# Validation and Pattern Discovery in the Canadian Community Health Survey - Mental Health (CCHS-MH) Support Utilization

by

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**Abstract**

Mental illness is one of the most pressing medical challenges facing society. Although identifying gaps in mental-health support utilization is important for public health, this topic has not been widely explored in the literature. The latest Canadian Community Health Survey - Mental Health Component on mental-health support utilization was conducted by the Canadian government and sampled 24,788 Canadians. It collected information on twelve mental-health support utilization items and nine sociodemographic items, namely province of residence, residence in a metropolitan/non-metropolitan area, age, sex, marital status, visible minority status, immigrant status, highest level of attained education, and household income. However, this instrument has not been validated yet. Hence, this research aims to 1) probe the structural validity and reliability of the CCHS-MH instrument using exploratory factor analysis (EFA) and confirmatory factor analyses (CFA); 2) use clustering unsupervised machine learning algorithms to find patterns of mental-health support utilization by grouping participants based on their support utilization; and 3) compare and contrast these patterns using chi-square analyses to examine group differences in demographic characteristics. Findings show that the reliability (i.e., internal consistency) of the measure was adequate ($\alpha = .79$). There is agreement among the EFA, CFA, and clustering analyses in revealing a 4-factor optimal model fit and in the nature of the factors: No Support, Social Support, and Professional Support were always relevant. The fourth factor, Mixed Support, which combines professional and social support systems, seems to yield the best fit, as reflected by the CFA. The final model yields 4 factors underlying mental-health support utilization: No Support, Social Support, Professional Support, and Mixed Support. The findings also show that Fuzzy C-Means clustering outperform the other two clustering algorithms employed (K-Means and Hierarchical Agglomerative Clustering). Post-hoc analyses found significant differential patterns of utilization in every demographic variable, except for visible minority status. Theoretical implications include support for the validation and reliability of a 4-factor model of the CCHS-MH support utilization and for the effectiveness of Fuzzy C-Means Clustering in finding patterns underlying large quantities of psychological data. Practical implications include more evidence for established patterns of support utilization observed in both the Canadian and global context as well as campaigns to encourage communities to talk openly about mental health, reverse biases in the field, and emphasize mental health in medical training.

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## List of Acronyms

| | |
|---|---|
| AM | Andersen Model |
| ATSPPH-SF | Attitudes Toward Seeking Professional Psychological Help - Short Form |
| BIC | Bayesian Information Criterion |
| CAI | Computer-Assisted Interview |
| CCHS | Canadian Community Health Survey |
| CCHS-MH | Canadian Community Health Survey – Mental Health |
| CFA | Confirmatory Factor Analysis |
| CFI | Comparative Fit Index |
| ChiSq | Chi-Square |
| CMA | Census Metropolitan Area |
| DI | Dunn Index |
| EFA | Exploratory Factor Analysis |
| FCM | Fuzzy C-Means Clustering |
| HAC | Hierarchical Agglomerative Clustering |
| HBM | Health Belief Model |
| KM | K-Means Clustering |
| RMSEA | Root Mean Square Error of Approximation |

| | |
|---|---|
| SABIC | Square Adjusted Bayesian Information Criterion |
| SES | Socioeconomic Status |
| SI | Silhouette Index |
| SRMR | Standardized Root Mean Square |
| TLI | Tucker Lewis Index |
| VSS | Very Simple Structure |
| WHO | World Health Organization |

## Chapter 1: Introduction

Mental health problems are pervasive throughout society. Mental health concerns as characterized by the Public Health Agency of Canada as alterations in thinking, mood or behaviour associated with significant distress and impaired functioning (Government of Canada, 2020). Approximately one fifth of Canadians struggle with mental health annually (Mental Health Commission of Canada, 2013; Statistics Canada, 2019). Of these, slightly over half have their needs fully met (Statistics Canada, 2019), suggesting a distinct lack of utilization of support by Canadians. Underutilization of a service by a group that is inconsistent with the expected need of that group should be viewed as evidence for policy change at the medical administration or governmental level. Surveys such as those conducted in the Canadian Community Health Survey - Mental Health Component (CCHS-MH) are important tools for collecting data at a national scale. The CCHS-MH is similar in function to the main-line CCHS, only narrowing its focus on mental health and expanding the mental health related data collection. It collects data on the mental-health status, mental-health care utilization, and outcomes for Canadians. It measures support utilization (professional or non-professional) for any mental-health issue and collects sociodemographic variables, including province of residence, residence in a metropolitan/non-metropolitan area, age, sex, visible minority status, immigrant status, highest level of attained education, and household income. Studying non-professional support provided by friends or family can unearth valuable information, as social support may be protective against poor mental health (Cadzow & Servoss, 2009; Wang, Mann, Lloyd-Evans, Ma, & Johnson, 2018).

However, there are no studies validating the mental-health utilization survey, so inferences built on the data are not demonstrably valid. Additionally, there is no existing psychological theory underlying the CCHS-MH instrument. This research aims to fill this gap in the literature.

The present research constitutes a multi-phasic project aiming to not only validate the CCHS-MH, but also to generate theory that explains the data and to analyze it with methodology rarely used in psychology, and never on the CCHS-MH. Validity evidence will be gathered from multiple complementary and convergent sources. First, the internal consistency of the instrument will be analyzed to determine whether it functions as a reliable metric. If the instrument is reliable across items, the next step will be to determine the number of underlying factors and identify the items that are useful in developing the best model. This will minimize redundancy across the variables and help reveal more powerful patterns in the data. The final phase will involve analyzing participants' responses to the survey and comparing the patterns across demographic variables.

Confirming the reliability of this survey is fundamental, as inferences made on an unreliable measure can say very little about the larger context. To measure this construct, the Cronbach's *alpha* (Cronbach, 1951) measure was calculated. Exploratory Factor Analysis (EFA) was another important step in validation, revealing the optimal number of factors emerging from the data. The thorough scoping review delineated in Chapter 3 aims to gather content validity evidence. Then, the Confirmatory Factor Analysis (CFA) confirms the optimal model based on the previous exploratory findings. This was important for the purposes of the ensuing cluster analysis, but also for future work using this data and, potentially, informing the survey when the federal government initiates another collection cycle of the CCHS-MH.

This study also employs machine learning to discover patterns of mental health support underutilization based on participants' responses to the CCHS-MH capturing mental health support utilization, comparing these patterns across demographic variables. Uncovering specific groups that are underutilizing mental health supports can dictate where energy should be expended in attempts to engage the populace. While health-care utilization overall is well researched, the 2012 CCHS-MH has been studied primarily with narrow variables or smaller subsets that do not reflect the state of health-care utilization across Canada. The present study uses unsupervised machine learning for the first time to uncover these patterns of utilization on the CCHS-MH sample, which constitutes a novel contribution to the existing body of mental-health research.

This study addresses the paucity of research focusing on the underutilization of mental health supports by investigating whether there are patterns in the support systems that individuals favor. The study poses the following questions: (1) *Is the survey data from the CCHS-MH internally consistent?* (2) *Can a more parsimonious factor-model of the data be construct-validated using Confirmatory Factor Analysis (CFA)?* (3) *Can an unsupervised machine learning technique such as clustering find mental-health utilization patterns efficiently in the CCHS-MH dataset?* (4) *Are cluster memberships validated by existing research on mental-health care utilization?* (5) *What can be learned from these patterns in the Canadian context?*

This research employs cluster analysis, a powerful unsupervised machine learning tool for pattern discovery in large data sets. Cluster analysis is a method that has been historically underutilized in the field of psychology, possibly due to the relative complexity of clustering algorithms required to effectively analyze large amounts of primarily categorical data. Although machine learning has not been often used in psychological research, this has begun to change as its utility becomes more apparent and large amounts of data are generated daily at unprecedented rates. The current study aims to address the dearth of research on predictors of mental health to determine whether different types of support are utilized differentially across individuals, in a large Canadian sample. This research makes the following contributions: (1) it validates the survey used in the CCHS-MH to assure that inferences from it are built on a solid foundation; (2) it performs an EFA and a CFA to explore and determine an optimal model of the data to display the consistent patterns of utilization among Canadians for their mental health; (3) it employs, for the first time, machine learning techniques to analyze mental-health utilization in the CCHS-MH dataset; (4) it reveals several findings that are also supported by theory: middle-aged individuals tend to seek no support for their mental health concerns, men tend to not seek any support for their mental health concerns and specifically abstain from social support, and immigrants tend to not seek support; and (5) it highlights that Canadians in rural areas tend to not seek support from friends and family, that women tend to seek support of all types, and low-income earners rely heavily on family doctors for support, all significant findings that were not previously studied in the Canadian context. Additionally, the study reveals a series of findings across other variables, with mixed support in the literature.

### 1.1. Chapter Summary

Chapter 1 describes the context of the problem, the gaps identified in the related literature, and the contributions of this research. The CCHS-MH offers a wealth of information, but it is exploratory in nature and in need of validation. Using clustering analysis to explore the data in new ways will also open up new research avenues. These analyses provide further support to the CCHS-MH design and show that clustering, in addition to more traditional statistical techniques, can be effective in analyzing this type of data.

# Chapter 2: Theoretical Framework

## 2.1. Mental Health Construct in the CCHS-MH

The CCHS-MH has an extremely broad concept of what constitutes poor mental health that a respondent utilized support for. It does not have a specific definition of mental illness defined based on an established expert regulatory body, such as the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013). Nor does it require an official diagnosis from a practitioner to confirm a standard of poor mental health. It simply refers to utilizing support for substance abuse problems, emotional health, or mental health. A reasonable way to conceptualize the construct is to utilize the definition held by the federal government, the regulatory body that created this survey, which is any alterations in thinking, mood or behaviour associated with significant distress and impaired functioning (Government of Canada, 2020).

## 2.2. Models of Support Utilization

The survey employed by the CCHS-MH has no explicitly stated framework that informed the design of both the types of supports studied and the demographic information collected from the participants. There are several popular theories regarding the factors that contribute to support utilization when struggling with poor health, both physical and mental. This chapter will explore some of the more well-established models to ascertain whether they support the variable categories found in the CCHS-MH.

### *2.2.1. Andersen Model of Health-Care Utilization*

The Andersen Model (AM; Andersen & Davidson, 2014), illustrated in Figure 1, is generally considered to be an effective framework for predicting health service use across multiple research studies (Babitsch, Gohl, & von Lengerke, 2012; Fleury et al., 2014). One of the limitations of this model is that the role of social and cultural factors is not explicitly included in the model. Psychosocial elements (i.e., relating to the interrelation of social factors with individual thought and behavior) have been confirmed to be predictive of health-related behaviours by analyses of the AM (Bradley et al., 2002) and the success of other similar models of health-care utilization. AM also does not consider informal support outcomes, which is reasonable, given that it was designed to influence policy surrounding American health care. However, informal supports constitute an important part of analyzing mental health care support.

The meta-analysis performed by Babitsch, Gohl, and von Lengerke (2012) found that, while using AM as a theoretical framework was effective in most articles analyzed, the variables studied using AM as justification tended to be narrow and used repeatedly across studies. For instance, age, marital status, sex, education, and ethnicity were the majority of predisposing traits studied, whereas income, health insurance, and having a family doctor were the only enabling factors found in the majority of studies. The present study aims to fill this gap by studying not only these fundamental demographic factors, but also other variables, such as province of residency, comparing rural and urban residency, and immigrant status.

### *2.2.2. Health Belief Model*

The Health Belief Model (HBM; Becker 1974), shown in Figure 2, is a model of health behavioural changes developed with a social psychological framework. The original HBM was found to have very poor predictive validity for strictly biological health conditions (Carpenter, 2010) and was refined to address original failings of the model (Orji, Vassileva, & Mandryk, 2012; Jones et al., 2015). Similar to the AM, the literature studying the HBM mainly focuses on physical health outcomes, though analyses that use the HBM to predict behaviours related to seeking mental health support show significant effects (Gipson & King, 2012; Henshaw & Freedman-Doan, 2009). Although the HBM has the capacity to be effectively applied to mental-health concerns, it has not been researched extensively. Thus, the present research also aims to fill a gap in the literature, by extending the analyses of variables that have the potential to predict health-care utilization for mental health issues.

One advantage of the HBM over the AM is that informal supports can be assumed as valid outcomes and incorporated into the model, because the HBM focuses on the factors that predict seeking help for health concerns broadly, rather than focusing on specific types of outcomes. As considerations of informal supports were not explicitly built into the HBM and were not considered during its creation, the extent to which the HBM can speak to informal support seeking remains limited. The HBM implicitly incorporates informal supports into the design by focusing exclusively on what motivates individuals to engage healthful behaviours. While much research using the HBM focuses on professional support systems, making extant literature on social supports limited, the HBM provides evidence that health support utilization models can account for social support systems and as a result this makes the CCHS-MH survey an opportunity to fill a gap in the research.

### *2.2.3. Attitudes Toward Seeking Professional Psychological Help: Short-Form Scale*

The Attitudes Toward Seeking Professional Psychological Help - Short Form (ATSPPH-SF) scale is a 3-dimensional model of attitudes contributing to the seeking of professional psychological help, updated from its original 1970 version (Fischer & Farina, 1995). The ATSPPH-SF measures the level of openness to seeking professional help, value in seeking professional help, and the preference to cope on one's own (Fischer & Farina, 1995). This scale offers some insight into help-seeking behaviour for mental health concerns, but it has the same drawbacks of the previously discussed models. Specifically, there is no consideration for social support in the outcomes measured by the model, though this is clearly intentional as the name indicates the primary focus is on professional help. Recent analyses of demographic effects on the model provide some evidence to support differential effects of gender, employment, income, and education on various aspects of the 3 factors of the ATSPPH-SF (Chen et al., 2020; Picco et al., 2016). The model is incomplete in its ability to inform the CCHS-MH data, but it does provide a basis for the influential role of demographic factors in predicting utilization of mental health supports, even if only for professional supports.

The validity of these existing models suggests that the CCHS survey is conceptually valid as well. Demographic variables are significant components in many, if not all, validated health-care support utilization models. While not all models focus on informal support systems as outcomes, there is evidence to support their inclusion in the survey.

### 2.3. Chapter Summary

Chapter 2 explores and critiques evidence-based theories of the drivers of mental-health support utilization. The theory underpinning these models indicates that the CCHS-MH survey is also evidence-based, even if it is not directly built upon an existing model. Social supports were not considered in these models and represent an area in need of more study.

# Chapter 3: Literature Review

The Canadian Community Health Survey (CCHS) is an annual cross-sectional survey created to collect information relating to health status, health-care utilization, and health determinants for the Canadian population (Statistics Canada, 2020). In 2002, the Mental Health Component (CCHS-MH) was added to the standard CCHS to understand the need and utilization of mental-health services across Canada as well as to generate data that could be used to formulate public policy (Statistics Canada, 2004). Since the initial cycle in 2002, the CCHS-MH has only been administered once, in 2012.

The present literature review is guided by the following questions: (1) Does the CCHS-MH survey of mental-health support utilization meet basic criteria to confirm a baseline content validity? (2) Are there any precedents set by other models of mental-health support utilization to inform the CCHS-MH survey? (2) What improvements for future data collection cycles can be made?

## 3.1. Validation of the Mental-Health Utilization Survey

The mental health care support utilization survey does not have any explicit underlying theoretical framework. This survey has not been validated so far and no validation studies have been conducted and made a part of the microdata provided by the Canadian government. The government engages in a form of criterion validity by comparing estimates of the health indicators that are taken from common content in prior years. Then, if significant errors are found, an examination is carried out to determine whether the data is erroneous in any way (Statistics Canada, 2020). Statistics Canada explicitly states that their validation process is left to external analysts studying the data (Statistics Canada, 2020), meaning that reviewing the literature is the only way to determine the validity of the CCHS measures. Validity has been framed in many ways in the literature, including in terms of "the concept or characteristic that a test is designed to measure" (p. 5; AERA, 2014, as cited in Pellegrino, DiBello, and Goldman, 2016).

The purpose of this chapter is to engage in a form of content validity (i.e., an aspect of validity that reflects whether an assessment represents critical aspects of the domain that is assessed; Pellegrino, DiBello, & Goldman, 2016). The general expectation for content validation studies is to present the material being validated to a panel of experts and then, based on their individual ratings of an item's efficacy, develop a composite score for each item and for the overall test. This methodology is outside of the scope of this analysis. Thus, another option, namely face validity, is employed as an informal content validity method in the context of the existing CCHS-MH survey. However, this chapter will expand on a surface-level analysis of the variables by performing a literature review of mental-health support utilization as it pertains to each variable, to determine whether it is appropriate to include that variable in the survey and to also critique that variable's role in collecting useful information.

### 3.2. Literature Review Method

The CCHS-MH mental-health support-utilization survey includes data on 12 types of mental health supports that range from professional supports (i.e., psychiatrists, family doctors, psychologists, nurses, and social workers or counsellors) to social supports (e.g., family members, friends, co-workers or bosses, and teachers or principals) to non-traditional supports (e.g., self-help groups and telephone helplines). Lastly, data was also collected for those who sought no mental health support.

All of these variables were subject to analysis in relevant databases: PSYCInfo, PubMed, and JStor databases. The keywords used in the search were “Mental Health”, “Support Utilization”, and “Canada.” Canadian data was prioritized, but other similar nations were used when the variables studied were expected to be broadly comparable. Using research published between 2010 and 2020 was prioritized, but earlier articles were selectively included if they conveyed concepts that remained relevant. Subject matter was then narrowed down by subject: PSYCInfo was filtered by “Health Care Utilization” to narrow results down to 1,760; JStor was filtered by “Health Policy”, “Psychology”, and “Public Health” to narrow results down to 353; and PubMed had no appropriate filters, returning 4,570 results. Articles were included based on two criteria: (1) peer-reviewed articles and (2) empirical studies. The total number of articles retrieved by the original search was 6,683. Due to the multiple keywords used and the width of the subject matter, many articles needed to be excluded if they were not aligned with the search criteria. Thus, the present literature review included 44 papers. Content validity was examined by studying other articles discussing mental-health support utilization and the effectiveness of those supports. All papers can be seen in Table 1. Table 2 shows the levels of effectiveness and accessibility found by the articles. Table 3 compares the articles based on whether they were Canadian, non-Canadian, or mixed-region data.

## 3.3. Analysis of the Survey Variables for Content Validity

### *3.3.1. Professional Supports*

#### *3.3.1.1. Family Doctor*

The most recent data collected by Statistics Canada (2019) shows that most Canadians have access to a regular health-care provider they see or talk to when they need care or advice for their health. This means that a family doctor serves as this point of contact for Canadians who do not require a specialist. Specifically, the College of Family Physicians in Canada states that nearly two thirds of mental-health issues are discussed with a family doctor (2018). According to the previously referenced meta-analysis on the subject, access to a family doctor should be a powerful enabling factor for utilizing health care, with mental-health care being no different. One should expect a family doctor to have reasonable competencies in the areas of mental health assessment, basic understanding of common mental health disorders, applying basic therapeutic techniques, the ability to explain mental health concepts and medication effects to the patient and those in their social support network, and referring to other professionals in the medical system where appropriate (Ng, Chan, Herrman, & Dowrick, 2020). However, they do not receive the same level of training in psychotherapeutic interventions as psychiatrics or psychologists and are not involved with the creation or implementation of specific care plans for patients. Since family doctors are generally the first point of contact in the healthcare system for many people, they should be effectively trained to treat mental-health concerns. Reports from both the *College of Family Physicians in Canada* (2018) and a study where psychiatrists evaluated and critiqued physicians suggest that family doctors require improvement in handling patients with complaints of poor mental health (Ng, Chan, Herrman, & Dowrick, 2020; Werner & Woodgate, 2017). In recent years, it has become clear that family doctors may be the single most critical point in the network of support-utilization seeking for mental-health concerns. This is not only because of the aforementioned direct consultations about mental-health between patients and family doctors, but also because family doctors are the primary route by which a patient is connected to a specialist, including mental-health specialists. Despite resources being expended to study and instruct such practitioners, more analysis is always needed when discussing something as critical as mental-health. Access to family doctors is fairly good due to Canada's Medicare, but there is still room for improvement. For instance, 15% of Canadians are without a family doctor (Statistics Canada, 2019) and weakness in online accessibility may be barring certain individuals from receiving care (Canadian Institute for Health Information, 2019).

The sum of all this information suggests that, to be valid, analyses of mental-health support utilization in the Canadian context must include family doctors. Studying family doctors will grant insight into what is likely the most important enabling factor for Canadians accessing formal health care.

#### *3.3.1.2. Psychiatrists*

Access to psychiatry is an important component of Canadian Medicare. Psychiatrists are primarily trained to clinically diagnose, treat, and provide ongoing care for their patients. In contrast to a psychologist, psychiatrists receive medical training that enables them to prescribe specialized medication as needed for mental health (Canadian Psychiatric Association, n.d.). Yet, the utilization of psychiatric medicine is drastically lower than that of family doctors for psychological ailments. There is massive inequality between rural and urban regions of Canada regarding the number of psychiatrists available, with some catchment areas lacking a single psychiatrist (Kurdyak et al., 2014). Furthermore, analyses of Vancouver and Toronto found that, despite having hundreds of accessible psychiatrists in their regions, they often would not be able to accept new referrals, adding another barrier to potential patients (Goldner, Jones, & Fang, 2011; Kurdyak et al., 2014; Kurdyak et al., 2020). An analysis by Paris, Goldbloom, and Kurdyak (2015) studied the traditional model of psychiatric care. Their results revealed that the traditional treatment model of long duration and high-visit frequency is not evidence-based

(2015) and create a scenario where there are rarely openings in a psychiatrist's practice for new referrals to enter the system. These logistical issues mean that utilization rates of psychiatrists will be much lower than expected for a component of the health care system covered by Medicare.

While numerous initiatives have called for reforms and improvements to psychiatric care (Grazter, 2020; Mental Health Commission of Canada, 2012, 2013; Kurdyak, 2020), the campaigns have begun in earnest too recently for the data to be reflected in the latest cycle of the CCHS-MH. Because psychiatric care is covered under Medicare in Canada, future comparisons may reveal large differences between cycles, as mental-health care is more and more prioritized as a result of these campaigns and the barriers to entry are removed. The data collected within the past decade is expected to reveal very low-utilization rates across all demographic groups.

#### *3.3.1.3. Psychologists*

Another important professional in the mental health support network is the clinical psychologist. Psychologists who work primarily in a medical care capacity will work to diagnose mental health concerns and deliver psychotherapy to patients with the goal of increasing their ability to manage their mental health. (Canadian Psychological Association, n.d.). Psychologists in the Canadian system function in a two-tier system: some are accessible through Medicare, whereas others have independent practices that are not covered by the Medicare mandate. Consequently, for the latter, the rates of utilization will be much lower than in the case of the universally accessible family doctors. This additionally complicates analysis where public versus private practice is not specified, as is the case with the CCHS-MH. However, it is well-documented that the public options for psychologists are inefficient, generally underfunded, and understaffed (Bartram & Stewart, 2018; Dobson 2016; Peachey, Hicks, & Adams, 2013). Consequently, most of the utilized psychological health-care services are likely to be in the private sector, which is likely to lead to large disparity between high-income and low-income Canadians. These private practices are accessed either through employment-tied insurance programs or through out-of-pocket payment. Since low-earning Canadians do not enjoy employment-based benefits nearly as often as high-earning Canadians, it would be expected that their ability to access psychological services not covered by Medicare is drastically reduced. Research conducted by Bartram and Stewart with the CCHS bore out these assumptions, showing that low-income individuals utilize much lower rates of psychological services than high income earners (2018).

Comparisons to other countries indicate that improved public access through policy can reduce these inequalities (Bartram & Stewart, 2018; Peachey, Hicks, & Adams, 2013). Dobson's 2016 analysis of clinical psychology in Canada discusses numerous policy problems that are reducing this public access. The practice of recategorizing psychological care as allied health in conjunction with a move away from having psychologists in management positions in hospitals means that psychologists can be replaced by any allied health professional during hiring - a choice that is incentivized by the lower cost of hiring other allied health workers over a registered psychologist. This points to a system of psychological medicine that is under-resourced and pushes more psychologists into the private sector, growing the divide between high-income and low-income individuals.

Beyond the financial barriers, psychologists are lacking in more rural and northern areas of Canada (Lints-Martindale, Goodwin, & Thompson, 2018). This disparity would reflect lower rates of utilization by those in non-CMA locations, as these individuals may not have an option to see a psychologist, even if they had the means to do so.

#### ***3.3.1.4. Nurses***

Nurses overlap with family doctors in this analysis, as they work in concert in the primary health care ecosystem. Worldwide, nurses have increasing involvement with mental-health care, prompted by a shift from symptom-oriented to recovery-oriented models (Cusack, Killoury, & Nugent, 2017; Slade et al., 2015). Nurses provide therapeutic support as well as monitor and manage patients' emotions, behaviours, and cognitions (Registered Psychiatric Nurse Regulators of Canada, 2021). Given the Canadian health care structure, one would expect that patterns of utilizing nurses would be similar to those of family doctors and primary-care physicians with lower frequencies. This is because not every interaction with a family doctor leads to interaction with nurses and it is not more common to meet with a nurse before contacting a family doctor. However, there may be value in specifically connecting with a nurse, as a recent study has shown a significant increase in the satisfaction with care received from community-health nurses and no significant effect with care received from psychiatrists (Stamboglis & Jacobs, 2020).

Canadian research less frequently investigates the differences between nurses and other forms of mental-health support, possibly due to the collaborative nature of nursing. Some relevant research was found in the United States. For instance, a study found increased utilization of nurses specifically by Americans in urban centers (Keller, Hooker, & Jacobs, 2018). Although research in the US context may not directly map onto the Canadian context, it may still inform the patterns that may emerge in future Canadian analyses.

#### *3.3.1.5. Social Workers and Counsellors*

The CCHS-MH combined the support systems of social workers and counsellors. The reason for creating this composite measure was not made clear by the federal government agency; social workers and counsellors are very different in their function and in how they are accessed by the general population. Consequently, information from this variable is not useful for broader analysis, as there is no way to differentiate between utilizing one or the other. This precludes making claims about either measure. However, individually, these measures would both likely be useful to study, so this literature review will still seek to provide content validity for each support.

**Social Workers.** There are many different specializations of social work (Canadian Association of Social Workers, n.d.). Broadly speaking, social workers engage in practice that is founded on theories of social work, social science, and the humanities (Canadian Association of Social Workers, n.d.). This broad range makes it difficult to pinpoint the degree and nature of involvement social workers have with mental health support. There is a dearth of research that focuses on utilization of social workers. This may be due to the fact that social workers tend to function almost entirely in integrated teams (Ashcroft, Kourgiantakis, Fearing, Robertson, & Brown, 2019). Additionally, due to the way social workers operate in the broader healthcare system, most Canadians are far more likely to see a family doctor or a psychiatrist when they interface with the professional medical system. Indeed, in the CCHS-MH survey, only 3.2% of Canadians consulted a social worker or counsellor for a mental-health problem. The combination of social worker and counsellor into the same category means that the actual number is even smaller.

Social workers are a core component of many mental-health treatment teams. Thus, studying social workers in the context of mental-health care in all contexts is very important. The level of training and increased reliance on social workers in the mental-health care ecosystem means that it is going to become incredibly important to study and improve their utilization rates, outcomes, and practices as much as one would expect of any medical professional (Ashcroft, Kourgiantakis, Fearing, Robertson, & Brown, 2019; Held et al., 2019; Saxe Zerden, Lombardi, & Jones, 2019). While the CCHS-MH data is lacking in practical information on the social worker variable by having it conflated with counselling support, there is still a clear reason to include social workers in any analysis of mental-health care and utilization patterns are no different.

**Counsellors.** Counsellors generally function in the mental healthcare ecosystem by forming relationships with clients in which self-knowledge, emotional acceptance, and personal growth are developed with the intention of improving the personal well-being of their clients (Canadian Counselling and Psychotherapy Association, n.d.). Counselling practices in Canada are similar to other Canadian psychological services, falling into the same two-tier structure. There is debate on the effectiveness of counselling compared to other therapeutic techniques, but some reviews suggest that, at least for short-term interventions, counselling can be effective (Bower, Knowles, Coventry, & Rowland, 2011). More recent data suggests that counsellors can effectively administer therapeutic techniques traditionally administered by psychologists (Jordans et al., 2019). Information like this reinforces that studying counselling is important, as it could reduce the burden of care on psychologists and, as a result, eliminate some barriers to professional care. However, the two most common places for a licensed counsellor to work are either independent practice or in a school system, neither of which are covered under Medicare in Canada (Bedi, Sinacore, & Christiani, 2016). As such, the financial barriers that remain would make utilization lower overall and especially amongst lower-income earners.

Research sampling students can provide an insight into the demographics of those who utilize counselling, as students are one of the groups with greater levels of access. Counselling seems to be more frequently used by white individuals compared to Asian and Latino individuals, according to a 2016 study examining student initial severity, attendance, and outcomes upon counselling termination (Kim et al., 2016). Other studies show that international students underutilize counselling services and that women utilize counselling more than men (Hwang, Bennett, & Beauchemin, 2014; Wu et al., 2017). The CCHS-MH can fill this gap in the research by studying Canadians generally to gain an insight into how counselling is utilized by other segments of the population.

#### ***3.3.2. Social Supports***

Although professional care can be utilized as protective and preventative, it is mostly used responsively to an illness. In contrast, social support can be protective as well as improve outcomes for existing illnesses (Cadzow & Servoss, 2009; Wang et al., 2018; Werner-Seidler, Afzali, Chapman, Sunderland, & Slade, 2017).

##### ***3.3.2.1. Family Members***

Family members are possibly one of the most influential social support for positive mental health. Family members are well known as being a critical support system for those struggling with mental health (Canadian Mental Health Association, 2006) and are sometimes not properly incorporated into the recovery process at the rate they should be (Kokanović et al., 2018). The nature of this relationship can be difficult to study. Some research has found that negative family interaction influences professional mental-health utilization by increasing the frequency of poor mental health (Villatoro & Aneshensel, 2014). This makes family members exceedingly important to study as support factors. The extent and impact that family members have can differ across cultural groups. For instance, the previously mentioned study did not find that positive familial relationships in African American families predicted mental-health service utilization (Villatoro & Aneshensel, 2014), but Latino families did find that positive family relationships predicted informal support usage (Villatoro, Morales, & Mays, 2014). American research suggests that Asian and Latino families tend to prefer informal over formal support systems, especially for immigrants who are not fluent in English (Alegría et al., 2007; Spencer, Chen, Gee, Fabian, & Takeuchi, 2010). Little Canadian data specifically studied familial support across various demographic variables, so this analysis will contribute to that body of work.

#### *3.3.2.2. Friends*

Research finds that, whereas family support networks are more important in middle-to-late life, support from friends remains critical in reducing the likelihood of depression (Rubin, Evans, & Wilkinson, 2016; Secor, Limke-McLean, & Wright, 2017; Werner-Seidler, Afzali, Chapman, Sunderland, & Slade, 2017). A recent large-scale study in the United Kingdom studied numerous demographic differences in social support network sizes, finding that younger people, those with greater levels of educational attainment, non-Asian people, and those with gainful employment all had significantly larger social support networks than their counterparts. Additionally, these increased supports translated into a protective factor for a number of poor symptoms of mental health (Smyth, Siriwardhana, Hotopf, & Hatch, 2015). Seeing these differential effects across demographics and the evidence that friendships are extremely important as support systems for mental health, it is worth analyzing them in the Canadian context.

#### *3.3.2.3. Co-Workers or Bosses*

Based on the present literature review conducted, no large-scale analysis of employers being utilized as support systems for mental-health concerns exists, likely reflecting the power dynamic not being conducive to disclosure of mental-health struggles in a non-medical setting. Peer support networks, however, are numerous and well-documented. Thus, when looking at the variable of consulting co-workers or employers for mental health, it is far more reasonable to assume that co-workers, as peers, were the support system utilized in those scenarios.

An examination of the efficacy of co-workers as a support system for mental health reveals a mixed level of effectiveness in the literature (Cabassa, Camacho, Vélez-Grau, & Stefancic, 2017; Chinman et al., 2014; Lloyd-Evans et al., 2014). There is a dearth of research that focuses on co-workers as support networks, so most reviews broaden their scopes to include generic “peer-support” as well. Recent analysis in this field does reveal positive effects, though research designs could be improved to make those findings more compelling (Cook et al., 2011; Sledge et al., 2011; van Vugt et al., 2012). This lack of both co-worker specific research and consensus means that this is an area of research requiring more inquiry, especially in the Canadian context. Another gap that future analysis could address is that most of the analyses in the area of co-worker support systems are focused on the efficacy of the projects and do not seem to divert efforts into performing demographic-based analysis. Despite the mixed findings in the effectiveness of these programs in meta-analyses and scoping reviews, there is clearly evidence that they are being utilized when available, so this is certainly a variable of interest.

#### *3.3.2.4. Teachers or Principals*

Educators are often the first point of contact for students who are suffering from mental-health issues. A study from the United Kingdom found that two-third of adolescents with mental health concerns spoke with a teacher about their struggles (Newlove-Delgado et al., 2015). In the Canadian context, there was widespread recognition by teachers that their students required mental-health care. However, there were numerous obstacles to providing care, the largest being the lack of trained professionals in the employment of their schools (Froese-Germain & Riel, 2012). Another concern of educators in numerous analyses was that they themselves were not adequately trained to provide basic mental-health care (Froese-Germain & Riel, 2012; Ekornes, 2017; Shelemy, Harvey, & Waite, 2019). These high rates of utilization by students and the discomfort of educators in acting as a support for their students indicates that increased training in mental-health care must be introduced into the education sector.

The groups that utilize educators as supports for mental-health skew younger by the nature of student demographics. These students tend to be heavy users of school-based mental-health care, according to the 2009 Intercamhs report (Rowling, Vince Whitman, & Biewener). Additionally, due to mental-health services in public school systems being accessed cost-free, there is a slightly higher proportion of lower-income individuals accessing these services (Froese-Germain & Riel, 2012). Most literature focusing on the role of educators and mental-health support systems look at groups of younger students. This results in gaps in the literature existing for older students, high-school age, and university-level especially. Reasonable explanations could exist for this. For example, higher educational institutions often have dedicated mental-health supports such as therapists and psychologists, removing the need to rely on educators for mental-health concerns. Regardless, the lack of data means that more evidence-based claims cannot be made, which constitutes a gap in the literature.

#### *3.3.3. Non-Traditional Supports*

##### *3.3.3.1. Self-Help Groups*

Self-help groups pose a similar problem as some of the other variables in the survey. As noted by Humphreys and Rappaport, the term has wide usage across several broad categories: there are groups directly dealing with common mental health concerns, some that focus on normative life transitions, or ones for stigmatized groups (1994). This nebulous definition has not changed with modernity. Additionally, some self-help groups are led by the members themselves, by external volunteers, or by professionals. This makes the information in this variable ambiguous. The survey specifies that the self-help group was accessed to help with mental and/or emotional distress but does not specify the type of self-help group accessed. Regardless, there seems to be evidence to suggest that, broadly speaking, self-help groups with a therapeutic focus are effective when professionally facilitated (Worrall et al., 2018). Even online self-help groups seem to be promissory in supporting some mental health concerns, though the research is in its infancy and further analysis would be required to speak conclusively (Griffiths, 2017; Griffiths et al., 2012).

The utilization rates amongst different demographics are also difficult to study, considering the wide array of different types of self-help groups. Analysis of Internet groups supporting those with depression show that younger women are the most common users of self-help groups (Griffiths et al., 2017). Analysis of 12-step groups such as Narcotics Anonymous or Alcoholics Anonymous find that, of all the groups included in the study, middle-aged men are the highest utilizers of self-help groups (Orwat et al., 2011). Some pharmacotherapeutic self-help groups found no significant differences between gender, age, race, occupation, or education level (Clark, 2012). As such, with no specificity in the self-help group variable in the CCHS-MH, it is impossible to predict any patterns of utilization or expect any findings from an analysis of that data.

#### *3.3.3.2. Telephone Helplines*

The final variable studied in the CCHS-MH was telephone helplines. Helplines function as short-term support services for individuals struggling with an immediate personal crisis, as a gateway to other support resources. This variable has a similar issue as the self-help variables because the variable is not specific and, as such, inferences are difficult to draw. Additionally, the effectiveness of telephone helplines is not clear, returning mostly short-term benefits to the caller, if any (Hoffberg et al., 2020; Tyson et al., 2017). In Canada, the provincial medical systems have such helplines staffed by medical professionals, such as nurses, psychologists, and social workers. There are other helplines operated by non-profit organizations not linked to the medical system, generally narrower and more diverse in the range of qualifications required to be part of the staff. This further complicates the information in the helpline variable, reducing its ability to give clear information in an analysis.

Regarding utilization, the mass rate is reported to be fairly high, utilized by thousands of people on a monthly basis (Morgan, Bullmore, & Lawton-Smith, 2012; Pirkis et al., 2016). Demographic breakdowns are interesting, as most reviews find that a few individuals account for the majority of calls to these centres (Pirkis et al., 2016; Spittal et al., 2015). Both of those reviews suggest that never-married men between 25-64 are the most likely to be frequent repeat callers. However, women between the ages of 25-54 who are in married or de-facto relationships have the highest levels of utilization total. These statistics were also found by a United Kingdom study, showing that white individuals are high-level users (Morgan, Bullmore, & Lawton-Smith, 2012). The current literature review did not find large-scale general reviews of demographic breakdown of helplines in the Canadian context, highlighting this as an area needing further study.

#### *3.3.4. Not Utilizing Support*

In the context of the CCHS-MH, not utilizing support could refer to either needing support but not getting it or never needing support in the first place. The survey did not have a flagging item at the beginning of the survey that differed between the two groups. As a result, this literature review will look at aspects of both patterns. Both are interesting to study for different reasons. First, individuals who need support, yet utilize none, should be engaged with the goal of increasing their support utilization rates and, by extension, their quality of life. Second, those who are less likely to utilize support because they do not have mental-health concerns would still constitute a valuable source of information. A systematic review of the literature by Magaard et al. (2017) examined numerous variables included in the CCHS-MH and reported their influence on utilizing support rates for depression. They found that being young or elderly, less educated, male, or a person of colour were all associated with utilizing no support when a need was perceived. Some analyses in this systematic review were using Canadian data. It was also found that Chinese immigrants had lower rates of utilization compared to those born in Canada. These findings have been largely supported by numerous other studies, as can be seen in other systematic reviews of the relevant literature (Roberts et al., 2018). These were not conclusive patterns occurring across every single study, but broadly it would seem that recent research finds these to be the main demographic variables predicting non-use of mental-health services. The strength of these systematic reviews is that they take social support into account, a consideration sometimes lacking in studies of mental-health support utilization.

The World Health Organization (WHO) drafted a report built on a large number of analyses conducted across the globe on the social determinants of mental health (WHO & Calouste Gulbenkian Foundation, 2014). Women, those in lower income households, lower levels of educational attainment, and unemployment all emerged as common social demographics that predicted poor mental health. These are also findings that are broadly found in more recent analysis on the same topic (Alegría, NeMoyer, Falgàs Bagué, Wang, & Alvarez, 2018; Jeon, Amidfar, & Kim, 2018). This information is useful to have, considering the aforementioned combination of need for support and non-need for support being in the same non-utilization variable. Demographics expected to have elevated rates of mental health concerns showing reduced levels of engagement with support are a red flag that they are not getting support at the rate they need it.

### 3.4. Summary of Content Validity of the Survey

The CCHS-MH survey is adequate in its aims to collect meaningful data on support utilization habits of the Canadian population. The information on professional support systems is a reasonable inclusion that is supported by literature. However, the combination of counsellors and social workers into the same category is confusing and may lead to erroneous conclusions. The two categories are different enough in their practice and in how they are accessed, thus, they should be separated. Even if separated, those two variables differ widely within their classification. Moreover, sub-items for each should be included for future data collection cycles to narrow in on the exact types of counselling and social workers that individuals utilize. The social supports are all reasonable inclusions as well; representing distinct categories of support types that all have at least some level of evidence for being included in the survey. The combination of co-workers and bosses probably does not gain from including the latter, as bosses were not found to be a factor in our literature review. Finally, the supports that fall outside of traditional professional or social supports are less obvious in their validity. Telephone helplines were not found to be consistently effective in their ability to treat mental health concerns in clients, but there were fairly consistent positive outcomes in the short-term for callers and the utilization rates themselves were high enough to be of interest. Thus, the variable remains useful in the scale, if for no other reason than to allow further analysis on telephone helplines as a therapeutic tool. The self-help groups also suffered from being too vague, similar to the counsellor variable. All self-help groups in the CCHS survey were specifically utilized for the treatment of mental health but having follow-up questions to specify the type of self-help group utilized will increase the amount of information that can be gained from this variable, increasing its usefulness.

#### *3.4.1. Limitations*

We identified several limitations of the present literature review. Firstly, many reviews did not collect demographic information. When they did, they often only collected data on a select few variables. Additionally, no analyses that included demographic variables studied interaction effects between variables, which could provide more intersectional information for future study.

Secondly, there is a dearth of factor analyses applied on large datasets to test for common underlying domains between a number of these variables. However, a surface reading of variables in the CCHS-MH reveals some commonalities professionally (e.g., doctors, psychologists, and nurses), socially (e.g., friends and family), and even self-directed alternative support-types (e.g., self-help groups or telephone helplines, though the low response rate in the CCHS-MH probably precludes robust analysis). Larger-scale analyses with these factors, if confirmed, could lead to more robust findings, and provide evidence for overarching models of mental-health support utilization. Specifically, it seems reasonable to assume that two individuals who may use a doctor and a psychologist, respectively, share commonalities in demographic characteristics that may be suppressed from simply studying every support type singularly.

Third, most research reviewed in this work is based on self-reported data, which constitutes another limitation of this study. There are exceptions where the data is not self-reported, such as studies examining medical professional supports based on hospital data. Underreporting can be expected when endorsing items that are associated with a stigma, interpretation of the items in ways not intended by the author, or deliberate misrepresentation in responses (e.g., individuals may want to present themselves in the most positive way possible). Additionally, readers may misinterpret what a question is asking and accidentally provide incorrect information to an interviewer. The CCHS-MH data is self-reported and would suffer from all the same limitations as the majority of the studies included in this literature review.

Finally when examining peer-reviewed research exclusively, more recent Canadian data is extremely limited. This is not to say that there is no information available, but most information is gathered by policy or governmental organizations that are often not clear about the quality assurance protocols in place to guarantee that the data and reports are well-designed and validated. More peer-reviewed academic interest into these areas is needed and the CCHS-MH may facilitate this endeavor.

### *3.4.2. Recommendations for Future Work*

After reviewing the literature, we found that the CCHS-MH survey instrument has adequate content validity. Thus, future work based upon the CCHS-MH survey can be conceptualized on a solid foundation. The main gains to be made by analysis with the CCHS-MH are: (1) an opportunity to use a large dataset to study utilization patterns of individuals across many different demographic variables simultaneously; (2) adding information on the subject of mental-health support utilization to the Canadian context, which is somewhat lacking compared to nations with differing cultures and policies around mental-health and health care; and (3) discovering new frameworks of mental-health support utilization that fill gaps in prior models. These are all important areas of inquiry in the field of public health, especially in the Canadian context.

Specific areas that could be improved on the part of the federal government, before another data collection cycle, would be splitting the social worker/counsellor variable and inclusion of follow-up items on broad variable types like self-help groups to tease out the exact nature of the support used. Another item that will likely be far more impactful, considering both the context of modern times and the coronavirus pandemic, will be the role of Internet therapy in future data collection cycles. It was included in the 1.2 collection survey, but in 2012 the advent of Internet therapies had not fully become commonplace. In fact, the data reflected this, as less than 0.05% of Canadians reported using Internet therapy.

A large body of research is concerned with discovering predictors of mental-health care utilization. It has been consistently found that higher socioeconomic status (SES), positive self- and family-perceptions about mental-health care, higher educational attainment, being a nonimmigrant, and being a female are all predictive of mental-health care utilization (Bartram & Stewart, 2019; Fleury et al., 2014; Henderson et al., 2013; Islam, 2014; Islam et al., 2018; Kirmayer et al., 2007; McAlpine & Mechanic, 2000). This study examines many of these variables as well as others collected by the CCHS-MH.

Some variables that are not studied often in the Canadian context are province of residence and living in a Census Metropolitan Area (CMA). They may have effects on mental-health support utilization due to health care policies, accessibility, or culture. Age is often studied in the context of mental-health utilization, but most research tends to focus on one specific age group. When comparing age groups, the age categories are often quite broad and could be hiding important information (Cheung et al., 2009; Findlay & Sunderland, 2014; Jang et al., 2009). Sex is well established as having differential effects of both prevalence of mental health concerns (Hyde et al., 2020; World Health Organization, 1993) as well as rates of health care utilization (Kazanjian et al., 2004; Koopmans & Lamers, 2007), but it is not well-researched in relation to mental-health care utilization specifically. For instance, in Canada, women tend to use mental-health services more often than men (Cox, 2014), but these differences may fade with increased severity of the mental health concerns (Smith et al., 2013). Marital status is understudied when mental health is concerned and it has yielded conflicting findings when examining health care more broadly (Joung et al., 1995; Pandey et al., 2019). For instance, research has found that married individuals utilized mental-health care more frequently than other groups (Ngui et al., 2012). Research conducted into ethnic differences in mental health shows that whites report more mental health concerns and lower professional utilization (Chiu et al., 2018; McGuire & Miranda, 2014), though this research does not include Indigenous individuals, which is very problematic as they have some of the highest rates of mental health concerns (Hasin et al., 2005). To our knowledge, this variable has not been studied Canada-wide with the CCHS data, as this survey used a binary white/non-white variable to operationalize ethnicity. Immigrants' utilization patterns have also been studied in small pockets in Canada, but not nationally. In Canada, research shows that immigrants utilize professional supports either the same or at higher rates than Canadian-born individuals (Kirmayer et al., 2007; Islam et al., 2018). Income is theorized to be predictive of mental-health support seeking, based on the economic barrier preventing access to most mental-health specialists. Even in the Canadian context, the Medicare system universal health care does not cover mental-health care, such as psychotherapy or counselling. Educational attainment's main effect is also linked to this economic barrier, due to the relationship of higher educational attainment to increased income (Bartram & Stewart, 2019; Fleury et al., 2014).

Another line of research explores the population groups that are most at risk for developing a mental illness to identify groups that are not being appropriately engaged according to their needs. According to the literature, women, those earning lower incomes, Indigenous individuals, and older individuals are consistently found to have higher rates of mental health concerns than the general population (Hasin et al., 2005; Hoebel et al., 2017; Meng et al., 2020; Patel et al., 2018; Statistics Canada, n.d.).

Analysis of health-care utilization tends to focus solely on professional supports, which leaves a few different types of support understudied. For example, telephone helplines are rarely considered in research on mental-health care utilization, despite servicing thousands of individuals (Mental Health Helplines Partnership, 2012). The efficacy of helplines is mixed in the literature when comparing proximal and distal outcomes (Hoffberg et al., 2020; Tyson et al., 2017). Additionally, non-professional social supports such as family and friends are not often studied as forms of mental-health supports, despite their impact on improving mental health outcomes and reducing their incidence entirely (Cadzow & Servoss, 2009; Rickwood et al., 2015; Sherbourne, 1988; Wang et al., 2018). They also tend to function as a first line of support for many individuals who experience trauma (Carleton et al., 2020), so they are a critical component of analysis when studying support systems.

### 3.5. Chapter Summary

Chapter 3 presents a literature review of 44 articles, which provides evidence that the CCHS-MH is a content-valid survey that covers all the obvious inclusions for an instrument designed to collect data on the mental-health support utilization habits of the Canadian population, as well as on relevant demographic variables. Its design is not perfect, but, with minor changes and improvements, the survey could be a useful tool for researchers and policymakers to gain insights into the way Canadians receive support for their struggles with poor mental health.

## Chapter 4: Methods

### 4.1. Background and Sampling

The CCHS is a cross-sectional, computer-assisted interviewing (CAI) survey that gathered data between January 2012 and December 2012 on Canadians' health status, health-care services usage, and health determinants (Statistics Canada, 2014). The CCHS information is collected directly from individuals aged 15 years and above, living in private residences in the 115 health regions across all provinces in Canada. CCHS excluded individuals living on Indian Reserves and on Crown Lands, institutional residents, full-time members of the Canadian Armed Forces, and residents of certain remote regions. After exclusions, a total of 25,113 valid samples were gathered during the period of collection. In the current study, 325 (1.29%) individuals did not complete the entire set of items and were removed from the analysis. Thus, the final sample used in the analyses consisted of 24,788 participants.

### 4.2. Variables of Interest

Two types of variables were included in the CCHS from each individual: demographic variables and the types of health care support utilized. More specifically, there are nine demographic variables, including province of residence, whether the individual lives in a CMA or non-CMA, age, sex, marital status, total household income, level of education, whether the individual is an immigrant, and whether the individual is white or a visible minority. These variables were chosen based on prior research suggesting that they may influence whether a person seeks mental-health care (Henderson et al., 2013; McAlpine & Mechanic, 2000; Rickwood et al., 2007, 2015; Sunderland & Findlay, 2014).The 12 types of mental-health care support that an individual has utilized include psychiatrists, family doctors, psychologists, nurses, social workers or counsellors, family members, friends, co-workers or bosses, teachers or principals, self-help groups, telephone helplines, and lastly, no support.

### 4.3. Statistical Analyses

All analyses in this research were conducted using the *R* open-ended statistical analysis platform (R Core Team, 2020). We organized the analyses into two major phases: an exploratory phase and a confirmatory phase.

#### *4.3.1. Exploratory Phase: Exploratory Factor Analysis (EFA) and Cluster Analyses*

As there is no working theory underlying the construction of the CCHS-MH survey, a data-science approach is used to infer a structure and patterns empirically from the data. One such way to derive a theory is to use the unsupervised machine learning techniques, specifically, cluster analyses. This technique identifies clusters (i.e., homogeneous groups) that are used to group participants based on their mental-health support-utilization survey responses. Concomitantly, we use EFA to explore the underlying structure of the CCHS-MH instrument and to derive its construct validity.

#### *4.3.2. Confirmatory Phase: Confirmatory Factor Analysis (CFA)*

Then, CFA is used to confirm the optimal structure of the model. With CFA, the fit of the model is confirmed, which will help to choose the best model as the internal structure for the instrument. This phase will facilitate researchers to connect the model to existing theory or to derive new theory underlying the CCHS-MH instrument.

### *4.3.3. Internal Reliability*

There is no existing research confirming the reliability of the mental-health support-utilization data collected in the CCHS-MH. So, before more complex analyses of the data are performed, Cronbach's *alpha* (1951) will be calculated to confirm internal consistency within the measure. Cronbach's *alpha*, hereby referred to as *alpha*, is one of the most famous and common reliability coefficients across all fields of research. Cronbach developed *alpha* as a more intuitive method of calculating reliability than the previous split-half reliability methodology (1951) and was proven to be equally valid as a metric of reliability (Novick & Lewis, 1967). This will be performed using the *alpha* function from the *psych* package (Revelle & Revelle, 2015). A cut-off of 0.7 will be considered an acceptable level of internal reliability (i.e., for further analysis to consider reliable findings).

### *4.3.4. Exploratory Factor Analysis (EFA)*

To uncover latent traits and probe content validity of the CCHS-MH instrument, an Exploratory Factor Analysis (EFA) was performed. Based on the literature review, we hypothesized that the instrument assessed four dimensions of the types of health care support from the 12 survey items: professional supports, non-professional social supports, self-directed supports, and no supports. However, we experimented with other numbers of factors. Parallel Analysis (PA), an analytic technique that determines the optimal number of factors for a model (Horn, 1965), will be used to find an optimal factor number. Additionally, a Very Simple Structure (VSS) analysis will be performed next. The VSS accepts a user-specified maximum number of factors to analyze, then delivers multiple different statistics that indicate the goodness of fit for models with factors ranging from 1 through the number of items (Revelle & Rocklin, 1979). The indices delivered by the VSS that are of interest are the chi-square value (ChiSq), the root mean square error of approximation (RMSEA), the standardized root mean square residual (SRMR), the Bayesian information criterion (BIC; Schwarz, 1978), and the Square Adjusted Bayesian information criterion (SABIC). For all listed indices, a value closer to 0 indicates better model fit. Model rotation must also be specified for the analysis. As some of the factors may be correlated, oblique rotation was selected for the EFA. Based on our hypothesis and the findings of the EFA, we then performed a Confirmatory Factor Analysis (CFA) to confirm the validity of the theorized model. The EFA was performed using the *fa* function in the *psych* package (Revelle & Revelle, 2015). This function takes a specified number of factors and assigns the variables to factors in the most optimal way that the factor constraints allow. This analysis returns the factor loadings of each variable, which is the correlation that a variable has with the assigned factor. Additionally, it provides some more information regarding model fit: the root-mean-square residual (RMSR) and BIC. As with the other indices used, a RMSR value closer to 0 indicates better model fit.

#### *4.3.5. Clustering Analyses*

Unsupervised learning is a subset of machine learning that attempts to find patterns in unlabeled data and minimal human involvement in the process. Clustering is a type of unsupervised learning that rearranges the data points (i.e., observations) into homogeneous groups or *clusters* based on similarity between certain data points and dissimilarity between other points. The level of similarity can be calculated by a number of different dissimilarity (i.e., distance) measures which generate relative distance between data points that form the basis for cluster membership. There are two further categories of clustering considered in the current study, hard and soft clustering. Hard clustering is a class of algorithms where each data point is assigned to only one cluster. In contrast, soft clustering can assign a data point to multiple clusters concomitantly, based on the probabilities of that data point belonging to each cluster. The cluster group of highest probability in soft clustering is the final cluster label of the data point. It is important to state that these clusters will not necessarily reflect the factor analysis, although some overlap would be expected. The clustering is more exploratory analysis and will further the goal of determining the best way to partition latent traits of utilization in the data.

Three clustering algorithms were compared. Two hard clustering algorithms, *K-means clustering* (KM) and *Hierarchical Agglomerative Clustering* (HAC), and one soft clustering algorithm, *Fuzzy C-Means Clustering* (FCM), were performed on the data sample. Evaluation metrics were calculated for each algorithm to determine the best clustering method suitable to reveal patterns in the CCHS dataset.

**K-means.** The first clustering method, K-Means, is an iterative partitioning algorithm that aims to minimize the total within-cluster variation. The actual K-means clustering process begins by randomly selecting *k* observations from the data set as the initial cluster centres (i.e., centroids), where *k* is specified by the analyst (i.e., the initialization step). Each cluster is represented by its centroid, which corresponds to the multidimensional mean of observation values assigned to the cluster. Then, it iteratively assigns the remaining observations to their closest centroids (i.e., the cluster assignment step). The closeness or similarity is operationalized using a distance measure between each observation's feature values and the corresponding centroid (i.e., the cluster mean, which is the mean value of all the observations assigned to that cluster). Each observation is assigned to a given cluster such that the sum of squared distances (i.e., measure of cluster compactness or goodness) of that observation to its assigned cluster centre is minimized. Then, the algorithm computes the new centre (or mean) of each cluster (i.e., the centroid update step). Each observation is checked again to ascertain whether it is closest to a different centroid and re-assigned to a different cluster accordingly. After no more observations change memberships (i.e., convergence is achieved), the process ceases, and the clusters can be observed. K-means aims to produce mutually-exclusive groups (i.e., clusters) such that observations within the same cluster are as similar as possible (i.e., high intra-class similarity) and observations from different clusters are as dissimilar as possible (i.e., low inter-class similarity). The distance measure chosen will influence the shape and size of the clusters.

**Hierarchical Agglomerative Clustering.** In contrast to the K-means partitioning algorithm, HAC is a hierarchical clustering algorithm that creates a hierarchy of clusters, so it does not require a user to specify the optimal number of clusters. HAC is a bottom-up hierarchical clustering technique that iteratively groups together the two nearest data points to generate a cluster until every data point has been merged into a single cluster. This linkage is determined by adjusting the appropriately-named linkage parameter. The most commonly used linkage types include complete, single, and average linkage. These links are based on the two furthest points, the two closest points, and the center of the points, respectively. Unlike partitioning methods (e.g., K-means clustering), hierarchical clustering methods such as HAC do not assign data points to specific clusters based on distances to the centroids. Instead, HAC identifies clusters by successively merging (i.e., agglomerating) pairs of clusters that are the closest to each other until all clusters have been merged into one large cluster containing all data points, as shown in Figure 3. Here, a dissimilarity or distance matrix between observations based on the Euclidean distance and a dissimilarity between clusters of observations based on the *complete* linkage agglomeration method were used to perform agglomerative hierarchical clustering. The complete or the maximum linkage clustering method computes all pairwise dissimilarities between the observations in one cluster and the observations in another cluster, and it considers the largest value of these dissimilarities as the distance between the two clusters. Thus, it tends to produce more compact clusters. HAC also generates a tree-based visualization of the relationship between clusters in the data called a *dendrogram*, as shown in Figure 3, where four clusters were highlighted. Each leaf in the dendrogram tree corresponds to one observation and observations that are similar to each other are grouped into branches, which can themselves be combined at a higher level (i.e., height) in the tree. The height of a branch between an observation and the clusters of observations below indicate the distance between the observation and that cluster to which it is joined. Even though HAC generates a fully-connected dendrogram representing the cluster relationships, it is useful to determine an optimal number of clusters (i.e., groups) to extract, similar to the procedure for K-Means.

**Fuzzy C-Means.** FCM is a soft clustering partitioning algorithm that assigns observations to multiple clusters and calculates the probabilities of the data point belonging to each cluster. FCM iterates over the data similar to K-means clustering, but it aims to minimize the within-cluster distances weighted by the probabilities mentioned above. The main advantage of FCM is its flexibility compared with hard clustering, as it allows a data point to be assigned to more than one cluster, according to its characteristics on different dimensions/variables.

All three clustering analyses were performed in R. We conducted KM using the *kmeans* function and HAC using the *hclust* function, both from the *stats* package that comes with the basic R installation (R Core Team, 2020), and FCM using the *cmeans* function from the *e1071* package in R (Meyer et al., 2019). The *fviz_nbclust* function from the R package *factoextra* (Kassambara & Mundt, 2020) was employed to determine and visualize the optimal number of clusters for each cluster technique, using three different methods: within cluster sums of squares (*wss* parameter), the average silhouette width (*silhouette* parameter), and the gap statistic (*gap_stat* parameter; Tibshirani, Walther, & Hastie, 2001), respectively.

#### *4.3.6. Confirmatory Factor Analysis (CFA)*

The main difference between EFA and CFA is that, while EFA requires no assumptions about the structure of the data, CFA demands that there is conception of what the model will be. The CFA was performed using the *cfa* function in the *lavaan* package (Rossel, 2012). Based on a combination of the pre-existing hypothesis that the instrument assessed four dimensions of the types of health-care support and any novel findings from the EFA, models will be manually created and entered into the *cfa* function to return fit indices for how well the model fits the data. Assessments of model fit for the CFA are the RMSEA, SRMR, RMSR, comparative fit index (CFI), and Tucker Lewis index (TLI). For both the CFI and TLI, values scale from 0 to 1, with values closer to 1 indicating better model fit (Bentler, 1990; Tucker & Lewis, 1973). Model rotation must also be specified here as with the EFA. Weighted Least Squares Mean (WLSMV) was the selected rotation, as it is a robust estimator that does not assume normally distributed variables (Brown, 2006).

#### *4.3.7. Chi-square Test*

After each participant has been assigned to a cluster, we conduct the chi-square difference test to examine whether the distributions of demographic variables differ among clusters. The chi-square analysis was performed using the *chisq.test* function from the *stats* package in R (R Core Team, 2020). Post-hoc analyses were performed using the *chisq.posthoc.test* function from the *chisq.posthoc.test* package in R (Ebbert, 2019) to test for statistical significance amongst variables that appeared to have powerful clustering tendencies in specific clusters. Due to the size of the dataset, the p-value we are considering to indicate statistical significance is $p < 0.001$.

### *4.3.8. Model Evaluation and Cluster Validation Metrics*

The EFA algorithm takes as a parameter the number of factors anticipated. We conducted a parallel analysis and a Very Simple Structure (VSS) test to determine the optimal numbers of factors. A parallel analysis calculates the number of principal components in a dataset by comparing the eigenvalues of the input data matrix with a null reference set of eigenvalues. A VSS determines the adequacy of a specific number of factors by evaluating which factor rotation results in factors having the highest amount of loading on certain variables and minimal loading on all others. The parallel analysis result and the VSS complexity measure were adopted as evaluation metrics.

In the clustering unsupervised-learning technique, the most important hyperparameter (i.e., a parameter provided by the researcher and not learned by the algorithm) is the number of total clusters, *k*. To determine the optimum *k*, we use two commonly used indices, Silhouette (Rousseeuw, 1987) and Dunn (Dunn, 1973), to evaluate our models. The *Silhouette index* is a normalized summation-type index which only depends on the actual clustering results, but not on the clustering algorithms. In addition, it requires no calculation of cluster and global centroids. Therefore, many previous studies used Silhouette to validate the clustering results. The *Silhouette index* can be calculated by:

$$Silhouette = 1/N \sum_{i=1}^{N} \frac{b(x_i)-a(x_i)}{max\{a(x_i),b(x_i)\}}$$

The $a(x_i)$ term represents the cohesion measure that is calculated by averaging the distance of $x_i$ to all other vectors in the same cluster and $b(x_i)$ is the separation measure that is calculated by averaging the distance of $x$ to the vectors in all other clusters. The *Silhouette index* ranges in the interval [-1, 1], where -1 indicates bad discrimination, 0 indicates indifferent discrimination, and 1 indicates good discrimination.

The *Dunn Index* (*DI*) is another widely used evaluation metric for clustering algorithms. The value of a clustering result is a ratio of the minimum cluster diameter to the maximum within-cluster distance. The DI is equal to the minimum inter-cluster distance divided by the maximum cluster size, which can be calculated by:

$$DI_m = \frac{\min\limits_{1 \leqslant i < j \leqslant m} \delta(C_i, C_j)}{\max\limits_{1 \leqslant k \leqslant m} \Delta_k}$$

The term $m$ represents the number of clusters, the size of cluster C is denoted by $\Delta C$, the distance between clusters i and j is denoted by $\delta(C_i, C_j)$. DI ranges from 0 to infinity, with larger inter-cluster distances (better separation) and smaller cluster sizes (more compact clusters) leading to a higher DI value.

In the present study, hyperparameter tuning is conducted by setting the hyperparameter values for the number of factors in EFA to range between 2 and 5, and the number of total clusters to range between 2 and 15. The number of total factors and clusters were determined by the evaluation indices described above.

### 4.4. Chapter Summary

Chapter 4 posits the working hypothesis of this research and it discusses the rationale of the analytical plan for the statistical methods used to carry out the analyses of the CCHS-MH data. It also examines the metrics used to evaluate the relative model fit of each of these analytic methods.

## Chapter 5: Results

### 5.1. Reliability: Internal Consistency

The analysis yields a value of Cronbach's alpha of 0.79. Thus, using a cut-off of adequate reliability as 0.7 (Tabachnick & Fidell, 2007), the instrument is sufficient to meet the requirements of internal consistency.

### 5.2. Exploratory Factor Analysis (EFA)

For the EFA, both the parallel analysis and the Very Simple Structure (VSS) criterion suggest 4 as the optimal number of factors, as evidenced by having the most optimal fit indices amongst the 4 tested models: ChiSq(24) = 618; $p < 0.001$; RMSEA = 0.032; BIC = 375; SRMR = 0.012. This confirmed the instrument's construct validity. Table 4 shows the factor loadings and model summaries of the 4-factor model. We assigned a label to each factor, such as *No Supports* (Factor 1); *Social Supports* (Factor 2); *Professional Supports* (Factor 3); and a *Combination of Self-Help/Social Worker or Counsellor Supports* (Factor 4). The results indicate that the factor loadings (Table 4) are consistent with the correlations between the 4 latent factors (Table 5). Factor 1 (No Supports) is negatively correlated with Factor 2 (Non-professional Supports), Factor 3 (Professional Supports), and Factor 4 (Self-directed Supports). The correlations between Factors 2, 3 and 4 are weak to moderate, confirming the divergent validity of the instrument (i.e., the 4 factors in the survey measure different latent traits). Ultimately, while the EFA has numeric power behind it, the content validity of the fourth factor is troubling and makes the model somewhat difficult to interpret.

### 5.3. Construct Validity: Factor Analysis

An exploratory factor analysis was conducted to reveal the optimal number of factors underlying the CCHS-MH instrument. The results revealed that both the PA and the VSS criteria concurred that 4 is the optimal number of factors. Table 4 shows the factor loadings and model summaries of the EFA 4-factor model, whereas Table 6 shows the VSS fit indices. Also, Table 7 shows the EFA eigenvalues of the components. Figure 4 and Figure 5 display the plotted data. Correlations between the EFA-generated factors can be found in Table 7. Results show that a number of items loaded poorly onto any factor. Also, consulting a teacher or principal, using a telephone helpline, and utilizing a self-help group all yielded loading values of less than 0.3 on any factor, as shown in Table 4. This indicates poor fit onto their optimal fitting factors.

As a result, the items that were loading poorly on any factor were dropped from the CFA. In the end, the CFA model yielded the following factors: (1) consulted no-one; (2) consulted a family member, friend, or co-worker/employer; (3) consulted a psychiatrist, psychologist, family doctor, or nurse practitioner; and (4) consulted a family member, friend, or family doctor. The findings also revealed that the CFA model fit the data well. The CFI is 0.999, the TLI is 0.997, the RMSEA value is 0.009, and the SRMR value is 0.017. This indicates a good factor model that validates the instrument. The latent variable estimates can be found in Table 8, which contributed evidence to convergent validity by illustrating to what degree items load more onto one specific factor rather than on the other factors. A complete standardized estimate greater than 0.4 indicates a relationship between an item and a factor. Regarding the discriminant validity measures, consulting no one yielded strong negative relationships to all other factors, as expected. Examining the other factors, the existence of the mixed-type support factor in the model reduces the information one can glean on discriminant validity amongst the 3 factors of support-usage. The relationships between these factors are proportional to the amount of overlap in the variables amongst factors. More detail is presented in Table 9 showing the covariances of the CFA factors. The covariance values for the *Mixed-Support* factor exceeded 1, due to the items co-occurring in multiple factors.

**5.4. Cluster Analyses**

As all the HAC, KM, and FCM clustering techniques returned $k = 5$ as the optimal numbers of clusters on all the evaluation indices (Silhouette and Dunn), with k = 4 yielding comparable indices, as shown in Table 10. Overall, the KM and FCM models provided equally high indices for numbers of clusters ranging from 2 to 5, also shown in Table 10. The elbow method (Figure 6), silhouette method (Figure 7), and gap statistic method (Figure 8) suggest 4, 9, and 5 as the optimal number of clusters for KM, respectively. Concomitantly, the elbow method (Figure 9), silhouette method (Figure 10), and gap statistic method (Figure 11) suggest 4 as the optimal number of clusters for HAC. Then, the dendrogram can be cut at a specific height to identify a corresponding number of subgroups or clusters. Finally, the elbow method (Figure 12), silhouette method (Figure 13), and gap statistic method suggest 4, 3, and 3 as the optimal number of clusters for FCM, respectively.

Figure 7 reveals that the optimal number of clusters was 9 for the KM algorithm. However, due to the relative flatness of the graph between $k = 2$-10, the smaller number of clusters is preferred, as it produces more stable clusters that are resilient to random noise in the data, thus being less prone to overfitting. Corroborating this with the agreement and consistency in the findings of the other clustering techniques (employing different cluster validity indices) and factor analyses (i.e., converging to 4 as the optimal number of clusters), we chose 4 as the optimal number of clusters for the KM algorithm as well. This logic also applies to the KM gap statistic (Figure 8), where 5 was calculated as optimal, but 4 is still preferred considering the narrow difference in fit. Thus, as the FCM and KM were comparable in fit, and FCM seems to be more stable across the three graphs and more reflective of the overlapping nature of the data, the FCM with $k = 4$ was selected in the current study, which matched the initial hypothesis. Table 11 displays the FCM cluster centroids.

In each column corresponding to one of the four clusters, we mark the most prevalent cluster centroids in bold font. Cluster 1 participants sought no mental-health support. Cluster 2 participants consulted most frequently with families and friends. Cluster 3 participants mainly sought consultations from family doctors. Finally, Cluster 4 participants tended to seek mental-health care support from professional and non-professional resources including family doctors, families, friends, social workers and counsellors, and co-workers, with a preference for consulting with families and friends. The distribution of observations in the cluster plot is demonstrated across the three different algorithms in Figure 14 and Figure 15. These clusters seem to have more content validity than those generated by the EFA model. The fourth cluster consisting of a combined professional/non-professional support utilization is far more compelling than the less precise fourth variable of Social Worker/Counsellor and Self-Help Group Factor yielded by the EFA.

### 5.5. Cluster Differences on Demographic Variables

Table 12 presents the demographic distributions of the 4 clusters, including province of residence, residency in a CMA or non-CMA, age, sex, marital status, level of education, total household income, immigrant status, and whether the individual identified as white or a visible minority. Most participants were residents of Ontario, British Columbia, Alberta, and Quebec, with no strong clustering tendencies for any province. Clusters 1 and 3 have a higher proportion of participants who do not live in a CMA, whereas Clusters 2 and 4 have a higher proportion of participants in a CMA. Cluster 2 has the highest proportion of females, whereas Cluster 1 has the lowest. Clusters 2 and 4 include the youngest participants of all the four clusters, being aged between 15-39. Conversely, most participants from Clusters 1 and 3 are aged between 45-59 and 55-69, respectively. Cluster 1 had an overrepresentation of married individuals. Cluster 2 and 4 had a large group of single people. Immigrants are clustered into Cluster 1 and non-immigrants into Cluster 2. Those with less than a secondary education are underrepresented in Cluster 2 and overrepresented in Cluster 1. Cluster 2 has the highest proportion of the highest income category, followed by Clusters 1 and 4. Cluster 3 has the lowest proportion of >=$80,000 category and the highest proportion of <$20000 category. Results of the chi-square tests for homogeneity (Table 13) suggest the differences in the distributions of the demographic variables are significant, which could facilitate a deeper understanding of the relationship between Canadians' mental-health support-utilization behaviors and their demographic information.

The post-hoc analyses finds significant differences in the chi-square test across every single demographic variable, except for the variable gathering information on whether the respondent was either white or a visible ethnic minority. A *p-value* cut-off for the chi-square was $p < 0.001$, which is more conservative that the generally utilized $p < 0.05$. The decision to use this stricter value was made based on how large the dataset was – with over 24,000 respondents it was possible that statistical significance could occur for variables that were not actually meaningful in any way. All differences will be explored in the *Discussion* sections individually. The *p-value* cut-off for the post-hoc analysis was determined based on the number of comparisons made. For example, since the province of residence variable has 10 response options, we multiply 4 (the number of clusters) by 10. We then divide that outcome by 0.05 to determine the post-hoc *p-value* cut-off (0.05/40 = 0.00125). The residuals and the *p-values* for the post-hoc Pearson *Chi-Square* test are shown in Table 14.

### 5.6. Chapter Summary

Chapter 5 illustrates that the factor analyses favoured a 4-factor model, split among professional, social, professional and social, and no support utilization. The cluster analysis also identified four as the optimal number of clusters or differential patterns of utilization across different demographic variables. The CFA confirmed 4 as the number of factors yielding the best-fit model. Collectively, these analyses support the construct validity and reliability (i.e., internal consistency) of the CCHS-MH instrument.

# Chapter 6: Discussion

## 6.1. Summary of Modeling

All approaches employed in analyzing the CCHS-MH data (EFA, clustering, and CFA) confirmed that a 4-factor model was the best fit for the data and overlapped regarding which item-to-factor loadings generated the best model fit. Due to complications with the variable concerning utilization of counsellors and social workers, that item was dropped from the CFA despite showing high levels of loading in the EFA. In the future, a more thoughtful variable design for those support-types will likely reveal that counsellors or social workers also fit into the model.

Ultimately, enough information was gleaned to support the claim that 4 broad patterns of support utilization exist in the data: *No Support*, *Social Support*, *Professional Support*, and *Mixed Support*. This finding could inform future analyses in the field of mental-health support utilization.

## 6.2. Summary of Clustering Findings

Individuals in British Columbia were less likely to utilize no support; those from Newfoundland were more likely to. Those living in Manitoba were more likely to utilize social support while those from Quebec were less likely. CMA versus Non-CMA show strong preference among those living in a CMA to utilize mixed supports and social supports far more than those in a Non-CMA. Differential effects exist amongst age as well: those using mixed supports or social supports tend to skew younger, middle-aged individuals utilize no support or social support, and the elderly tend to be overrepresented in the professional cluster. Sex differences were noted; women are much more likely to engage with professional, social, and mixed supports than men. Men are most represented in engaging with no supports. White and non-white groups do not have powerful differences across clusters. Immigrants are most likely to not utilize support and non-immigrants were most likely to utilize social support. Educational groups show that those with less than secondary education utilize no support more and social support less, those with some post secondary are less likely to seek no support are more likely to seek social or mixed support, and finally those with completed post-secondary more often use social supports. Finally, those with annual household incomes below $20,000 are underrepresented in the *No Support* cluster and overrepresented in the *Professional Support* cluster.

### ***6.2.1. Province of Residence***

There is some significance in the way that healthcare is organized regionally in Canada, as compared to a nation with comparable socialized medicine like the UK, which is fully nationalized under the National Health Services. The fact that numerous health regions exist in Canada, each with their own regulations, increases the possibility for differential effects due to care being non-uniform. Despite health care being operated provincially in Canada and different governments having different priorities on health care, no major inequalities on a province-wise basis would be expected as the baseline assumption. However, A few significant findings emerged. British Columbia has a significant underrepresentation in Cluster 1 (*No Support),* Manitoba has significant overrepresentation in Cluster 2 (*Social Support),* Newfoundland and Labrador are overrepresented in Cluster 1 (*No Support),* and Quebec iss underrepresented in Cluster 2 (*Social Support).* These significant findings could justify deeper inquiry into differences on a provincial level.

### *6.2.2. Residency in a CMA/Non-CMA*

Those living in a CMA are most represented in Cluster 2 (*Social Support*) and Cluster 4 (*Mixed Support*). Non-CMA individuals are overrepresented in Cluster 1 (*No Support).* An analysis of the same dataset found similar results, but only analyzed Canadians aged 15 to 24 (Findlay & Sunderland, 2014). There is a scarcity of research on how often other age groups utilize informal supports in Canada on the basis of CMA residency, but some Statistics Canada reports indicate that rural citizens have more active relationships with family, neighbours, and do not differ from urbanites on questions of whether they felt as though they had access to social support (Turcotte, 2005). This is in contrast with the present findings, which other studies corroborate, showing that individuals living in rural areas utilize family and friends as mental-health supports less than those living in urban areas (Bardach, Tarasenko, & Schoenberg, 2011; Gale, Janis, Coburn, & Rochford 2019). However, due to differences in mental-health care between nations, interpretations must be made cautiously. Future research on whether rural Canadians of all ages are willing to find support in family and friends is an important area of study.

### *6.2.3. Age*

Cluster 2 (*Social Support*) and Cluster 4 (*Mixed Support*) overlapped amongst the represented age groups and comprised individuals with age ranging between 15 and 39 years. Older individuals are underrepresented in these clusters. The findings that younger individuals favor social over medical support is corroborated by existing studies (Gulliver, Griffiths, & Christensen, 2010; Rickwood et al., 2007), but these studies generally focus on adolescents. Studying the types of support that individuals in their mid-twenties up to middle age utilize is less common in the related literature. Considering discussions around the elongation of adolescence (Sawyer, Azzopardi, Wickremarathne, & Patton, 2018), it seems likely that trends in adolescents can trend upwards into “millennial” age brackets. Cluster 1 (*No Support*) comprises mostly middle-aged and older individuals and have reduced amounts of younger respondents. One explanation for these findings could be that the stigma of mental illness is much greater for older individuals (Schomerus et al., 2015; Jang, Chiriboga, & Okazaki, 2009). CCHS data revealed that middle-aged and older individuals do not have a marked lower rate of mental health concerns, as it was found that their incidence of mental health concerns is higher than the overall rate (Hasin, Goodwin, Stinson, & Grant, 2005, Statistics Canada, n.d.). Consequently, their membership into Cluster 1 comprising individuals who seek no help would not be due to a lower rate of mental health concerns. It is possible that culture is a strong factor in this clustering, as stigmatization of mental health concerns seems to be less prevalent in younger individuals and increases with age (Schomerus, Van der Auwera, Matschinger, Baumeister, & Angermeyer, 2015; Watson, Miller, & Lyons, 2005). This is problematic, as even informal supports have a protective factor, revealing that middle-aged individuals are at risk for more pronounced mental health concerns.

#### ***6.2.4. Sex***

Sex is represented differentially in the clusters. Men are significantly overrepresented in Cluster 1 (*No Support*) than would be expected by chance and are significantly underrepresented in all other clusters (especially in Cluster 2, *Social Support*). The opposite findings were found for women. This finding is supported by other analyses of the differences between how, and if, men and women confide in others about their mental health (Cole & Ingram, 2019; Cox, 2014; Fiori & Denckla, 2012; McKenzie, Collings, Jenkin, & River, 2018).

#### *6.2.5. Marital Status*

Single individuals are predominantly found in Cluster 2 (*Social Support*) and Cluster 4 (*Mixed Support*), whereas married individuals are most represented in Cluster 1 (*No Support*), a finding supported by existing research of both mental-health care and general health care utilization (Ngamini Ngui, Perreault, Fleury, & Caron, 2012; Roberts et al., 2018). Divorced individuals are overrepresented in Cluster 3 (*Professional Support),* Cluster 4 (*Mixed Support),* and are underrepresented in Cluster 1 *(No Support).* Widowers are far less likely to use any support types and were overrepresented in Cluster 1 *(No Support).* The strong utilization of social support over professional support for single individuals may be confounded by age and stage of life development. For example, the single individual would tend to be younger than their married, divorced, common-law, or widowed counterparts, and data exists showing age is positively correlated to accessing physicians for any reason (Statistics Canada, 2017).

#### *6.2.6. White/Visible Minority*

No large differences are found between white and non-white Canadians, nor were strong difference noted between cluster membership.

#### *6.2.7. Immigrant Status*

Immigrants are underrepresented in all three of the support-utilization clusters and overwhelmingly grouped into Cluster 1 (*No Support).* The opposite is found for non-immigrants. This finding has mixed support from Canadian studies (Islam, 2018; Islam, Khanlou, Macpherson, & Tamim, 2014; Kirmayer et al., 2007), so more research is required before concrete steps in policy building should be undertaken.

### *6.2.8. Education*

Participants with some post-secondary graduate education are quite overrepresented in Cluster 2 (*Social Support*), and those with less than a secondary education are underrepresented in this cluster. A similar mirroring was found with Cluster 1 *(No Support)*: those with less than a secondary education are overrepresented, whereas those with some post-secondary education are underrepresented. Previous research provides a theoretical underpinning to support this cluster membership: individuals with more than a secondary education do not have more mental disorders, yet some research with CCHS data suggests that being a highly educated individual strongly predicted utilizing professional mental-health supports without diagnosed mental disorders (Fleury et al., 2014). This group's willingness to engage with professionals about mental health when having no serious disorders could explain why overall they most often connect with friends, as they would be an even more readily available resource.

### *6.2.9. Total Household Income*

Finally, the >=$80,000 income group has the lowest representations in Cluster 3 (*Professional Support)*. This underrepresentation likely reflects that higher-income individuals have a lower prevalence of mental health concerns and the severity mental health concerns tend to be significantly lower (Fleury, et al., 2014; Meng, Liu, D'Arcy, & Caron, 2020; Schlax et al., 2019). This lower severity may play a role in their lowest representation in Cluster 3 (*Professional Support*), as professional aid may be unnecessary to manage mental-health struggles. An alternative reading of the low membership of Cluster 3 (*Professional Support)* is that higher-income individuals access private mental-health support not accounted for in the clustering more often due to reduced economic barriers (Bartram & Stewart, 2019; Slaunwhite, 2015). Those in the lowest income bracket have sharply reduced levels of membership in Cluster 1 (*No Support*) and the highest proportion in Cluster 4 (*Mixed Support)* and Cluster 3 (*Professional Support*). This is congruent with both findings that prevalence and severity are drastically increased for those living in poverty (Fleury, et al., 2014; Meng et al., 2020; Schlax, 2019), and free access to family doctors means low income is not a barrier to utilizing medical practitioners.

#### ***6.2.10. Validation***

Results show that, largely, the survey scale in the CCHS-MH is effective, but there is still room for improvement. The counsellors and social workers variables are ineffective in design, as they are too different to be mapped to the same variable. Additionally, more specificity in the self-help group variable and, to a lesser extent the telephone helpline variable, will allow more specific information to be gleaned that may reveal differential effects and predictors between sub-types. However, considering the bulk of utilization rates being recorded in other areas of support the data collected with the CCHS-MH retains a large amount of relevancy.

Internal consistency has never been calculated for this survey, so determining that the survey has adequate internal consistency is important for building an evidence-based narrative of the collected data. In addition, adequate internal consistency is necessary for the building of the factor model, which found that a small set of the support-types were overwhelmingly utilized to the exclusion of nearly all others.

The exploratory and confirmatory factor analysis also contribute new information to the field by creating a novel framework of the CCHS-MH data, conceptualizing four broad patterns of utilization: primarily professional supports, primarily social supports, a blend of both (family doctors in specific being the professional of choice for these individuals), and no support at all.

### *6.2.11. Clustering*

The clustering analysis also considered the optimal cluster number to be 4; which serves to strengthen the narrative written by the factor analysis, in that there are four patterns of utilization within the data. No utilization, social utilization, professional utilization, and mixed utilization was reflected in the clustercounsell. The problems with those two variables make the fourth cluster uninformative, but the broad overlap was encouraging that the model had construct validity.

Clustering is a fairly uncommon methodology to employ in this area of research, so using it on this dataset specifically is a completely novel contribution to the field. Machine learning has great potential in numerous different fields, so generating evidence of its effectiveness in the area of public health is encouraging.

## 6.3. Limitations

First, as a secondary-sample analysis, we could exert no control over the sample characteristics. Specifically, while the sampling data collected by the CCHS was extensive and may have been representative of most Canadians, certain categories of demographics dominated the proportions. The Territories were excluded from the sampling. While not composing a large portion of the Canadian populace, they are still worth sampling, and their absence does cause the sample to lack full representation across the different regions of Canada. Variables such as *White* versus *Non-White*, *Education*, and *Income* were not as informative to study due to the imbalances between the categories, clouding information from the underrepresented groups that may have been clearer otherwise. Also, other variables that were not measured may have played a role in characterizing the individuals who elected certain health care supports. The most problematic issue with the demographic sampling is the exclusion of reserves and other Aboriginal settlements. The overrepresentation of mental illness in the Indigenous community is well established (Kielland & Simone, 2014) and the large exclusion of these areas in the catchment together with the simplistic variable breakdowns into *White* and *Non-White* are extremely reductive aspects and hide information necessary to help groups most in need.

Additionally, the survey items on mental illness could be improved in future cycles. The data in this study only has one item as a “flag” for mental health concerns, asking whether participants had been hospitalized for a mental illness within the past year. This is a woefully imperfect survey item, as many mental health concernsand those afflicted do not ever have to be hospitalized. In future cycles of data collection, an item asking respondents whether they had engaged with any support type to help cope with existing mental health concerns would be much more successful at collecting data that are representative of true experiences with mental health concerns, as opposed to the current item about being hospitalized for mental illness. In addition to this, other items that ask more nuanced questions about existing mental health concerns will make future data collection cycles more robust and allow for more complex and genuine interpretations of Canadian experiences with mental illness. Additionally, the items would not be able to differentiate between single and repeated uses of these services; including this distinction in the data would help identify heavy users of any given support. All of these inclusions in future cycles of the CCHS-MH would allow for a much more complete sampling.

Finally, the survey is a self-reported voluntary interview, so while the relative anonymity of a phone interview may help ease discomfort in the respondent, it is likely that reporting was skewed in a direction that the respondents would consider more favorable. In future research, it would also be useful to have information on whether the mental health concerns were diagnosed by a professional, as defined and classified by the DSM-5 (American Psychiatric Association, 2013).

## 6.4. Implications

### *6.4.1. Theoretical implications*

This study has provided a factorized model of the CCHS-MH, suggesting a 4-factor model split among professional, social, mixed, and no supports utilization. This corresponds to four broad patterns of utilization amongst Canadians. Additionally, this study has shown that soft clustering analysis can effectively uncover patterns in mental-health care data that may be missed by other clustering methods (e.g., hard clustering). For instance, when respondents report utilizing multiple mental-health supports that transcend groups (e.g., consulting family doctors concomitantly with consulting friends), the flexibility of soft clustering can be very useful, as it can assign every observation to each group with varying probabilities adding up to 1, rather than assigning each observation to just one group. The study also found that four distinct clusters of utilization occur in Canada.

### *6.4.2. Practical Implications*

The findings that individuals in CMAs are more likely to engage with social supports would suggest that smaller municipalities need to encourage their communities to talk openly about mental health. Middle-aged individuals tend to avoid seeking mental-health support, which does not match the rate at which they experience issues with mental health. Considering that family doctors tend to be a first point of contact for the majority of mental-health conversations, medical training needs to emphasize this area of health. Women are utilizing all types of support more than men, suggesting attempts must be made to reduce stigma around mental health for men in Canada. Marital status seems to have some consistent differential effects on utilization;

single and divorced people tend to utilize support; married and widowed individuals tend to not utilize support, though the reasons why are not clear based on existing literature. Immigrants are underutilizing all types of support compared to non-immigrants; perhaps resources should be creating and disseminated to help bridge the gap for those emigrating to Canada. There are significant differences between lower and higher levels of education on predicted levels of mental-health support utilization; education potentially is an avenue to reduce stigma and increase awareness of mental health resources. Finally, low-income Canadians utilize family doctors much more often than other types of support. The Canadian context of this finding is important; looking at nations with private health care like the United States, where low-income individuals rarely utilize mental-health care, as the present findings suggest that economic barriers may be the largest for low-income individuals.

### 6.5. Contribution

This research contributes to the existing literature by providing a measure of the internal consistency, a review of the variables to find content validity, and the creation and construct validity testing of a factor model of the data that could be used in future analyses of this or similar data. Further exploration with cluster analysis provided more evidence to the model and discovered patterns and differential effects in mental-health utilization across demographics.

### 6.6. Conclusions

This study examines the responses of participants to the 2012 CCHS mental-health support survey. FCM was found to successfully group the sample into meaningful and valid clusters, which was further supported by current research on mental-health support. Additionally, the clusters reveal distinct patterns in the way Canadians manage struggles with mental health concerns. The clusters also provide evidence that unsupervised machine learning techniques are useful when studying mental-health data. As mental illness is a defining medical challenge of this era, using evidence-supported, multi-disciplinary strategies to understand and refine the way society aids individuals is of the utmost importance.

**6.7. Future Directions**

There are a few directions this research can take in the future. The new model can be utilized with other datasets to study the differential mental-health utilization patterns. It is reasonable to believe that, if individuals exemplify these larger patterns of utilization in this dataset, then those patterns could be found in other areas and this could contribute to literature on social determinants of mental-health support utilization, addressing a gap in the current literature. To ascertain the stability in group membership over time (e.g., in income levels), together with any possible consequences for mental-health support utilization, longitudinal studies may be designed and conducted in future studies. Following the success of the clustering analysis, other machine learning techniques are being considered for this data. Using a deep learning algorithm to predict utilization patterns based on demographic variables would be useful to verify the results of the present research and it would present further evidence that machine learning methods (e.g., deep neural networks, in this case) can be used to gain insights from this type of data.

Looking at the future of the survey in the context of 2021; another item that will likely be far more impactful, considering both the context of modern times and the coronavirus pandemic, will be the role of internet therapy in future data collection cycles. It was included in the 1.2 collection survey, but in 2012 the advent of internet therapies had not fully become commonplace. In fact, the data reflected this, as less than 0.05% of Canadians reported using internet therapy. In all likelihood this variable will be far more commonly utilized going forward and studying it will be of extreme importance in order to maximize its accessibility and effectiveness.

### 6.8. Chapter Summary

Chapter 6 discusses the theoretical and practical implications of the present findings, the limitations imposed by the dataset and by the nature of the analyses and concludes by briefly outlining the contributions to the larger field of research as well as potential areas of future research. The results of these analyses could inform both the current and future academic space of Canadian public health.

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## Tables

**Table 1**

*Articles Included in the Literature Review*

| Ref. | APA Reference of Reviewed Articles |
|---|---|
| [1] | Ng, R. M. K., Chan, T. F., Herrman, H., & Dowrick, C. (2020). What do psychiatrists think about primary mental health competencies among family doctors? A WPA–WONCA global survey. *BJPsych International* , 1-5. doi:10.1192/bji.2020.32 |
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| [3] | Kurdyak, P., Stukel, T. A., Goldbloom, D., Kopp, A., Zagorski, B. M., & Mulsant, B. H. (2014). Universal coverage without universal access: A study of psychiatrist supply and practice patterns in ontario. *Open Medicine : A Peer-Reviewed, Independent, Open-Access Journal, 8*(3)*,* e87-e99. |
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*Note: Ref.: Reference*

**Table 2**

*Support Systems and Their Efficacy and Accessibility in the Literature*

| Support Type | Effective and Accessible | Ineffective or Inaccessible | Mixed Findings |
|---|---|---|---|
| Family Doctor | | | [1][2] |
| Psychiatrist | | [3][4][5] | [6] |
| Psychologists | | | [7][8] |
| Nurses | [9][10][11][12] | | [2] |
| Social Workers | | | [13][14] |
| Counsellors | | | [15][16] |
| Family Members | [20][21] | [23][28] | [22][24] |
| Friends | [20][21][27] | | |
| Co-Workers or Bosses | | | [30][31][32] |
| Teachers or Principals | | [34][35] | [33] |
| Self-Help Groups | | | [37][38] |
| Telephone Helplines | | | [40][41] |

**Table 3**

*Regions where Analyses Were Conducted*

| Support Type | Canadian Data | Non-Canadian Data | Mixed-Region Data |
|---|---|---|---|
| Family Doctor | [2][3] | | [1] |
| Psychiatrist | [4][5][6] | | |
| Psychologists | [8] | | [7] |
| Nurses | | [9][10][11][12] | |
| Social Workers | | [13][15] | |
| Counsellors | [16] | [17][18][19] | |
| Family Members | | [20][21][22][23][24][25][29] | |
| Friends | | [20][21][27][28][29] | |
| Co-Workers or Bosses | | [30][31][32] | |
| Teachers or Principals | [47] | [33][34][35] | [50] |
| Self-Help Groups | | [37][38][39] | |
| Telephone Helplines | | [40][41] | |

**Table 4**

*Factor Loadings of the EFA*

| Support Types (Item #) | No Support | Social Support | Professional Support | Mixed Support |
|---|---|---|---|---|
| Consulted Friend (7) | -0.09 | **0.74** | -0.05 | 0.03 |
| Consulted Family Member (6) | -0.07 | **0.71** | 0.04 | -0.02 |
| Consulted Co-Worker or Boss (8) | 0.17 | **0.59** | 0.06 | 0.02 |
| Consulted Teacher or Principal (9) | 0.05 | **0.15** | 0.00 | 0.11 |
| Consulted No one (10) | **1.08** | -0.02 | -0.01 | -0.01 |
| Consulted Psychiatrist (1) | -0.09 | -0.06 | **0.52** | 0.04 |
| Consulted Nurse (4) | 0.12 | 0.14 | **0.44** | 0.05 |
| Consulted Psychologist (3) | -0.10 | 0.07 | **0.35** | -0.02 |
| Consulted Family Doctor (2) | -0.31 | 0.05 | **0.34** | 0.05 |
| Used Telephone Helpline (12) | 0.04 | 0.02 | **0.27** | 0.07 |
| Consulted Social Worker or Counsellor (5) | 0.00 | 0.00 | 0.00 | **0.74** |
| Consulted Self-Help Group (11) | 0.02 | 0.02 | 0.13 | **0.26** |

*Note: Bolded values indicate the highest loading value amongst the 4 clusters.*

Model Summary

| Measures | No Support | Social Support | Professional Support | Mixed Support |
|---|---|---|---|---|
| Sum-of-Squares (SS) loadings | 1.42 | 1.54 | 0.94 | 0.73 |
| Proportion Variance | 0.12 | 0.13 | 0.08 | 0.06 |
| Cumulative Variance | 0.25 | 0.13 | 0.33 | 0.39 |
| Proportion Explained | 0.31 | 0.33 | 0.20 | 0.16 |
| Cumulative Proportion | 0.64 | 0.33 | 0.84 | 1.00 |

**Table 5**

*Correlation Matrix of the EFA*

| | No Support | Social Support | Professional Support | Mixed Support |
|---|---|---|---|---|
| No Support | 1 | -0.73 | -0.45 | -0.49 |
| Social Support | -- | 1 | 0.42 | 0.48 |
| Professional Support | -- | -- | 1 | 0.51 |
| Mixed Support | -- | -- | -- | 1 |

**Table 6**

*The Very Simple Structure (VSS) Fit Indices Show That a Four-Factor Model Is Optimal*

| Factor | VSS1 | VSS2 | Chi-Squares (df) | RMSEA | BIC | SRMR |
|---|---|---|---|---|---|---|
| 1 | 0.64 | 0.00 | 9782 (54) | 0.085 | 9236 | 0.052 |
| 2 | 0.49 | 0.59 | 4167 (43) | 0.062 | 3732 | 0.026 |
| 3 | 0.39 | 0.45 | 1150 (33) | 0.037 | 816 | 0.019 |
| 4 | 0.37 | 0.46 | 618 (24) | 0.032 | 375 | 0.012 |

*Note: p-values < .001; df: degrees of freedom*

**Table 7**

*EFA Eigenvalues of Factors Composed of the Items from 1 to 12*

| Factors | Eigenvalue |
|---|---|
| 1 | 3.73 |
| 2 | 1.22 |
| 3 | 0.98 |
| 4 | 0.95 |
| 5 | 0.89 |
| 6 | 0.83 |
| 7 | 0.79 |
| 8 | 0.71 |
| 9 | 0.67 |
| 10 | 0.64 |
| 11 | 0.38 |
| 12 | 0.20 |

*Note: Rounded-up eigenvalues greater than or equal to 1 indicate stable factors.*

**Table 8**

*Latent Variable Estimates of the CFA*

| Latent Variables | β | SE | B | Complete Standardized Variable |
|---|---|---|---|---|
| Utilized No Support =~ | | | | |
| Consulted No One | 1 | | 0.39 | 1 |
| Utilized Social Support =~ | | | | |
| Consulted Family Member | 1 | | 0.187 | 0.642 |
| Consulted Friend | 0.905 | 0.051 | 0.169 | 0.556 |
| Consulted Co-Worker or Boss | 0.387 | 0.021 | 0.072 | 0.464 |
| Utilized Professional Support =~ | | | | |
| Consulted Psychiatrist | 1 | | 0.079 | 0.502 |
| Consulted Family Doctor | 1.629 | 0.175 | 0.128 | 0.485 |
| Consulted Psychologist | 0.975 | 0.051 | 0.077 | 0.491 |
| Consulted Nurse | 0.567 | 0.035 | 0.045 | 0.411 |
| Utilized Mixed Support =~ | | | | |
| Consulted Family Member | 1 | | | |
| Consulted Friend | 1.560 | 0.130 | | |
| Consulted Family Doctor | 1.252 | 0.158 | | |

Note: *p*-values < .001; SE: standard Error; *Utilized Mixed Support* was automatically selected as a free-loading factor

**Table 9**

*Covariances of the Factors of the CFA*

| Factor | Unstandardized Variance | SE | Standardized Variance | Complete Standardized Variable |
|---|---|---|---|---|
| Utilized No Support ~~ | | | | |
| Utilized Social Support | -0.052 | 0.002 | -0.718 | -0.718 |
| Utilized Professional Support | -0.02 | 0.001 | -0.645 | -0.645 |
| Utilized Mixed Support | -0.023 | 0.002 | -2.549 | -2.549 |
| Utilized Social Support ~~ | | | | |
| Utilized Professional Support | 0.009 | 0.001 | 0.585 | 0.585 |
| Utilized Mixed Support | 0.01 | 0.001 | 2.238 | 2.238 |
| Utilized Professional Support ~~ | | | | |
| Utilized Mixed Support | 0.002 | 0.001 | 0.877 | 0.877 |

Note: *p*-values < .001; Est.: Estimate; SE: Standard Error; *Utilized Mixed Support* free-loading factor

**Table 10**

*Cluster Validity Indices (CVI) Results Across Clusters. The Optimal Number of Clusters Obtained Using the Elbow and Silhouette Methods is 4*

| KM | 2 | 3 | **4** | 5 |
|---|---|---|---|---|
| Silhouette index | 0.82 | 0.84 | **0.85** | 0.86 |
| Dunn's index | 0.30 | 0.32 | **0.32** | 0.33 |

| HAC | 2 | 3 | **4** | 5 |
|---|---|---|---|---|
| Silhouette index | 0.73 | 0.77 | **0.77** | 0.77 |
| Dunn's index | 0.30 | 0.32 | **0.32** | 0.33 |

| FCM | 2 | 3 | **4** | 5 |
|---|---|---|---|---|
| Silhouette index | 0.82 | 0.84 | **0.85** | 0.85 |
| Dunn's index | 0.30 | 0.32 | **0.30** | 0.30 |

*Note: Marked in bold are the indices for the optimal number of clusters, 4, revealed by all three algorithms (KM, HAC, and FCM).*

**Table 11**

*Summary of the Four Cluster Centroids for FCM Clustering*

| Cluster | No Support (1) | Social Support (2) | Professional Support (3) | Mixed Support (4) |
|---|---|---|---|---|
| N | 20141 | 2059 | 1135 | 1453 |
| Psychiatrist | 0.00 | 0.07 | 0.09 | 0.12 |
| Family Doctor | 0.00 | 0.18 | 0.84 | 0.24 |
| Psychologist | 0.00 | 0.07 | 0.08 | 0.12 |
| Nurse | 0.00 | 0.04 | 0.04 | 0.05 |
| Social Worker or Counsellor | 0.00 | 0.12 | 0.11 | 0.20 |
| Family Member | 0.00 | 0.87 | 0.17 | 0.33 |
| Friend | 0.00 | 0.83 | 0.14 | 0.73 |
| Co-Worker or Boss | 0.00 | 0.12 | 0.05 | 0.13 |
| Teacher or Principal | 0.00 | 0.02 | 0.01 | 0.02 |
| Self-Help Group | 0.00 | 0.04 | 0.04 | 0.07 |
| Telephone Helpline | 0.00 | 0.02 | 0.02 | 0.03 |
| Consulted No One | 1.00 | 0.00 | 0.01 | 0.01 |

*Note: A cluster centroid represents the multidimensional mean of the feature values of all the observations in that cluster.*

**Table 12**

*Distributions of the Demographic Variables by Clusters Obtained Using FCM Clustering*

| Cluster | No Support (1) | Social Support (2) | Professional Support (3) | Mixed Support (4) |
|---|---|---|---|---|
| | 20141 | 2059 | 1135 | 1453 |
| Province of Residence | | | | |
| AB | 2197(10.90%) | 278(13.50%) | 137(12.10%) | 156(10.70%) |
| BC | 2330(11.60%) | 294(14.30%) | 150(13.20%) | 218(15.00%) |
| MB | 1444(7.20%) | 205(9.90%) | 62(5.50%) | 104(7.20%) |
| NB | 1406(7.00%) | 112(5.40%) | 86(7.60%) | 62(4.30%) |
| NL | 1188(5.90%) | 86(4.20%) | 48(4.20%) | 48(3.30%) |
| NS | 1367(6.80%) | 150(7.30%) | 78(6.90%) | 106(7.30%) |
| ON | 4386(21.80%) | 434(21.10%) | 275(24.20%) | 329(22.60%) |
| PEI | 895(4.40%) | 70(3.40%) | 33(2.90%) | 57(3.90%) |
| QC | 3523(17.50%) | 277(13.40%) | 211(18.60%) | 286(19.70%) |
| SK | 1405(7.00%) | 153(7.40%) | 55(4.80%) | 87(6.00%) |
| Lives in CMA | | | | |
| No | 8827(43.80%) | 750(36.40%) | 457(40.30%) | 526(36.20%) |
| Yes | 11314(56.20%) | 1309(63.60%) | 678(59.70%) | 927(63.80%) |
| Age | | | | |
| >=80 | 1474(7.30%) | 24(1.20%) | 46(4.10%) | 15(1.00%) |
| 15-19 | 1468(7.30%) | 239(11.70%) | 56(4.90%) | 234(16.10%) |
| 20-24 | 1410(7.00%) | 298(14.50%) | 73(6.40%) | 188(13.00%) |
| 25-29 | 1175(5.80%) | 248(12.00%) | 62(5.50%) | 112(7.70%) |
| 30-34 | 1402(7.00%) | 249(12.00%) | 73(6.40%) | 120(8.30%) |
| 35-39 | 1284(6.40%) | 197(9.60%) | 79(7.00%) | 148(10.10%) |

| | | | | |
|---|---|---|---|---|
| 40-44 | 1296(6.40%) | 172(8.30%) | 98(8.60%) | 102(7.10%) |
| 45-49 | 1274(6.30%) | 162(7.90%) | 107(9.40%) | 105(7.20%) |
| 50-54 | 1543(7.70%) | 149(7.20%) | 123(10.80%) | 121(8.40%) |
| 55-59 | 1829(9.10%) | 118(5.80%) | 147(13.00%) | 115(7.90%) |
| 60-64 | 1895(9.40%) | 101(4.90%) | 105(9.30%) | 80(5.50%) |
| 65-69 | 1692(8.40%) | 50(2.50%) | 89(7.80%) | 60(4.10%) |
| 70-74 | 1303(6.50%) | 32(1.50%) | 42(3.70%) | 34(2.40%) |
| 75-79 | 1096(5.40%) | 20(1.00%) | 35(3.10%) | 19(1.30%) |
| Sex | | | | |
| Female | 10535(52.30%) | 1448(70.30%) | 725(63.90%) | 897(61.70%) |
| Male | 9606(47.70%) | 611(29.70%) | 410(36.10%) | 556(38.30%) |
| Marital status | | | | |
| Common-Law | 1753(8.70%) | 225(10.90%) | 112(9.90%) | 126(8.70%) |
| Divorced or Separated | 2086(10.40%) | 250(12.10%) | 195(17.20%) | 222(15.30%) |
| Married | 8925(44.30%) | 635(30.80%) | 390(34.40%) | 290(19.90%) |
| Single | 5286(26.20%) | 871(42.40%) | 337(29.70%) | 754(51.80%) |
| Widowed | 2091(10.40%) | 78(3.80%) | 101(8.90%) | 61(4.20%) |
| Minority | | | | |
| Non-White | 3301(16.40%) | 349(17.00%) | 162(14.30%) | 267(18.30%) |
| White | 16840(83.60%) | 1710(83.00%) | 973(85.70%) | 1186(81.70%) |
| Immigration status | | | | |
| No | 16489(81.90%) | 1837(89.20%) | 993(87.50%) | 1271(87.40%) |
| Yes | 3652(18.10%) | 222(10.80%) | 142(12.50%) | 182(12.60%) |
| Level of education | | | | |
| <Secondary | 4467(22.20%) | 311(15.10%) | 236(20.80%) | 280(19.30%) |
| Post-Secondary Grad. | 11181(55.50%) | 1236(60.00%) | 632(55.70%) | 807(55.50%) |

| | | | | |
|---|---|---|---|---|
| Secondary Grad. | 3274(16.30%) | 302(14.70%) | 190(16.70%) | 233(16.10%) |
| Some Post-Secondary | 1219(6.10%) | 210(10.20%) | 77(6.80%) | 133(9.10%) |
| Total household income | | | | |
| <$20000 | 1192(5.90%) | 175(8.50%) | 159(14.00%) | 155(10.70%) |
| $20,000-$39,999 | 3541(17.60%) | 315(15.30%) | 224(19.70%) | 249(17.10%) |
| $40,000-$59,999 | 4344(21.60%) | 382(18.60%) | 230(20.30%) | 273(18.80%) |
| $60,000-$79,999 | 3368(16.70%) | 365(17.70%) | 159(14.00%) | 247(17.00%) |
| >=$80,000 | 7696(38.20%) | 822(39.90%) | 363(32.00%) | 529(36.40%) |

**Table 13**

*Chi-square Tests on the Demographic Variables Among the Four FCM Clusters*

| Demographic Variable | Chi-square | df | *p* |
|---|---|---|---|
| Total household income | 192.48 | 12.00 | <.001 |
| Province of residence | 160.53 | 27.00 | <.001 |
| Level of education | 121 | 9.00 | <.001 |
| Immigration status | 111.58 | 3.00 | <.001 |
| White or visible minority | 7.98 | 3.00 | <.05 |
| Marital status | 923.58 | 12.00 | <.001 |
| Sex | 319.09 | 3.00 | <.001 |
| Age | 1308.60 | 39.00 | <.001 |
| Lives in CMA or not | 71.34 | 3.00 | <.001 |

*Note: df: degrees of freedom*

**Table 14**

*Chi-Square Post-Hoc Tests on the Demographic Variables Among the Four FCM Clusters: Cluster 1 (No Support), Cluster 2 (Social Support), Cluster 3 (Professional Support), and Cluster 4 (Mixed Support)*

<u>*Province of Residence*</u>

| Cluster | Value | AB | BC | MB | NB | NL | NS | ON | PEI | QC | SK |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Frequency | 11.17% | 12.07% | 7.32% | 6.72% | 5.53% | 6.86% | 21.88% | 4.26% | 17.34% | 6.86% |
| 1 | Count | 2197 | 2330 | 1444 | 1444 | 1188 | 1367 | 4386 | 895 | 3523 | 1405 |
| | % in Cluster | 10.90% | 11.60% | 7.20% | 7.00% | 5.90% | 6.80% | 21.80% | 4.40% | 17.50% | 7.00% |
| | Residuals | -2.691 | **-5.050** | -1.921 | 3.401 | **5.330** | -0.973 | -0.833 | 3.046 | 1.357 | 1.526 |
| | *p-values* | 0.285 | **<0.001** | 1.000 | 0.027 | **<0.001** | 1.000 | 1.000 | 0.093 | 1.000 | 1.000 |
| 2 | Count | 278 | 294 | 205 | 112 | 86 | 150 | 434 | 70 | 277 | 153 |
| | % in Cluster | 13.50% | 14.30% | 9.90% | 5.40#% | 4.20% | 7.30% | 21.20% | 3.40% | 13.40% | 7.40% |
| | Residuals | 3.513 | 3.212 | **4.792** | -2.425 | -2.800 | 0.793 | -0.921 | -2.010 | **-4.859** | 1.074 |
| | *p-values* | 0.018 | 0.053 | **<0.001** | 0.612 | 0.205 | 1.000 | 1.000 | 1.000 | **<0.001** | 1.000 |
| 3 | Count | 137 | 150 | 62 | 86 | 48 | 78 | 434 | 70 | 277 | 153 |
| | % in Cluster | 12.10% | 13.20% | 5.50% | 7.60% | 4.20% | 6.90% | 21.10% % | 3.40% | 13.40% | 7.40% |
| | Residuals | 0.990 | 1.213 | -2.462 | 1.179 | -1.959 | 0.014 | 1.958 | -2.304 | 1.144 | -2.746 |
| | *p-values* | 1.000 | 1.000 | 0.553 | 1.000 | 1.000 | 1.000 | 1.000 | 0.849 | 1.000 | 0.241 |
| 4 | Count | 156 | 218 | 104 | 62 | 48 | 106 | 329 | 57 | 286 | 87 |
| | % in Cluster | 10.70% | 15.00% | 7.20% | 4.30% | 3.30% | 7.30% | 22.60% | 3.90% | 19.70% | 6.00% |
| | Residuals | -0.537 | 3.537 | -0.248 | -3.850 | -3.823 | 0.673 | 0.723 | -0.648 | 2.437 | -1.353 |
| | *p-values* | 1.000 | 0.016 | 1.000 | 0.005 | 0.005 | 1.000 | 1.000 | 1.000 | 0.592 | 1.000 |

*<u>Residency in CMA</u>*

| Cluster | Value | No | Yes |
|---|---|---|---|
| | Frequency | 42.60% | 57.40% |
| 1 | Count | 8827 | 11314 |
| | % in Cluster | 43.80% | 56.20% |
| | Residuals | **8.118** | **-8.118** |
| | *p-values* | **<0.001** | **<0.001** |
| 2 | Count | 750 | 1309 |
| | % in Cluster | 36.40% | 63.60% |
| | Residuals | **-5.918** | **5.918** |
| | *p-values* | **<0.001** | **<0.001** |
| 3 | Count | 457 | 678 |
| | % in Cluster | 40.30% | 59.70% |
| | Residuals | -1.630 | 1.630 |
| | *p-values* | 0.825 | 0.825 |
| 4 | Count | 526 | 927 |
| | % in Cluster | 36.20% | 63.80% |
| | Residuals | **-5.085** | **5.085** |
| | *p-values* | **<0.001** | **<0.001** |

*Age*

| Cluster | Value | 15-19 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 | 45-49 |
|---|---|---|---|---|---|---|---|---|
| | Frequency | 6.29% | 8.06% | 7.94% | 6.44% | 7.44% | 6.89% | 6.73% |
| 1 | Count | 1468 | 1410 | 1175 | 1402 | 1284 | 1296 | 1274 |
| | % in Cluster | 7.30% | 7.00% | 5.80% | 7.00% | 6.40% | 6.40% | 6.30% |
| | Residuals | **-9.246** | **-11.427** | **-8.127** | **-5.973** | **-6.669** | -3.852 | -4.249 |
| | *p-values* | **<0.001** | **<0.001** | **<0.001** | **<0.001** | **<0.001** | 0.007 | 0.001 |
| 2 | Count | 239 | 298 | 248 | 249 | 197 | 172 | 162 |
| | % in Cluster | 11.70% | 14.50% | 12.00% | 12.00% | 9.60% | 8.30% | 7.90% |
| | Residuals | **6.183** | **11.443** | **10.813** | **8.405** | **5.009** | 3.073 | 2.320 |
| | *p-values* | **<0.001** | **<0.001** | **<0.001** | **<0.001** | **<0.001** | 0.119 | 1.000 |
| 3 | Count | 56 | 73 | 62 | 73 | 79 | 98 | 107 |
| | % in Cluster | 4.90% | 6.40% | 5.50% | 6.40% | 7.00% | 8.60% | 9.40% |
| | Residuals | -3.957 | -1.928 | -1.377 | -1.324 | 0.095 | 2.623 | 3.847 |
| | *p-values* | 0.004 | 1.000 | 1.000 | 1.000 | 1.000 | 0.488 | 0.007 |
| 4 | Count | 234 | 188 | 112 | 120 | 148 | 102 | 105 |
| | % in Cluster | 16.10% | 13.00% | 7.70% | 8.30% | 10.10% | 7.10% | 7.20% |
| | Residuals | **11.618** | **7.258** | 2.025 | 1.227 | **5.111** | 0.456 | 0.912 |
| | *p-values* | **<0.001** | **<0.001** | 1.000 | 1.000 | **<0.001** | 1.000 | 1.000 |

| Cluster | Value | 50-54 | 55-59 | 60-64 | 65-69 | 70-74 | 75-79 | >=80 |
|---|---|---|---|---|---|---|---|---|
| | Frequency | 6.65% | 7.81% | 8.91% | 8.80% | 7.63% | 5.69% | 4.72% |
| 1 | Count | 1543 | 1829 | 1895 | 1692 | 1303 | 1096 | 1474 |
| | % in Cluster | 7.70% | 9.10% | 9.40% | 8.40% | 6.50% | 5.40% | 7.30% |
| | Residuals | -1.823 | 1.949 | **7.059** | **9.533** | **10.994** | **11.153** | **13.894** |
| | *p-values* | 1.000 | 1.000 | **<0.001** | **<0.001** | **<0.001** | **<0.001** | **<0.001** |
| 2 | Count | 149 | 118 | 101 | 50 | 32 | 20 | 24 |
| | % in Cluster | 7.20% | 5.80% | 4.90% | 2.50% | 1.50% | 1.00% | 1.20% |
| | Residuals | -1.013 | **-5.290** | **-6.513** | **-9.283** | **-8.463** | **-8.377** | **-10.001** |
| | *p-values* | 1.000 | **<0.001** | **<0.001** | **<0.001** | **<0.001** | **<0.001** | **<0.001** |
| 3 | Count | 123 | 147 | 105 | 89 | 42 | 35 | 46 |
| | % in Cluster | 10.80% | 13.00% | 9.30% | 7.80% | 3.70% | 3.10% | 4.10% |
| | Residuals | 3.890 | **4.890** | 0.551 | 0.276 | -2.965 | -2.661 | -3.177 |
| | *p-values* | 0.006 | **<0.001** | 1.000 | 1.000 | 0.170 | 0.436 | 0.083 |
| 4 | Count | 121 | 115 | 80 | 60 | 34 | 19 | 15 |
| | % in Cluster | 8.40% | 7.90% | 5.50% | 4.10% | 2.40% | 1.30% | 1.00% |
| | Residuals | 0.757 | -1.375 | **-4.567** | **-5.179** | **-5.684** | **-6.322** | **-8.507** |
| | *p-values* | 1.000 | 1.000 | **<0.001** | **<0.001** | **<0.001** | **<0.001** | **<0.001** |

*Sex*

| Cluster | Value | Female | Male |
|---|---|---|---|
| | Frequency | 54.89% | 45.11% |
| 1 | Count | 10535 | 9606 |
| | % in Cluster | 52.30% | 47.70% |
| | Residuals | **-16.989** | **16.989** |
| | *p-values* | **<0.001** | **<0.001** |
| 2 | Count | 1448 | 611 |
| | % in Cluster | 70.30% | 29.70% |
| | Residuals | **14.703** | **-14.703** |
| | *p-values* | **<0.001** | **<0.001** |
| 3 | Count | 725 | 410 |
| | % in Cluster | 63.90% | 36.10% |
| | Residuals | **6.232** | **-6.232** |
| | *p-values* | **<0.001** | **<0.001** |
| 4 | Count | 897 | 556 |
| | % in Cluster | 61.70% | 38.30% |
| | Residuals | **5.407** | **-5.407** |
| | *p-values* | **<0.001** | **<0.001** |

*Marital Status*

| Cluster | Value | Common-Law | Divorced | Married | Single | Widowed |
|---|---|---|---|---|---|---|
| | Frequency | 8.94% | 11.11% | 41.31% | 29.24% | 9.40% |
| 1 | Count | 1753 | 2086 | 8925 | 5286 | 2091 |
| | % in Cluster | 8.70% | 10.40% | 44.30% | 26.20% | 10.40% |
| | Residuals | -2.713 | **-7.815** | **19.986** | **-21.582** | **10.983** |
| | *p-values* | 0.133 | **<0.001** | **<0.001** | **<0.001** | **<0.001** |
| 2 | Count | 225 | 250 | 635 | 871 | 78 |
| | % in Cluster | 10.90% | 12.10% | 30.80% | 42.40% | 3.80% |
| | Residuals | 3.301 | 1.562 | **-10.076** | **13.608** | **-9.117** |
| | *p-values* | 0.019 | 1.000 | **<0.001** | **<0.001** | **<0.001** |
| 3 | Count | 112 | 195 | 390 | 337 | 101 |
| | % in Cluster | 9.90% | 17.20% | 34.40% | 29.70% | 8.90% |
| | Residuals | 1.122 | **6.668** | **-4.867** | 0.342 | -0.597 |
| | *p-values* | 1.000 | **<0.001** | **<0.001** | 1.000 | 1.000 |
| 4 | Count | 126 | 222 | 290 | 754 | 61 |
| | % in Cluster | 8.70% | 15.30% | 19.90% | 51.80% | 4.20% |
| | Residuals | -0.369 | **5.217** | **-17.036** | **19.565** | **-7.007** |
| | *p-values* | 1.000 | **<0.001** | **<0.001** | **<0.001** | **<0.001** |

*Minority Status*

| Cluster | Value | Non-White | White |
|---|---|---|---|
| | Frequency | 16.46% | 83.54% |
| 1 | Count | 3301 | 16840 |
| | % in Cluster | 16.40% | 83.60% |
| | Residuals | -0.584 | 0.584 |
| | *p-values* | 1.000 | 1.000 |
| 2 | Count | 349 | 1710 |
| | % in Cluster | 17.00% | 83.00% |
| | Residuals | 0.632 | -0.632 |
| | *p-values* | 1.000 | 1.000 |
| 3 | Count | 162 | 973 |
| | % in Cluster | 14.30% | 85.70% |
| | Residuals | -2.030 | 2.030 |
| | *p-values* | 0.339 | 0.339 |
| 4 | Count | 267 | 1186 |
| | % in Cluster | 18.30% | 81.70% |
| | Residuals | 2.035 | -2.035 |
| | *p-values* | 0.335 | 0.335 |

*Immigrant Status*

| Cluster | Value | No | Yes |
|---|---|---|---|
| | Frequency | 83.06% | 16.94% |
| 1 | Count | 16489 | 3652 |
| | % in Cluster | 81.90% | 18.10% |
| | Residuals | **-10.457** | **10.457** |
| | *p-values* | **<0.001** | **<0.001** |
| 2 | Count | 1837 | 222 |
| | % in Cluster | 89.20% | 10.80% |
| | Residuals | **7.775** | **-7.775** |
| | *p-values* | **<0.001** | **<0.001** |
| 3 | Count | 993 | 142 |
| | % in Cluster | 87.50% | 12.50% |
| | Residuals | **4.069** | **-4.069** |
| | *p-values* | **<0.001** | **<0.001** |
| 4 | Count | 1271 | 182 |
| | % in Cluster | 87.40% | 12.60% |
| | Residuals | **4.619** | **-4.619** |
| | *p-values* | **<0.001** | **<0.001** |

*Education Level*

| Cluster | Value | < Secondary | Secondary Grad. | Some Post Secondary | Post-Secondary Grad. |
|---|---|---|---|---|---|
| | Frequency | 21.36% | 16.13% | 6.61% | 55.90% |
| 1 | Count | 4467 | 3274 | 1219 | 11181 |
| | % in Cluster | 22.20% | 16.30% | 6.10% | 55.50% |
| | Residuals | **6.571** | 1.092 | **-7.383** | -2.538 |
| | *p-values* | **<0.001** | 1.000 | **<0.001** | 0.179 |
| 2 | Count | 311 | 302 | 210 | 1236 |
| | % in Cluster | 15.10% | 14.70% | 10.20% | 60.00% |
| | Residuals | **-7.230** | -1.888 | **6.840** | **3.943** |
| | *p-values* | **<0.001** | 0.945 | **<0.001** | **0.001** |
| 3 | Count | 236 | 190 | 77 | 632 |
| | % in Cluster | 20.80% | 16.70% | 6.80% | 55.70% |
| | Residuals | -0.475 | 0.569 | 0.239 | -0.149 |
| | *p-values* | 1.000 | 1.000 | 1.000 | 1.000 |
| 4 | Count | 280 | 233 | 133 | 807 |
| | % in Cluster | 19.30% | 16.10% | 9.10% | 55.50% |
| | Residuals | -2.000 | -0.104 | **4.018** | -0.283 |
| | *p-values* | 0.727 | 1.000 | **<0.001** | 1.000 |

*Total Household Income*

| Cluster | Value | < $20,000 | $20,000-$39,999 | $40,000-$59,999 | $60,000-$79,999 | >=$80,000 |
|---|---|---|---|---|---|---|
| | Frequency | 6.78% | 17.46% | 21.09% | 16.70% | 37.96% |
| 1 | Count | 1192 | 3541 | 4344 | 3368 | 7696 |
| | % in Cluster | 5.90% | 17.60% | 21.60% | 16.70% | 38.20% |
| | Residuals | **-11.254** | 1.010 | 3.801 | 0.215 | 1.680 |
| | *p-values* | **<0.001** | 1.000 | 0.003 | 1.000 | 1.000 |
| 2 | Count | 175 | 315 | 382 | 365 | 822 |
| | % in Cluster | 8.50% | 15.30% | 18.60% | 17.70% | 39.90% |
| | Residuals | 3.237 | -2.703 | -2.953 | 1.308 | 1.914 |
| | *p-values* | 0.024 | 0.138 | 0.063 | 1.000 | 1.000 |
| 3 | Count | 159 | 224 | 230 | 159 | 363 |
| | % in Cluster | 14.00% | 19.70% | 20.30% | 14.00% | 32.00% |
| | Residuals | **9.914** | 2.064 | -0.702 | -2.486 | **-4.250** |
| | *p-values* | **<0.001** | 0.781 | 1.000 | 0.258 | **<0.001** |
| 4 | Count | 155 | 249 | 273 | 247 | 529 |
| | % in Cluster | 10.70% | 17.10% | 18.80% | 17.00% | 36.40% |
| | Residuals | **6.072** | -0.339 | -2.221 | 0.318 | -1.258 |
| | *p-values* | **<0.001** | 1.000 | 0.527 | 1.000 | 1.000 |

*Note: Post-hoc analysis of Minority Status was not necessary, as it was not significant in the Chi-Square Test. It was performed here simply to include the totality of the information.*

## Figures

### Figure 1

*Behavioral Model of Health Services Use (Andersen, 2008)*

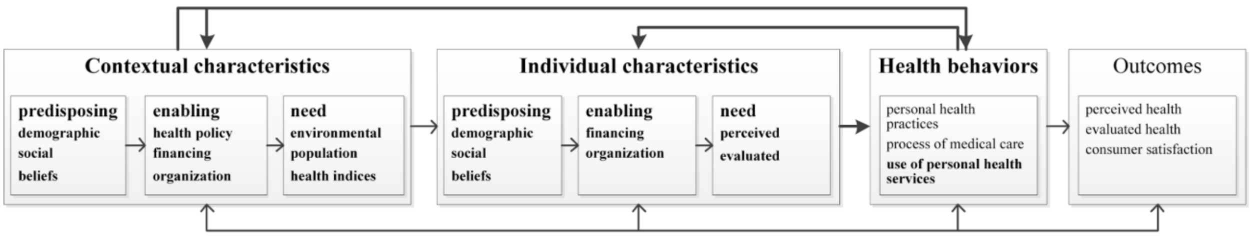


**Figure 2**

*Abridged Health Belief Model (Becker, 1974)*

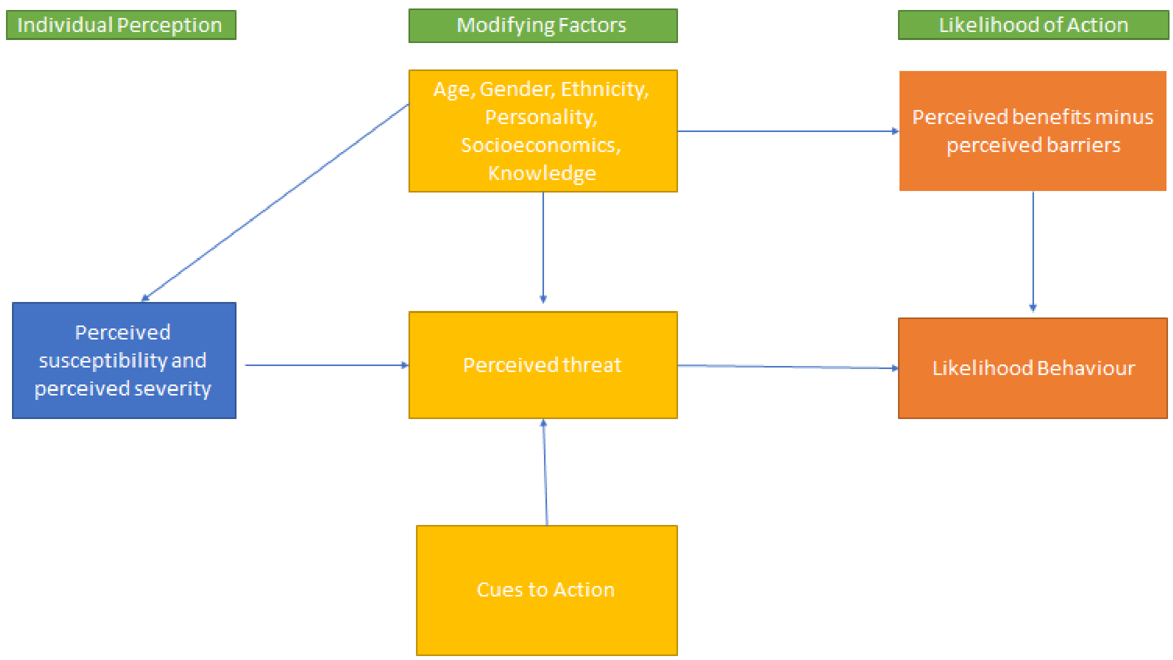


**Figure 3**

*HAC Dendrogram With Four Clusters*

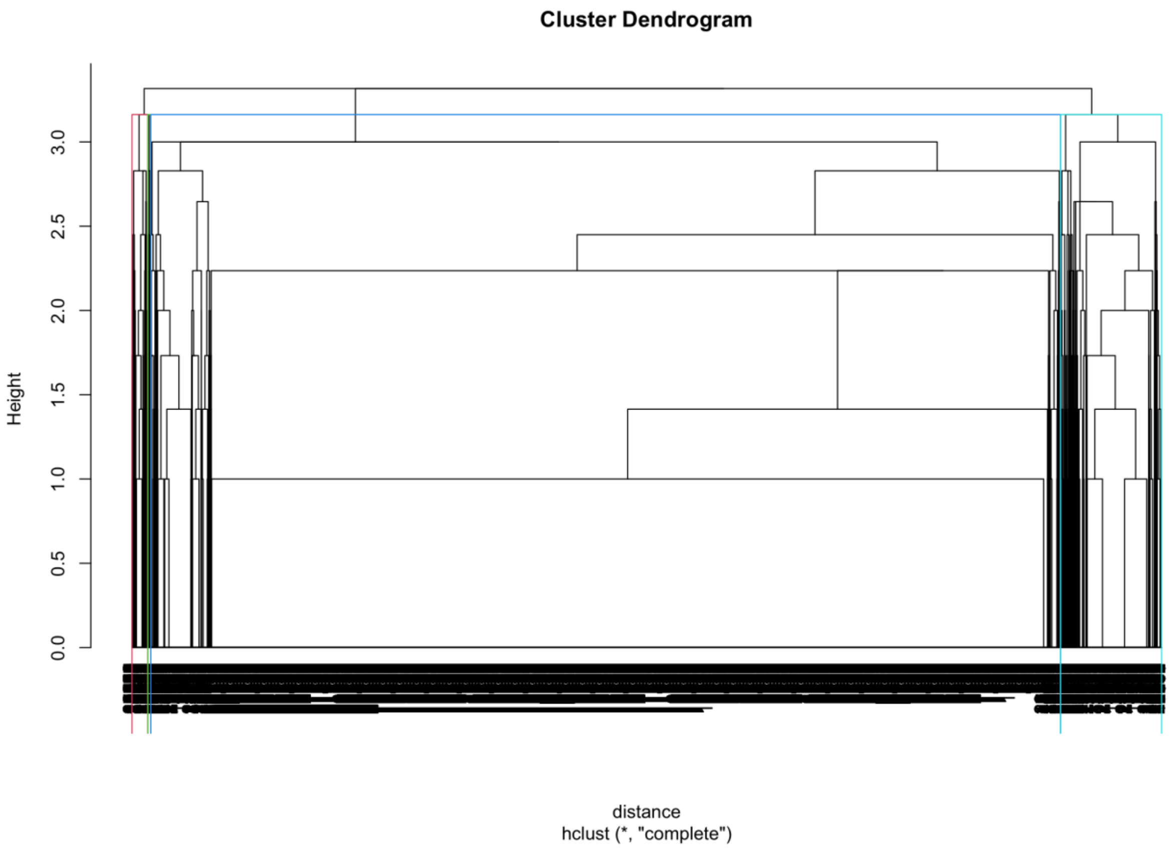


**Figure 4**

*Parallel Analysis Scree Plots*

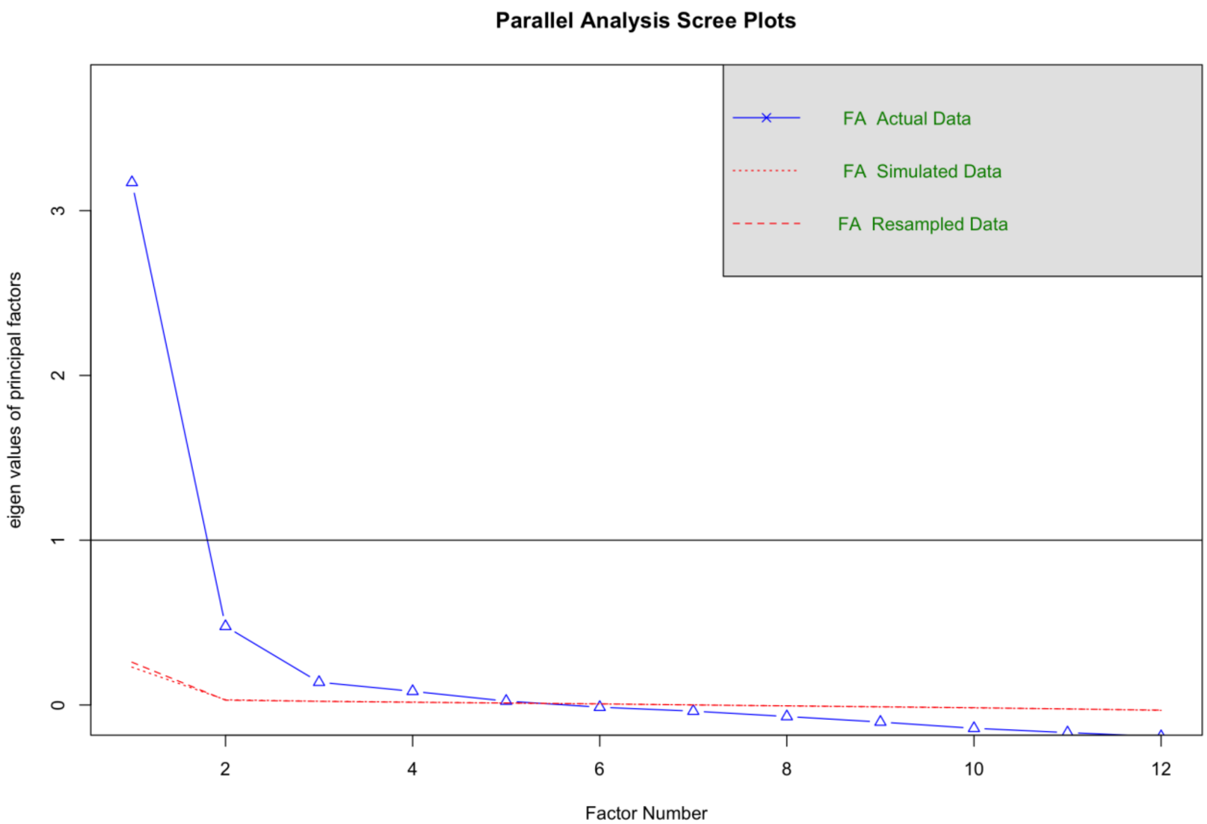


**Figure 5**

*Very Simple Structure (VSS) Plot*

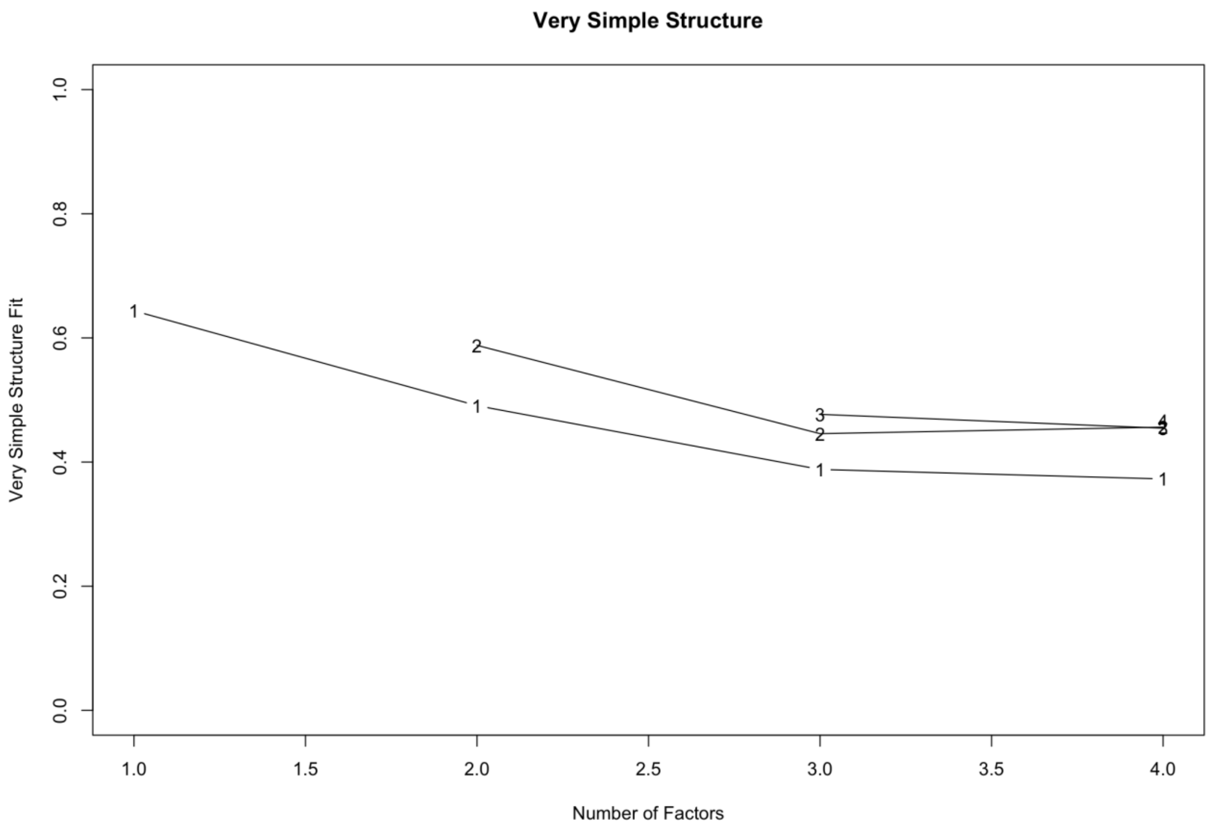


**Figure 6**

*Determining and Visualizing the Optimal Number of Clusters for the K-Means Clustering Algorithm: The Elbow Method*

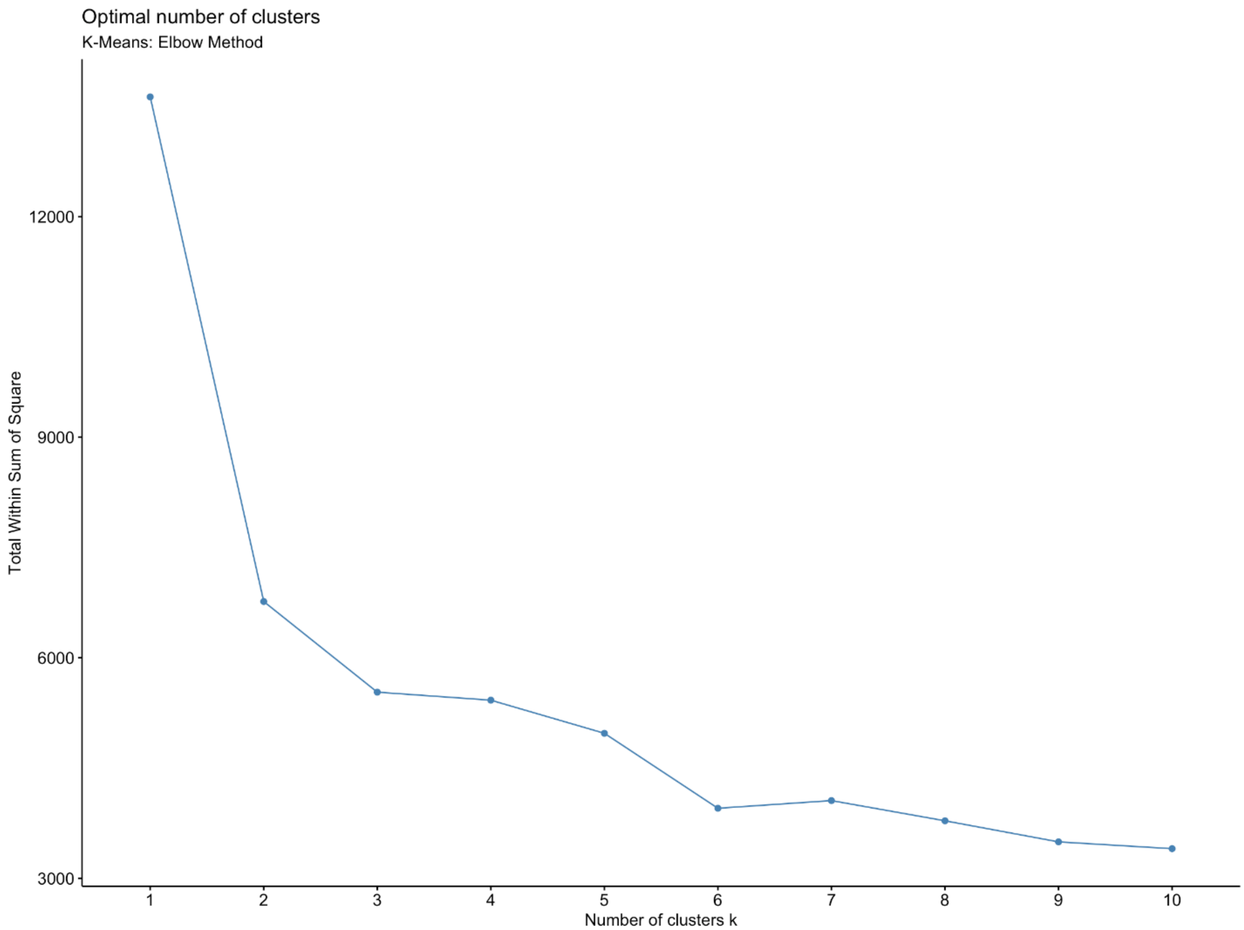


**Figure 7**

*Determining and Visualizing the Optimal Number of Clusters for the K-Means Clustering Algorithm: The Silhouette Method*

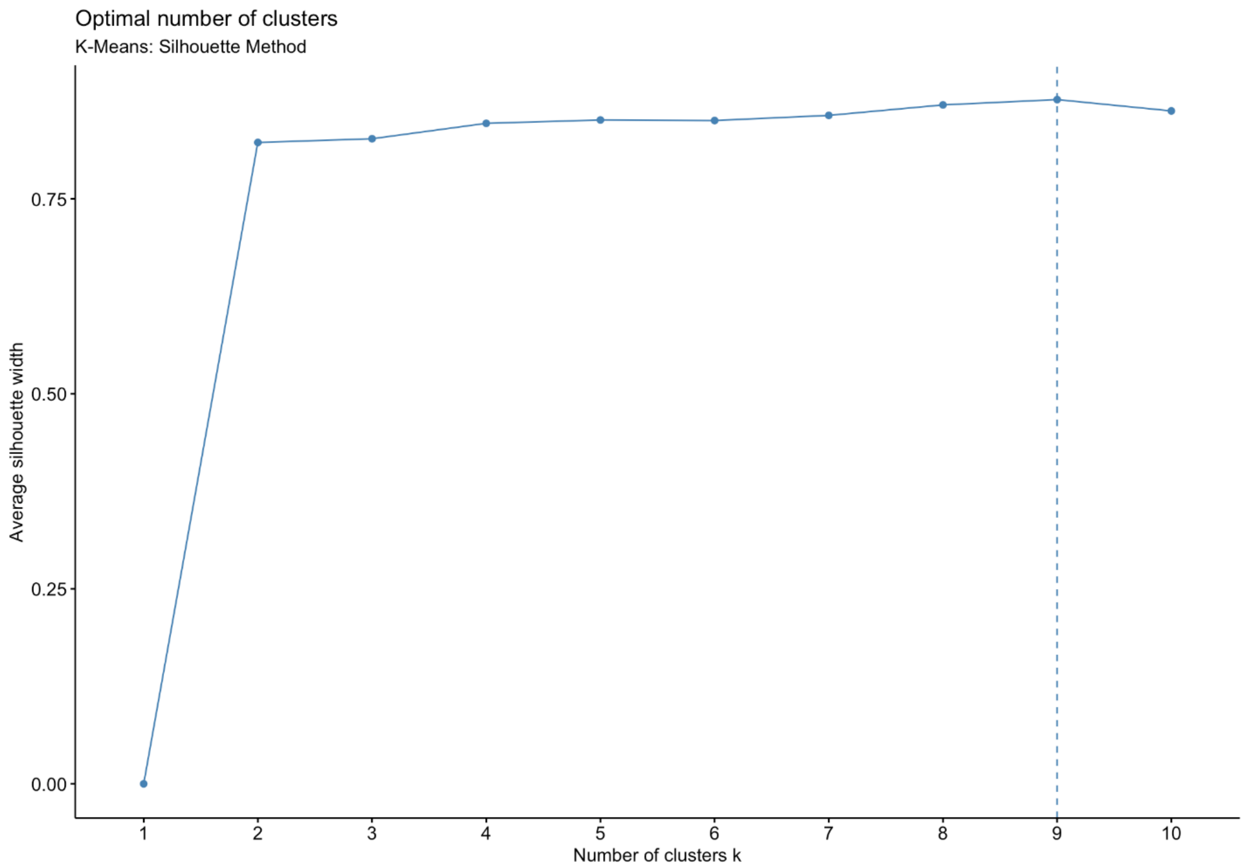


**Figure 8**

*Determining and Visualizing the Optimal Number of Clusters for the K-Means Clustering Algorithm: The Gap Statistic Method*

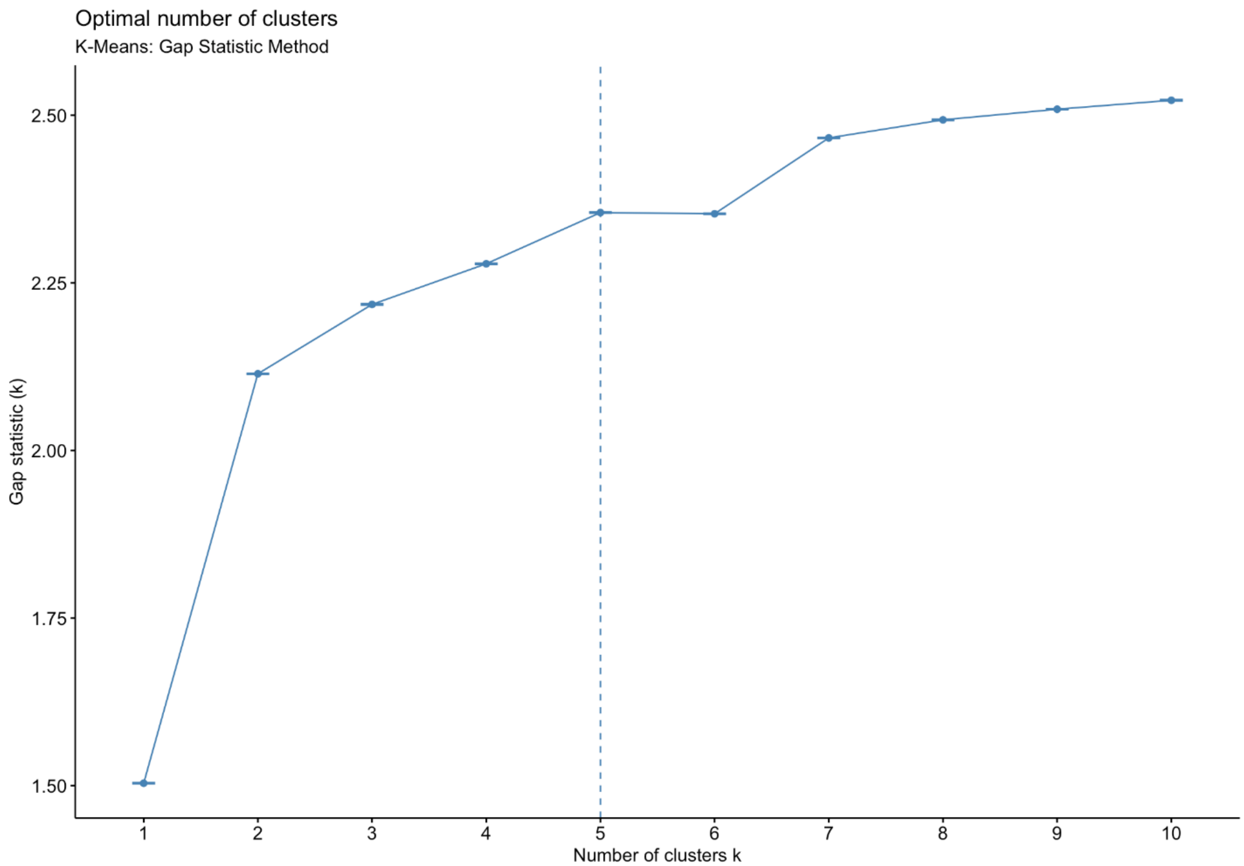


**Figure 9**

*Determining and Visualizing the Optimal Number of Clusters for the HAC Clustering Algorithm: The Elbow or Within Cluster Sums of Squares (WSS) Method*

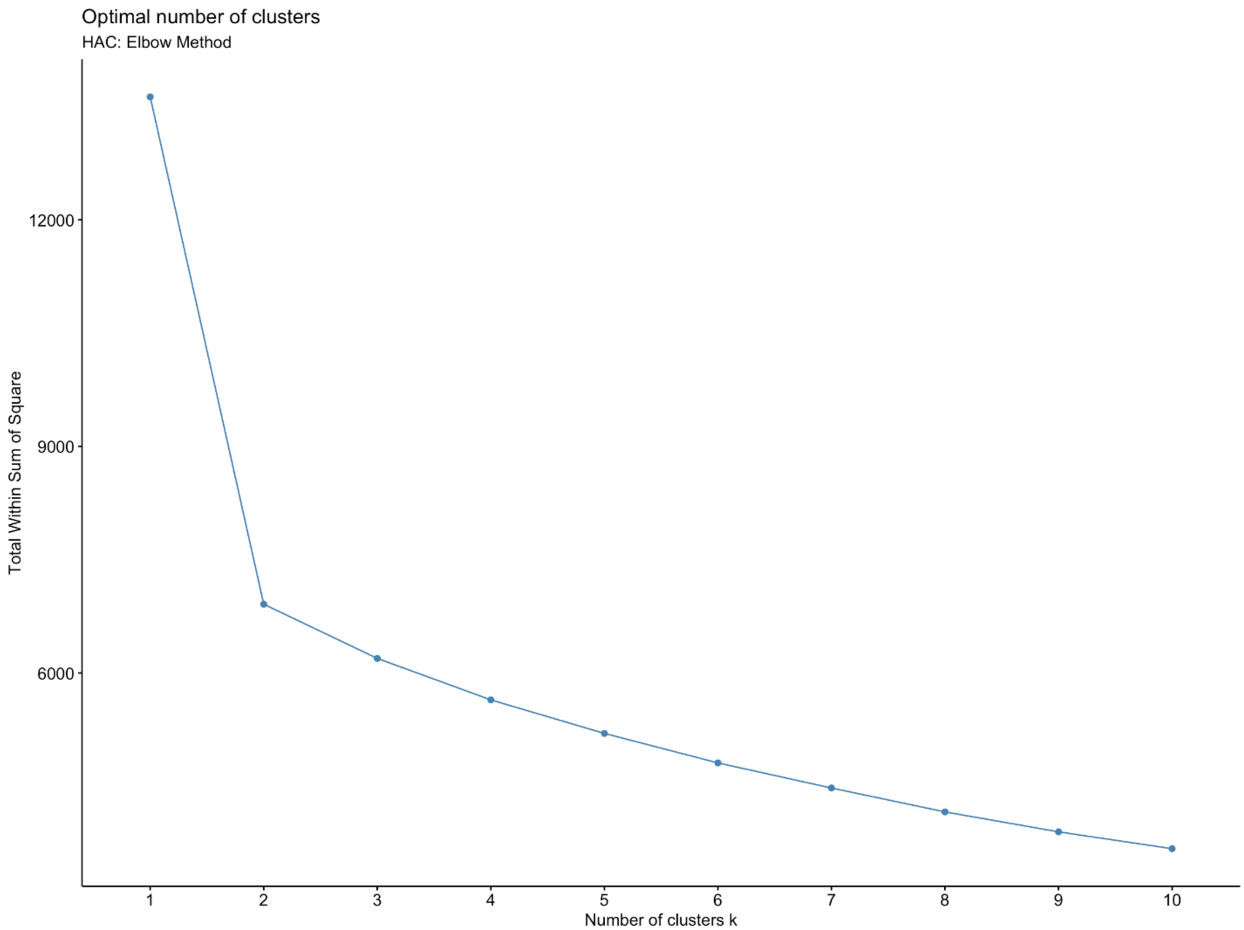


**Figure 10**

*Determining and Visualizing the Optimal Number of Clusters for the HAC Clustering Algorithm: The Average Silhouette Width Method*

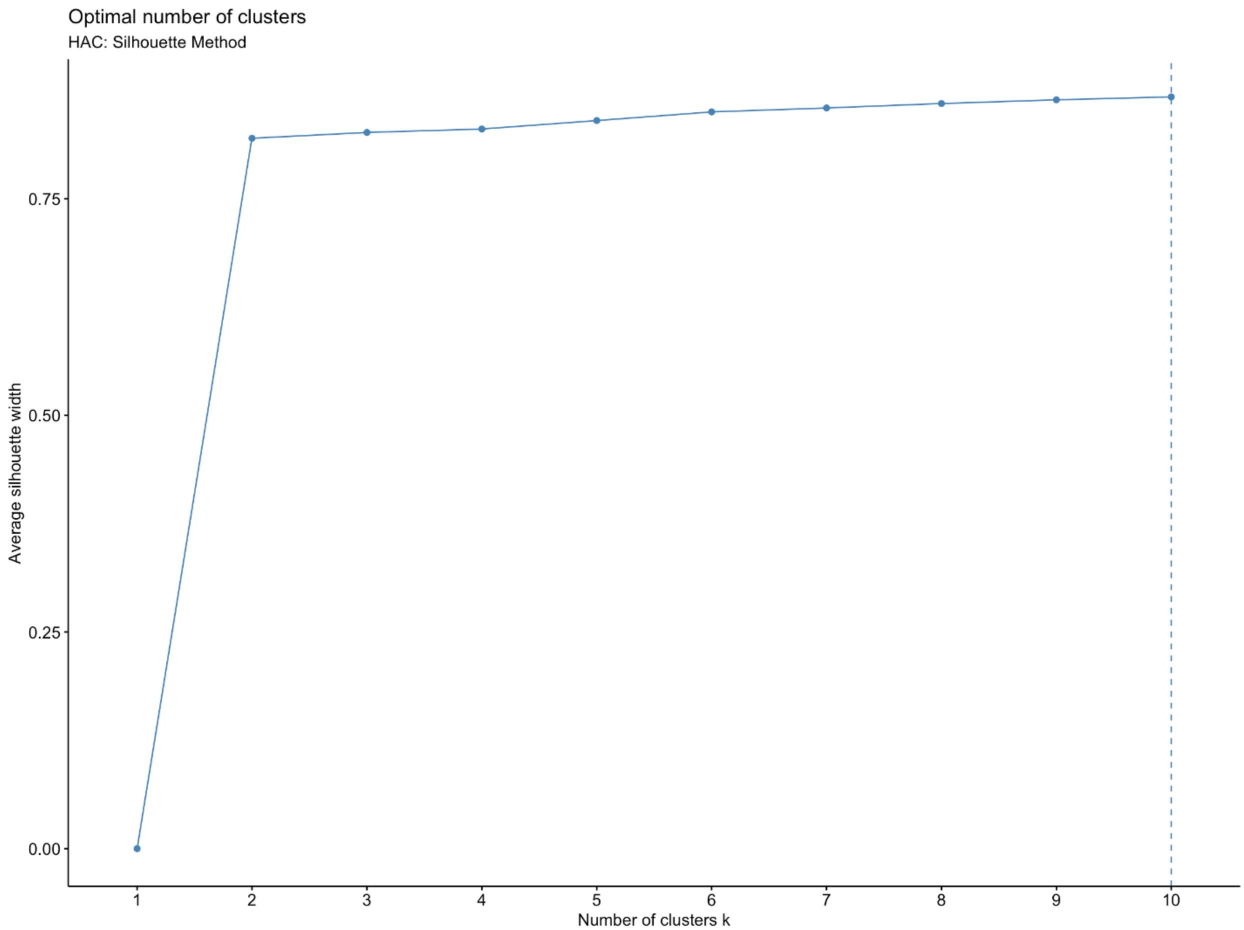


**Figure 11**

*Determining and Visualizing the Optimal Number of Clusters for the HAC Clustering Algorithm: The Gap Statistic Method*

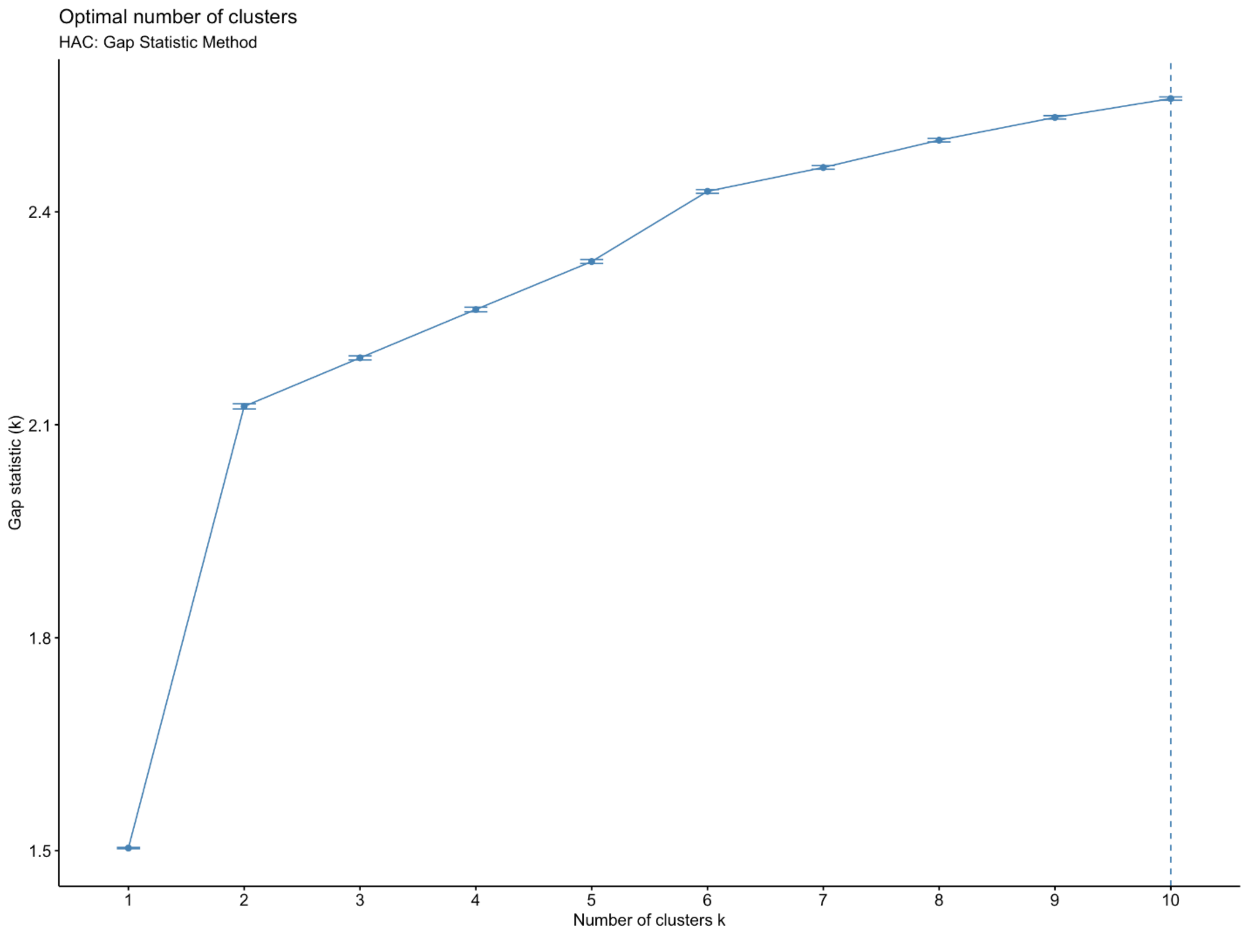


**Figure 12**

*Determining and Visualizing the Optimal Number of Clusters for the FCM Clustering Algorithm: The Elbow Method*

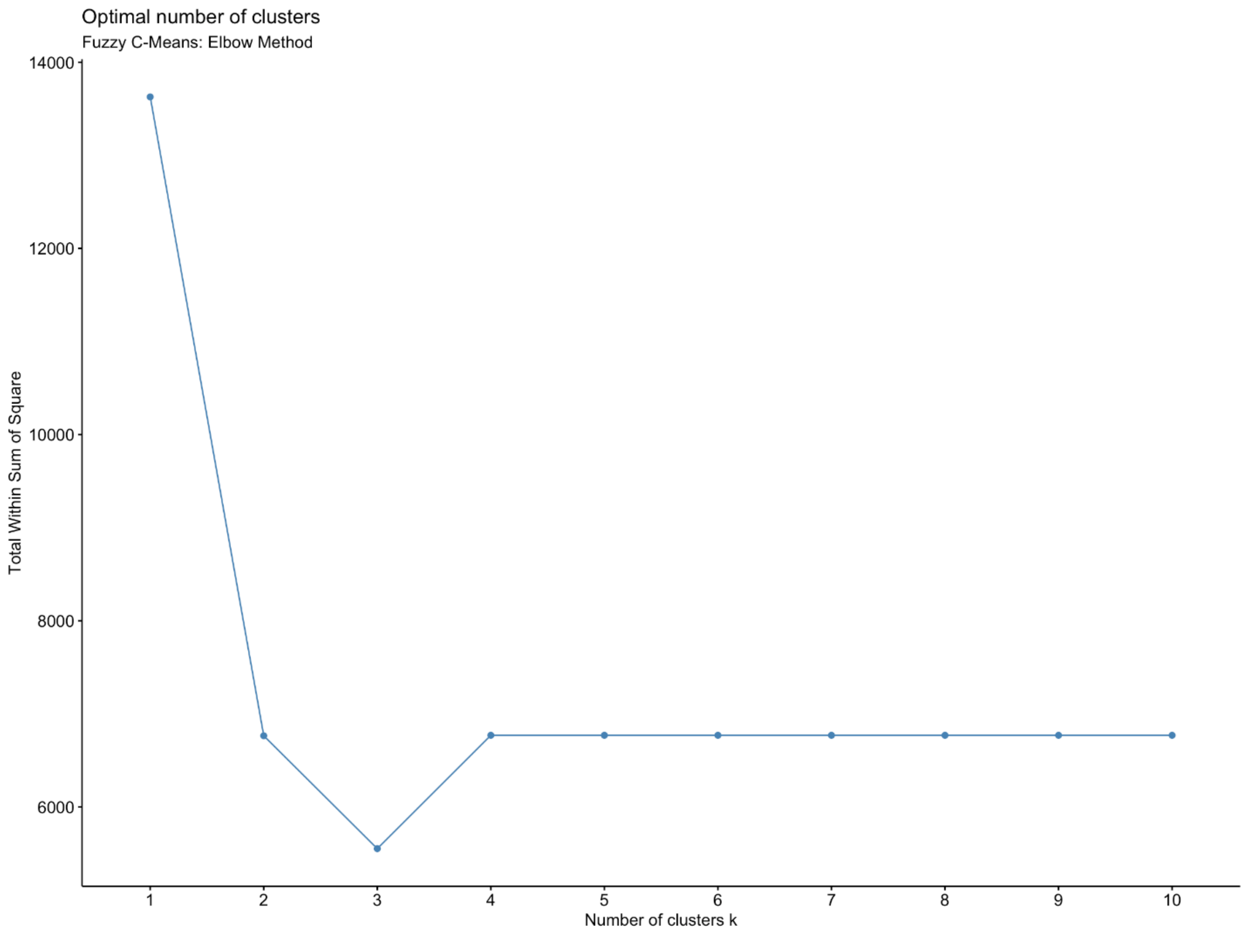


**Figure 13**

*Determining and Visualizing the Optimal Number of Clusters for the FCM Clustering Algorithm: The Silhouette Method*

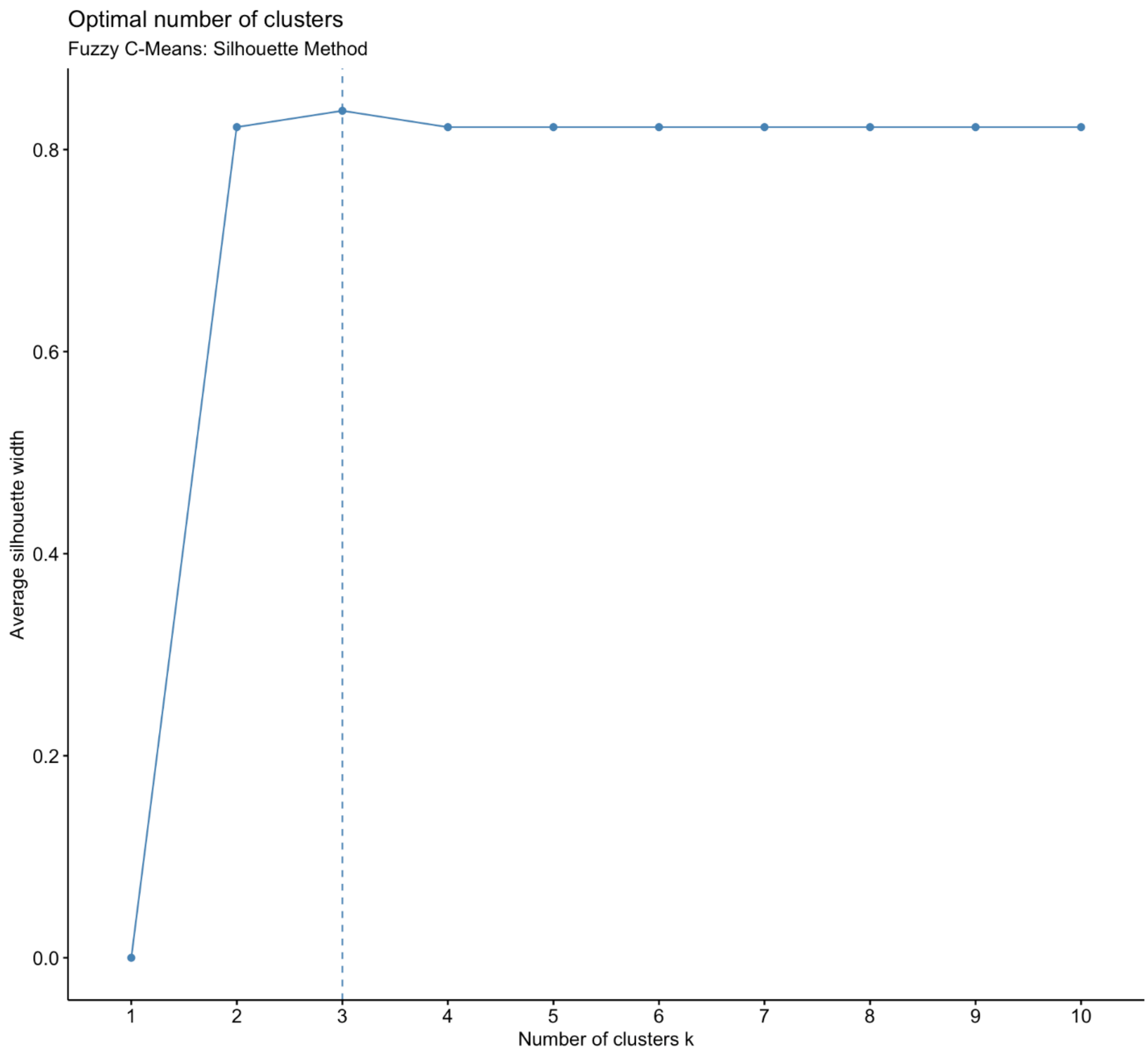


**Figure 14**

*Determining and Visualizing the Optimal Number of Clusters for the FCM Clustering Algorithm: The Gap Statistic Method*

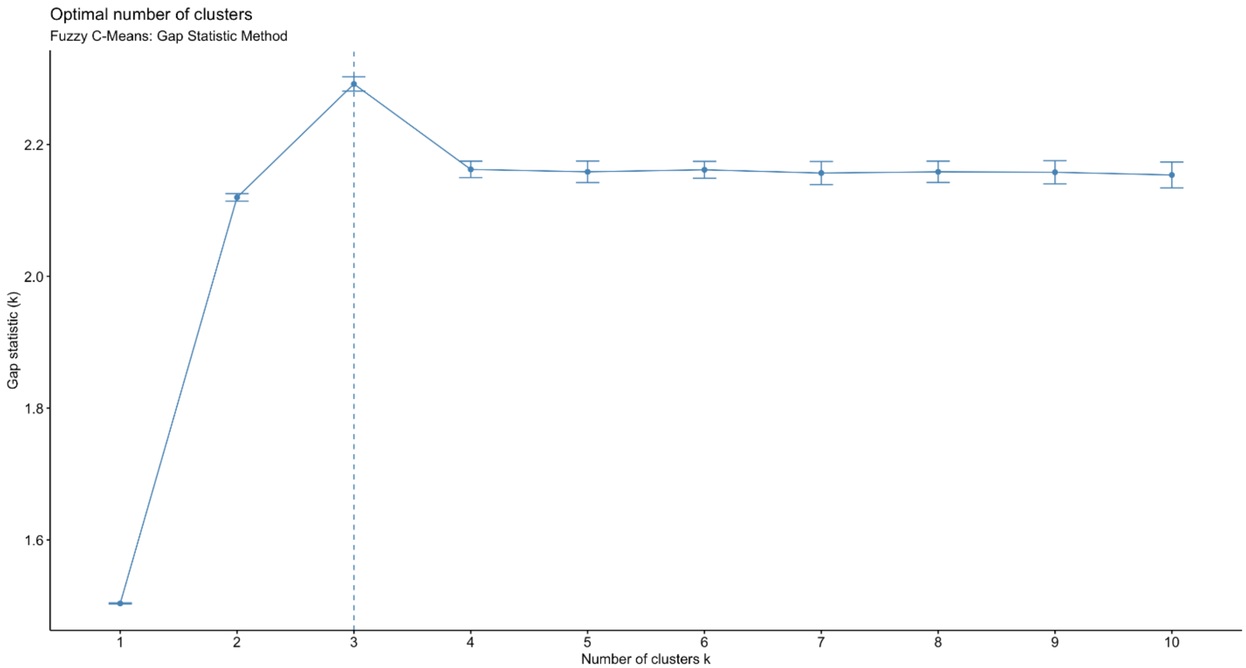


**Figure 15**

*Cluster Plot of CCHS Using the FCM Clustering Algorithm for Four Clusters*

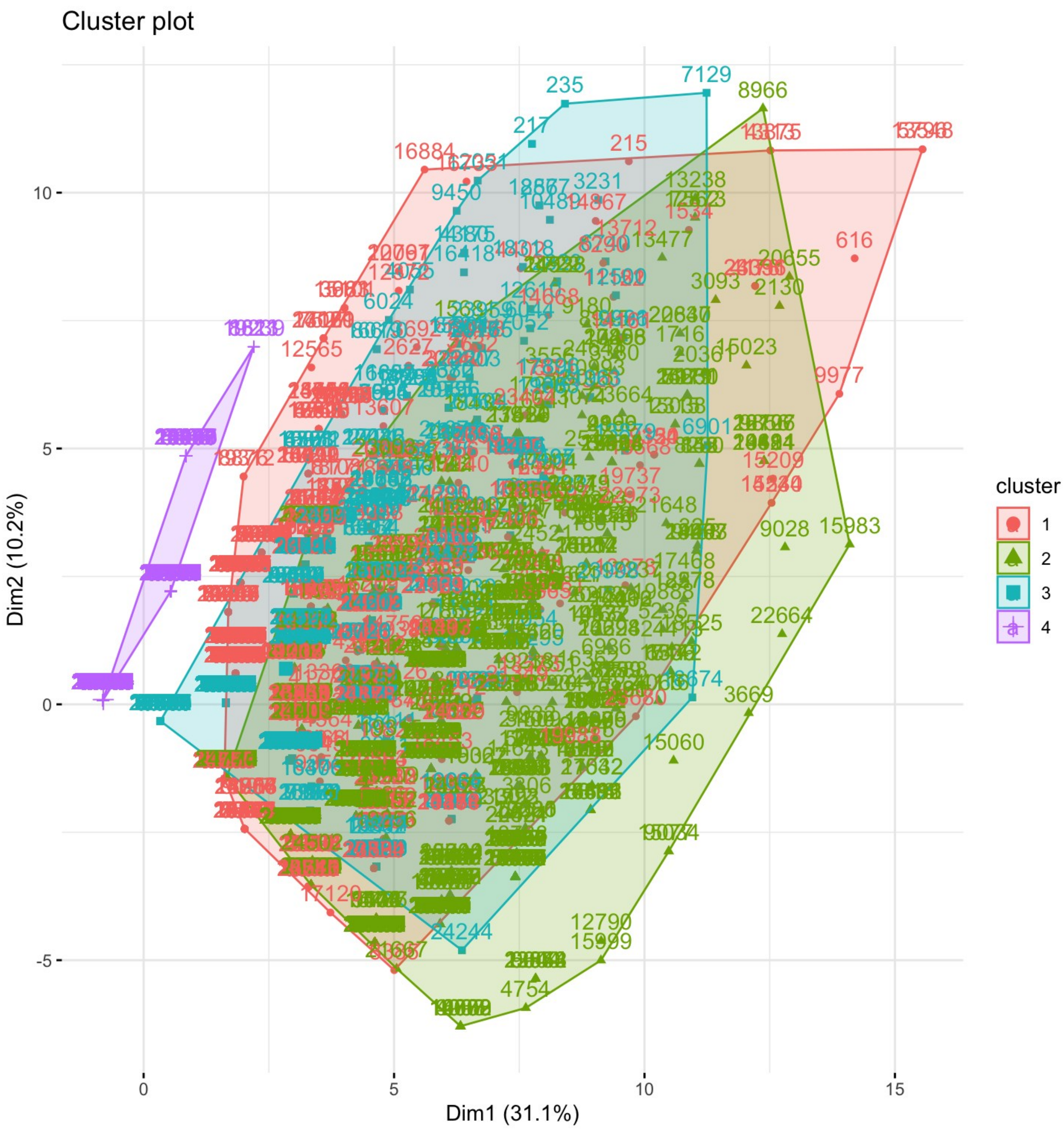
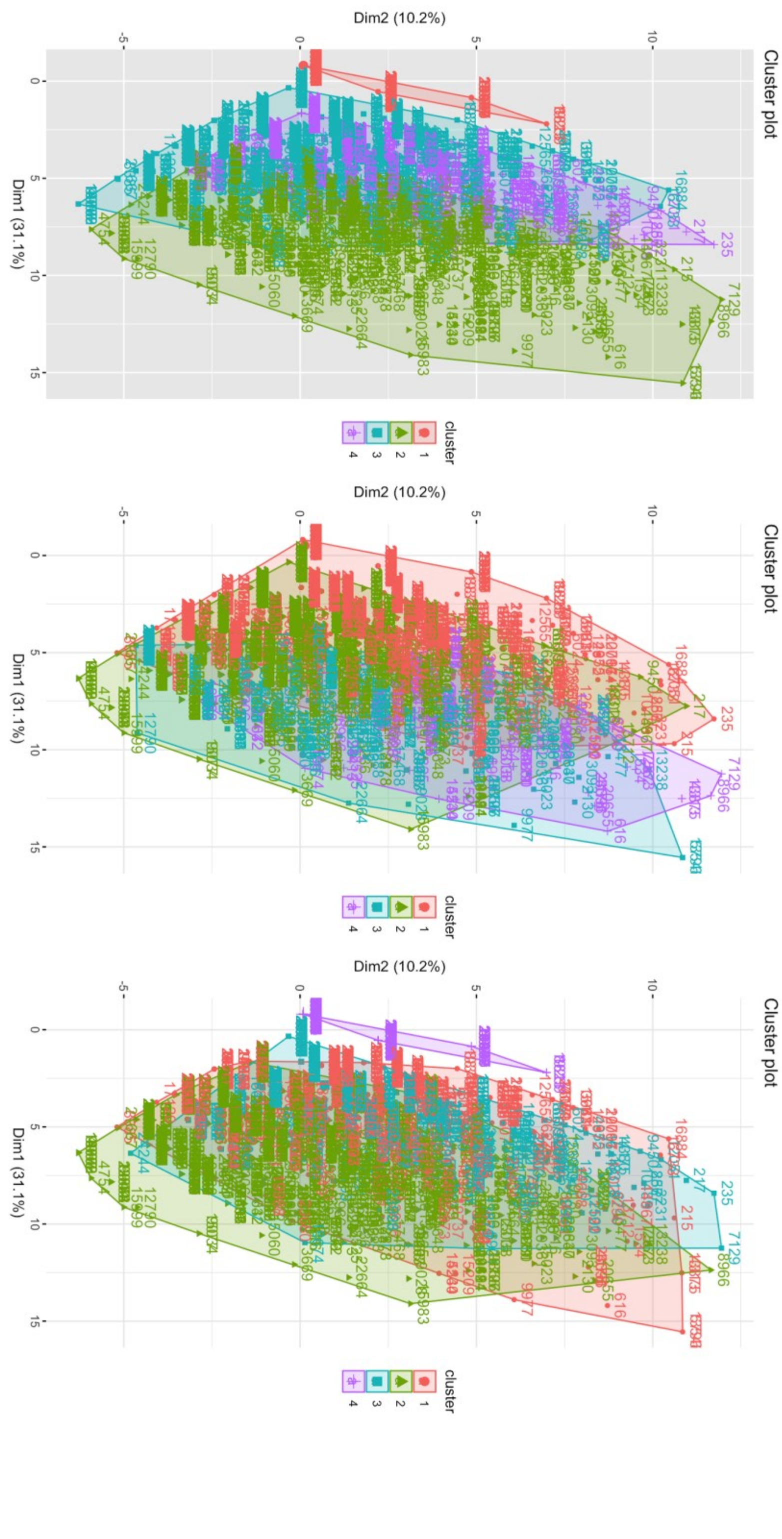


**Figure 16**

*Cluster Plot of CCHS Using the KM, HAC, and FCM Clustering Algorithms for Four Clusters*



# Appendices

## Appendix A. *Support Utilization Questionnaire*

**Table A1**

*During the past 12 months, have you ever seen, or talked on the telephone, to any of the following people about your emotions, mental health or use of alcohol or drugs? - Psychiatrist*

| Value | Label | Cases |
|---|---|---|
| 1 | Yes | 639 |
| 2 | No | 24449 |
| 6 | Not Applicable | 0 |
| 7 | Don't Know | 7 |
| 8 | Refusal | 18 |
| 9 | Not Stated | 0 |

**Table A2**

*During the past 12 months, have you ever seen, or talked on the telephone, to any of the following people about your emotions, mental health or use of alcohol or drugs? - Family doctor or general practitioner*

| Value | Label | Cases |
|---|---|---|
| 1 | Yes | 1901 |
| 2 | No | 23187 |
| 6 | Not Applicable | 0 |
| 7 | Don't Know | 7 |
| 8 | Refusal | 18 |
| 9 | Not Stated | 0 |

**Table A3**

*During the past 12 months, have you ever seen, or talked on the telephone, to any of the following people about your emotions, mental health or use of alcohol or drugs? - Psychologist*

| Value | Label | Cases |
|---|---|---|
| 1 | Yes | 632 |
| 2 | No | 24456 |
| 6 | Not Applicable | 0 |
| 7 | Don't Know | 7 |
| 8 | Refusal | 18 |
| 9 | Not Stated | 0 |

**Table A4**

*During the past 12 months, have you ever seen, or talked on the telephone, to any of the following people about your emotions, mental health or use of alcohol or drugs? - Nurse*

| Value | Label | Cases |
|---|---|---|
| 1 | Yes | 299 |
| 2 | No | 24789 |
| 6 | Not Applicable | 0 |
| 7 | Don't Know | 7 |
| 8 | Refusal | 18 |
| 9 | Not Stated | 0 |

**Table A5**

*During the past 12 months, have you ever seen, or talked on the telephone, to any of the following people about your emotions, mental health or use of alcohol or drugs? - Nurse*

| Value | Label | Cases |
|---|---|---|
| 1 | Yes | 299 |
| 2 | No | 24789 |
| 6 | Not Applicable | 0 |
| 7 | Don't Know | 7 |
| 8 | Refusal | 18 |
| 9 | Not Stated | 0 |

**Table A6**

*During the past 12 months, have you ever seen, or talked on the telephone, to any of the following people about your emotions, mental health or use of alcohol or drugs? - Social worker, counsellor or psychotherapist*

| Value | Label | Cases |
|---|---|---|
| 1 | Yes | 954 |
| 2 | No | 24134 |
| 6 | Not Applicable | 0 |
| 7 | Don’t Know | 7 |
| 8 | Refusal | 18 |
| 9 | Not Stated | 0 |

**Table A7**

*During the past 12 months, have you ever seen, or talked on the telephone, to any of the following people about your emotions, mental health or use of alcohol or drugs? - Family Member*

| Value | Label | Cases |
|---|---|---|
| 1 | Yes | 2334 |
| 2 | No | 22754 |
| 6 | Not Applicable | 0 |
| 7 | Don’t Know | 7 |
| 8 | Refusal | 18 |
| 9 | Not Stated | 0 |

**Table A8**

*During the past 12 months, have you ever seen, or talked on the telephone, to any of the following people about your emotions, mental health or use of alcohol or drugs? - Friend*

| Value | Label | Cases |
|---|---|---|
| 1 | Yes | 2588 |
| 2 | No | 22500 |
| 6 | Not Applicable | 0 |
| 7 | Don’t Know | 7 |
| 8 | Refusal | 18 |
| 9 | Not Stated | 0 |

**Table A9**

*During the past 12 months, have you ever seen, or talked on the telephone, to any of the following people about your emotions, mental health or use of alcohol or drugs? - Co-worker, supervisor, or boss*

| Value | Label | Cases |
|---|---|---|
| 1 | Yes | 624 |
| 2 | No | 24464 |
| 6 | Not Applicable | 0 |
| 7 | Don't Know | 7 |
| 8 | Refusal | 18 |
| 9 | Not Stated | 0 |

**Table A10**

*During the past 12 months, have you ever seen, or talked on the telephone, to any of the following people about your emotions, mental health or use of alcohol or drugs? - Teacher or school principal*

| Value | Label | Cases |
|---|---|---|
| 1 | Yes | 109 |
| 2 | No | 24979 |
| 6 | Not Applicable | 0 |
| 7 | Don't Know | 7 |
| 8 | Refusal | 18 |
| 9 | Not Stated | 0 |

**Table A11**

*During the past 12 months, have you ever seen, or talked on the telephone, to any of the following people about your emotions, mental health or use of alcohol or drugs? - None*

| Value | Label | Cases |
|---|---|---|
| 1 | Yes | 20374 |
| 2 | No | 4714 |
| 6 | Not Applicable | 0 |
| 7 | Don't Know | 7 |
| 8 | Refusal | 18 |
| 9 | Not Stated | 0 |

## **Appendix B.** ***Demographic Variable Questionnaire***

**Table B1**

*Province of Residence of Respondent*

| Value | Label | Cases |
|---|---|---|
| 10 | Newfoundland and Labrador | 1413 |
| 11 | Prince Edward Island | 1098 |
| 12 | Nova Scotia | 1714 |
| 13 | New Brunswick | 1672 |
| 24 | Quebec | 4348 |
| 35 | Ontario | 5492 |
| 46 | Manitoba | 1826 |
| 47 | Saskatchewan | 1709 |
| 48 | Alberta | 2785 |
| 59 | British Columbia | 3056 |
| 60 | Yukon | 0 |
| 61 | NWT | 0 |
| 62 | Nunavut | 0 |
| 96 | Not Applicable | 0 |
| 97 | Don’t Know | 0 |
| 98 | Refusal | 0 |
| 99 | Not Stated | 0 |

**Table B2**

*Census Metropolitan Area/CMA*

| Value | Label | Cases |
|---|---|---|
| 1 | Is a Census Metropolitan Area (CMA) | 14424 |
| 2 | Is not a Census Metropolitan Area | 10689 |
| 6 | Not Applicable | 0 |
| 7 | Don't Know | 0 |
| 8 | Refusal | 0 |
| 9 | Not Stated | 0 |

**Table B3**

*Province of Residence of Respondent*

| Value | Label | Cases |
|---|---|---|
| 1 | 15 to 19 years | 2024 |
| 2 | 20 to 24 years | 1989 |
| 3 | 25 to 29 years | 1617 |
| 4 | 30 to 34 years | 1869 |
| 5 | 35 to 39 years | 1729 |
| 6 | 40 to 44 years | 1691 |
| 7 | 45 to 49 years | 1670 |
| 8 | 50 to 54 years | 1956 |
| 9 | 55 to 59 years | 2245 |
| 10 | 60 to 64 years | 2206 |
| 11 | 65 to 69 years | 1918 |
| 12 | 70 to 74 years | 1432 |
| 13 | 75 to 79 years | 1184 |
| 14 | 80 years or more | 1583 |
| 96 | Not Applicable | 0 |
| 97 | Don’t Know | 0 |
| 98 | Refusal | 0 |
| 99 | Not Stated | 0 |

**Table B4**

*Sex*

| Value | Label | Cases |
|---|---|---|
| 1 | Male | 11340 |
| 2 | Female | 13773 |
| 6 | Not Applicable | 0 |
| 7 | Don't Know | 0 |
| 8 | Refusal | 0 |
| 9 | Not Stated | 0 |

**Table B5**

*Marital Status*

| Value | Label | Cases |
|---|---|---|
| 1 | Married | 10338 |
| 2 | Common-Law | 2331 |
| 3 | Widowed | 2359 |
| 4 | Divorced or Separated | 2785 |
| 5 | Single | 7332 |
| 6 | Not Applicable | 0 |
| 7 | Don't Know | 0 |
| 8 | Refusal | 0 |
| 9 | Not Stated | 0 |

**Table B6**

*Total Household Income*

| Value | Label | Cases |
|---|---|---|
| 1 | No Income or Less Than $20,000 | 1736 |
| 2 | $20,000-$39,999 | 4410 |
| 3 | $40,000-$59,999 | 5289 |
| 4 | $60,000-$79,999 | 4176 |
| 5 | $80,000 or more | 9488 |
| 6 | Not Applicable | 0 |
| 7 | Don’t Know | 0 |
| 8 | Refusal | 0 |
| 9 | Not Stated | 14 |

**Table B7**

*Immigrant*

| Value | Label | Cases |
|---|---|---|
| 1 | Yes | 4245 |
| 2 | No | 20726 |
| 6 | Not Applicable | 0 |
| 7 | Don’t Know | 0 |
| 8 | Refusal | 0 |
| 9 | Not Stated | 142 |

**Table B8**

*White or Non-White Race/Visible Minority*

| Value | Label | Cases |
| --- | --- | --- |
| 1 | White | 20871 |
| 2 | Non-White | 4141 |
| 6 | Not Applicable | 0 |
| 7 | Don’t Know | 0 |
| 8 | Refusal | 0 |
| 9 | Not Stated | 101 |

**Table B9**

*Highest Level of Education*

| Value | Label | Cases |
| --- | --- | --- |
| 1 | < Than Secondary | 5338 |
| 2 | Secondary Grad. | 4022 |
| 3 | Some Post-Sec | 1655 |
| 4 | Post-Sec. Grad | 13987 |
| 6 | Not Applicable | 0 |
| 7 | Don’t Know | 0 |
| 8 | Refusal | 0 |
| 9 | Not Stated | 111 |