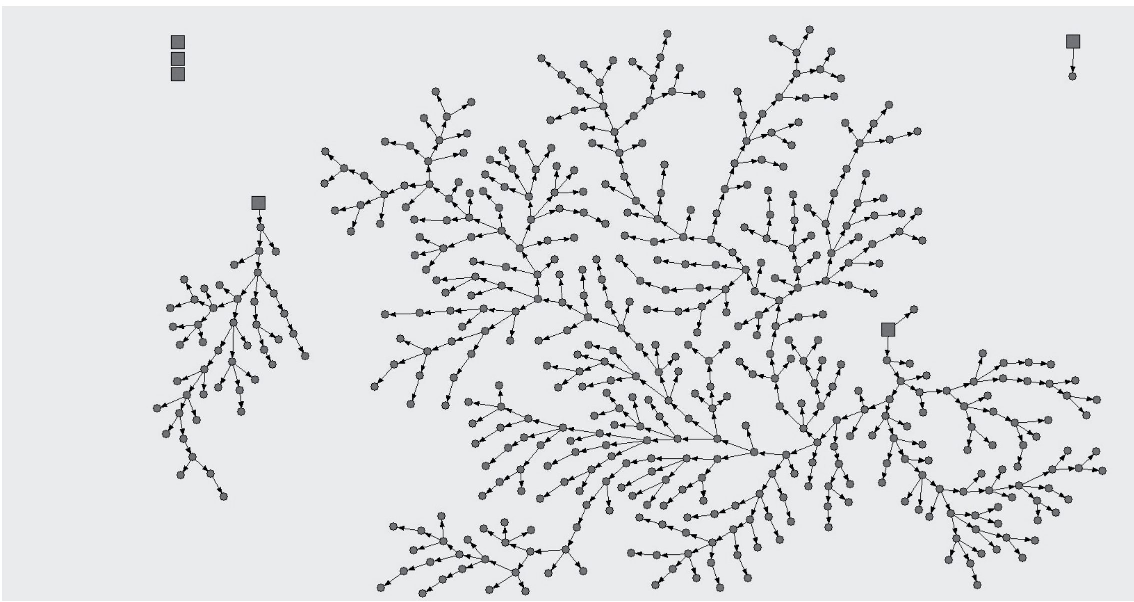

Figure A3. RDS recruitment network diagram for OHC London. Squares represent seeds and circles represent recruits.

Table A3. Number of recruits and recruitment waves per seed for OHC London

Seed ID	Number of recruits	Number of recruitment waves
00-6-001	457	28
00-6-002	1	0
00-6-003	47	13
00-6-009	1	0
00-6-015	2	1
00-6-052	1	0

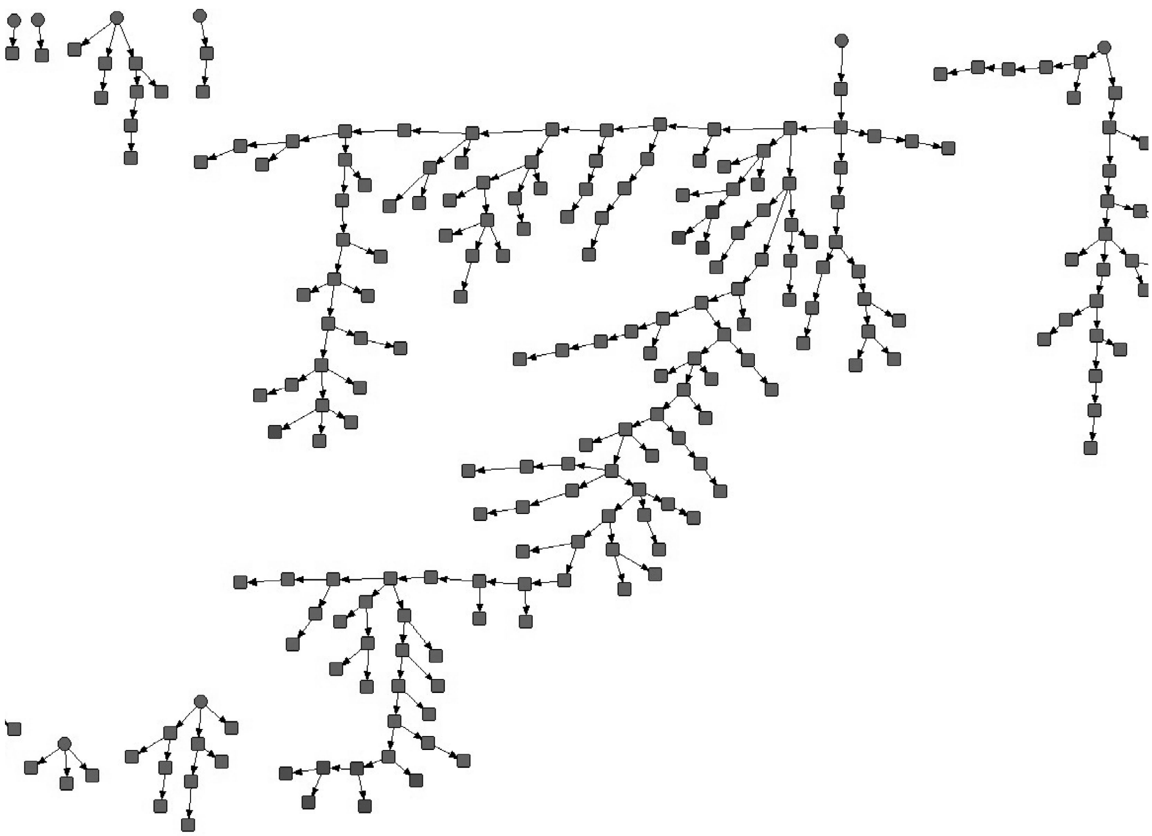

Figure A4. RDS recruitment network diagram for OHC Kenora. Circles represent seeds and squares represent recruits.

Table A4. Number of recruits and recruitment waves per seed for OHC Kenora

Seed ID	Number of recruits	Number of recruitment waves
00-13-001	1	0
00-13-002	1	0
00-13-003	1	0
00-13-005	1	0
00-13-007	1	0
00-13-008	1	0
00-13-009	2	1
00-13-011	1	0
00-13-012	1	0
00-13-013	1	0
00-13-014	1	0
00-13-015	1	0
00-13-016	12	3
00-13-019	9	4
00-13-020	2	1
00-13-025	101	18
00-13-028	29	10
00-13-098	6	4
00-13-105	37	9
00-13-167	1	0
00-13-175	1	0
00-13-181	33	10
00-13-195	2	1
00-13-247	1	0
00-13-248	1	0
00-13-249	1	0
00-13-252	1	0
00-13-258	2	1
00-13-261	1	0
00-13-262	1	1
00-13-263	1	0
00-13-264	1	0
00-13-265	2	1

Table A4. Number of recruits and recruitment waves per seed for OHC Kenora

Seed ID	Number of recruits	Number of recruitment waves
00-13-272	2	1
00-13-273	1	0
00-13-277	6	2
00-13-289	1	0
00-14-002	1	0
00-14-003	16	8
00-14-004	1	0
00-14-005	1	0
00-14-007	1	0
00-14-008	5	2
00-14-019	1	0
00-14-020	6	3
00-15-001	1	0
00-15-002	1	0
00-16-002	3	1
00-16-005	1	0
00-16-008	1	0
00-16-011	5	2

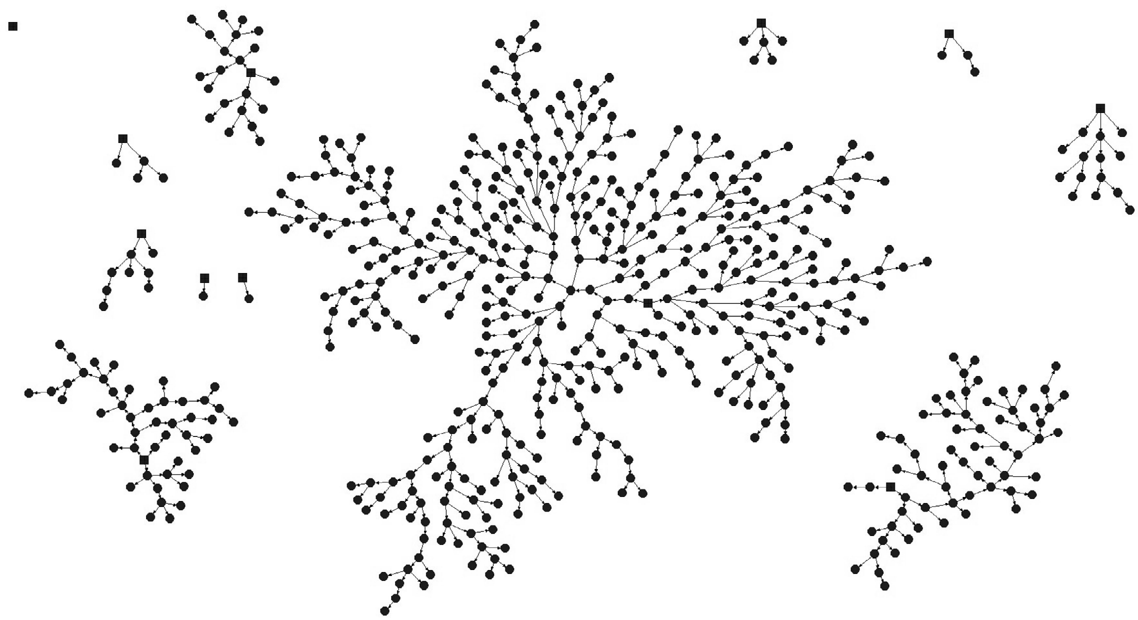

Figure A5. RDS recruitment network diagram for OHC Thunder Bay. Squares represent seeds and circles represent recruits.

Table A5. Number of recruits and recruitment waves per seed for OHC Thunder Bay

Seed ID	Number of recruits	Number of recruitment waves
00-8-001	6	2
00-8-002	66	13
00-8-003	422	24
00-8-015	5	2
00-8-147	4	2
00-8-206	2	1
00-8-243	15	5
00-8-416	9	4
00-8-491	22	4
00-8-507	1	0
00-9-002	47	10
00-8-007	2	1

Appendix B Our Health Counts demographics

Table B1. RDS-II estimates of the prevalence (%) (95% CI) of Our Health Counts demographics

	Sites				
Demographics	Hamilton	Toronto	London	Kenora	Thunder Bay
Indigenous identity*					
First Nations	99.4 (98.8, 100.0)	86.0 (82.0, 89.9)	95.1 (91.9, 98.3)	96.1 (91.5, 100.0)	98.4 (96.7, 100.0)
Métis	0	13.0 (9.1, 16.8)	2.8 (-0.4, 6.0)	3.7 (-0.9, 8.3)	1.5 (-0.2, 3.3)
Inuit	0	0.3 (-0.2, 0.8)	1.9 (1.6, 2.1)	0	0
Other	0	0.3 (0.0, 0.6)	0.1 (-0.4, 0.6)	0.02 (-0.02, 0.05)	0
Multiple	0.2 (-0.2, 0.6)	0.5 (-0.4, 1.3)	0.1 (-0.1, 0.4)	0.2 (-0.5, 0.8)	0.5 (-0.5, 1.6)
Age (years)					
15 - 24	13.1 (8.6, 17.5)	21.5 (16.9, 26.0)	33.6 (25.9, 41.4)	25.7 (19.5, 31.9)	17.1 (12.3, 22.0)
25 - 34	23.5 (16.9, 30.1)	18.9 (14.5, 23.4)	21.1 (14.3, 27.9)	17.2 (10.4, 24.1)	30.8 (25.0, 36.5)
35 - 44	17.1 (11.3, 23.0)	21.4 (16.9, 25.9)	16.8 (11.7, 21.8)	8.7 (3.0, 14.3)	20.7 (15.6, 25.8)
45 - 54	24.2 (17.9, 30.5)	24.4 (19.6, 29.1)	14.2 (9.1, 19.2)	26.2 (18.7, 33.6)	15.8 (11.1, 20.6)
55 - 64	8.7 (5.0, 12.5)	10.5 (6.9, 14.0)	8.3 (4.0, 12.6)	9.3 (2.2, 16.4)	13.0 (8.9, 17.1)
65 and over	13.4 (9.0, 17.8)	3.3 (0.6, 6.0)	6.0 (2.9, 9.0)	12.5 (5.2, 19.7)	2.6 (0.6, 4.5)

Table B1. RDS-II estimates of the prevalence (%) (95% CI) of Our Health Counts demographics

	Sites				
Demographics	Hamilton	Toronto	London	Kenora	Thunder Bay
Gender					
Woman	40.6 (33.6, 47.5)	48.4 (42.8, 54.0)	45.5 (37.8, 53.3)	45.7 (36.6, 54.7)	46.9 (40.7, 53.2)
Man	59.3 (52.3, 66.2)	50.1 (44.5, 55.7)	53.7 (46.0, 61.5)	54.3 (45.2, 63.3)	53.1 (46.8, 59.4)
Transgendered†	0	1.0 (0.3, 1.7)	0.7 (0.6, 0.9)	0	0
Other	0	0.5 (-0.5, 1.5)	0.01 (0.0, 0.01)	0	0
Household income (CAD)					
<20,000	73.0 (66.5, 79.0)	24.9 (19.8, 30.0)	44.4 (36.8, 52.1)	20.0 (12.0, 28.0)	0.7 (0.5, 0.8)
20,000 to <30,000	11.9 (7.7, 16.2)	61.0 (55.4, 66.5)	40.4 (32.7, 48.0)	3.9 (1.7, 6.1)	86.5 (82.0, 90.9)
30,000 to <40,000	3.2 (0.3, 6.1)	3.3 (1.5, 5.1)	5.9 (2.1, 9.7)	2.5 (1.9, 3.1)	3.2 (0.9, 5.5)
40,000 to <50,000	2.0 (0.3, 3.6)	2.9 (1.3, 4.5)	2.1 (-0.1, 4.2)	0.2 (0.0, 0.4)	0.8 (-0.4, 2.0)
50,000 to <60,000	2.2 (-0.4, 4.4)	1.5 (-0.2, 3.2)	1.0 (-0.5, 2.5)	0.3 (-0.6, 1.2)	0.4 (-0.5, 1.4)
60,000 to <70,000	0.1 (-0.2, 0.4)	0.9 (-0.3, 2.2)	1.9 (-0.3, 4.1)	0.1 (0.0, 0.1)	0.1 (0.0, 0.1)
70,000 to <80,000	0.04 (-0.03, 0.1)	0.2 (-0.2, 0.5)	0.5 (-1.0, 2.0)	0.1 (-0.4, 0.7)	0.7 (0.2, 1.2)
80,000 or more	0.9 (0.2, 1.7)	5.3 (2.9, 7.7)	3.8 (0.3, 7.2)	8.3 (3.1, 13.5)	7.7 (4.0, 11.3)

* Those who did not identify as Indigenous were excluded. 0.3% (-0.1, 0.8) of Hamilton participants had missing responses.

† E.g., transgender, transsexual, genderqueer