Literature Review

**Team:**

Kavya Bulusu (0734186)

Vanita Patel (0734890)

Jinali Patel (0734623)

1. [The Economic Burden of Mental Health Problems in Canada](#_Toc33357333)

Thomas Stephens and Natacha Jouber

1. [Mental Health of the Canadian Population: A Comprehensive Analysis](#_Toc33357334)

Thomas Stephens, Corinne Dulberg and Natacha Jouber

1. Machine learning in mental health: a scoping review of methods and applications

Adrian B. R. Shatte, Delyse M. Hutchinson and Samantha J. Teague

1. Machine learning for precision psychiatry

Prof. Danilo Bzdok, M.D., Ph.D. & Prof. Andreas Meyer-Lindenberg, M.D.

1. Perceived need for mental health care in Canada: Results from the 2012 Canadian Community Health Survey–Mental Health

by Adam Sunderland and Leanne C. Findlay

# **The Economic Burden of Mental Health Problems in Canada**

Link: Retrieved 23 February 2020, from <https://www.researchgate.net/profile/Michel_Lavoie/publication/11942928_The_storage_of_household_long_guns_The_situation_in_Quebec/links/54cabb8e0cf2517b756002eb.pdf#page=20>

This study provides a comprehensive estimate of the economic burden of mental health problems in Canada in 1998. The source of data for the original analyses in this study was the 1996/97 NPHS “share” file. The NPHS is the biennial survey conducted by Statistics Canada to describe health status and health determinants.

They used NPHS (National Population Health Survey) questions on depression and distress as evidence of mental health problems. The distress scale includes many symptoms of anxiety (e.g., feeling nervous, restless or fidgety) and, with the depression scale, provides a reasonably comprehensive view of population mental health problems. Depression was defined according to the Statistics Canada definition as a probability of 90% or greater of a major depressive episode in the previous year; the overall prevalence rate is 4%. Unlike depression, there is no independently verified definition of “high distress” for the measure used in the NPHS. They used as a definition a response of “a lot” or “some” to the question “How much do these (distressing) experiences interfere with your life or activities?” regardless of level of distress on the 24-item scale preceding the question on impact. By this definition, 15% of Canadians can be regarded as distressed.

In result, it estimates the cost of non-medical services that have not been previously published and the value of short-term disability associated with mental health problems that was previously underestimated. The costs of consultations with psychologists and social workers not covered by public health insurance was $278 million, while the value of reduced productivity associated with depression and distress over the short term was $6 billion. Several data limitations suggest that these are underestimates. The estimated total burden of $14.4 billion places mental health problems among the costliest conditions in Canada.

Only more “services” will not help in fulfilling to the population’s mental health needs. What is evidently needed is support from the family and the community. Social support can be increased by fostering the development of meaningful relationships in families and social environments – in schools, workplaces, the community and institutions.

# **Mental Health of the Canadian Population: A Comprehensive Analysis**

Link: Retrieved 23 February 2020, from <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.110.7477&rep=rep1&type=pdf#page=16>

This study involved secondary analysis of the public use data file of the 1994/95 National Population Health Survey (NPHS). Data from the National Population Health Survey (NPHS), analyzed by logistic regression, reveal consistently strong, graded, independent associations of current stress, social support, life events, education and childhood traumas with both positive and negative indicators of mental health status. Sex differences exist for four of eight measures. For most indicators, mental health is relatively poor among youth and improves with age. Physical and mental health problems are associated.

Independent of all other variables, age was clearly related to psychological well-being (SOC), which increased impressively with age. Poorer mental health is more common among youth than older age groups, at least on these indicators. Education was strongly related to six measures of mental health and had a consistent, graded association with four. Self-esteem, mastery and happiness/interest in life all increased with amount of formal education. Interestingly, with more education the impact of distress became increasingly more likely to affect one’s life. Social support was second only to current stress in its importance for mental health: it was strongly and positively associated with SOC, self-esteem, mastery and happiness, and negatively related to depression, level of distress and impact of distress. Persons with high levels of social support had only half the odds of being affected by distress, even when the amount of distress was held constant.

Analysis of associations of demographic and psychosocial factors with all of these outcome measures leads to an important conclusion: the psychosocial and demographic factors associated with mental health problems were also found to be (inversely) associated with the indicators of positive mental health. This implies that strategies that promote resilience and other psychological resources will also contribute to problem reduction or even prevention.

More generally, health promotion and disease prevention can be seen as two sides of the same coin and entirely compatible, even mutually reinforcing. Mental health promotion consists of establishing those conditions that will foster resilience and support, and lead to positive states such as satisfaction and happiness. It is clear from the analysis that such conditions include, broadly stated, a reduction in current stressors and childhood traumas and a fostering of social support.

**Machine learning in mental health: a scoping review of methods and applications**

**Link:** (2020). Retrieved 24 February 2020, from <https://www.cambridge.org/core/services/aop-cambridge-core/content/view/0B70B1C827B3A4604C1C01026049F7D9/S0033291719000151a.pdf/machine_learning_in_mental_health_a_scoping_review_of_methods_and_applications.pdf>

This paper aims to synthesise the literature on machine learning (ML) and big data applications for mental health, highlighting current research and applications in practice. They employed a scoping review methodology to rapidly map the field of ML in mental health. Eight health and information technology research databases were searched for papers covering this domain.

Articles were assessed by two reviewers, and data were extracted on the article’s mental health application, ML technique, data type, and study results. Articles were then synthesised via narrative review. Three hundred papers focusing on the application of ML to mental health were identified. Four main application domains emerged in the literature, including: (i) detection and diagnosis; (ii) prognosis, treatment and support; (iii) public health, and; (iv) research and clinical administration. The most common mental health conditions addressed included depression, schizophrenia, and Alzheimer’s disease.

For each article, data were extracted regarding: (i) the aim of research; (ii) area of mental health focus; (iii) data type; (iv) ML methods used; (v) results; (vi) the country of the author group; and, (vii) the discipline area of authors (e.g. health fields, data science fields, or both). To analyse the data, a narrative review synthesis method was selected to capture the large range of research investigating ML and big data for mental health. It should be noted that a meta-analysis was not appropriate for this review given the broad range of mental health conditions, ML techniques, and types of data used in the studies identified

ML techniques used included support vector machines, decision trees, neural networks, latent Dirichlet allocation, and clustering. the application of ML to mental health has demonstrated a range of benefits across the areas of diagnosis, treatment and support, research, and clinical administration. With the majority of studies identified focusing on the detection and diagnosis of mental health conditions, it is evident that there is significant room for the application of ML to other areas of psychology and mental health. The challenges of using ML techniques are discussed, as well as opportunities to improve and advance the field.

**Machine learning for precision psychiatry**

Link: (2020). Retrieved 24 February 2020, from <https://arxiv.org/ftp/arxiv/papers/1705/1705.10553.pdf>

Current drug treatment choices are only successful in roughly every second patient , and similar considerations apply to psychotherapy. An alternative research strategy that does not depend on full understanding of complex disease mechanisms may therefore be cheaper and incur shorter delays between bench and beside. Indeed, the psychiatrist's choice of the best-possible treatment option often does not depend on knowledge of what has caused or maintains the mental disease of a given patient. Systematically benchmarking the predictability of clinical quantities in single patients could faster improve clinical symptoms and reduce subjective suffering in many mental diseases. Even moderately successful predictive models can be highly useful in clinical practice. This is because of the unfortunate normal case of trial-and-error treatment with psychotropic drugs and other types of treatment for many mental diseases. While the traditional research goal was to introduce novel treatment options that benefit some majority of the respective clinical group, an attractive alternative research goal is to improve the choice of existing treatment options by predicting their effectiveness in single patients.

Machine learning methods have always had a strong focus on prediction as a metric of statistical quality (12). Support vector machines, neural-network algorithms, and many other predictive models are hence readily able to estimate an outcome from only one data point, such as when querying answers from behavioural, neural, or genetic measurements of a single patient (20, 21). In contrast, classical statistical methods are often used in medical research to explain variance of and formally test for group effects.

Machine learning offers a statistical culture that can readily appreciate the smooth transition between well-being and illness as well as the foggy boundaries between disease categories. Learning algorithms hold promise for the biologically grounded reconstruction of psychiatric disease descriptions by uncovering and leveraging inter-individual variation across behaviour, experience, brain, and genetics. Data-derived disease manifolds can transcend the traditional disease categories portrayed in the DSM and ICD that today govern treatment choice and prognosis (24). The statistical properties of learning algorithms could thus enable clinical translation of empirically justified single patient prediction in a fast, cost-effective, and pragmatic manner. Patient-level predictive analytics might help psychiatry to move from strong reliance on symptom phenomenology to catch up with biology-centred decision-making in other medical specialities.

**Perceived need for mental health care in Canada: Results from the 2012 Canadian Community Health Survey–Mental Health**

Link: Retrieved 24 February 2020, from <https://pdfs.semanticscholar.org/23c8/97b7a04a68e51c2177a05b8429c59e817e9e.pdf>

Many Canadians experience a need for mental health care (MHC), but not all of those needs are met. This is the study based on Past research and national survey data on Canadians’ perceived need for mental health care (MHC) have focused on unmet needs overall and have not considered speciﬁc types of MHC needs or the extent to which needs are met. Rates of unmet needs were higher among people with the criteria for mental illness,8 especially those with depression.9 This is relevant considering that, in 2012, an estimated 10% of Canadians experienced a mental disorder (depression, bipolar disorder, generalized anxiety disorder, or alcohol, cannabis or substance abuse or dependence) in the past year.

They used data from 2012 Canadian Community Health Survey–Mental Health (CCHS-MH), and based on the data this article describes the prevalence of four types of perceived MHC needs for information, medication, counselling, and other services. The degree to which they are met in relation to risk factors for MHC needs, speciﬁcally, mental disorders, distress, or chronic physical health condition(s). Possible barriers to receiving MHC are also explored. Associations between risk factors for having MHC needs and the extent to which needs were met are investigated.

The data provides national estimates of major mental disorders and the provision of MHC services. The survey sample consisted of the household population aged 15 or older in the 10 provinces The CCHS–MH contained questions about four types of help for problems with emotions, mental health or the use of alcohol or drugs: 1) information about problems, treatments or services; 2) medication; 3) counselling, therapy, or help for problems with personal relationships; and 4) other mental health services. Respondents were asked which types of help they had received in the previous 12 months. Based on this information, a four-level need status variable was created for each type of MHC: 1) no need; 2) unmet (did not receive that type of help but perceived a need for it); 3) partially met (received help but perceived a need for more); and 4) met (received help and did not perceive a need for more).

Analyses of MHC needs often employ Andersen’s Behavioural Model of Health Services Use,8,23,24 which identiﬁes certain predisposing characteristics (related to the tendency to use health care services), enabling resources (availability of facilities and personnel, and the knowledge and ability to access them) and needs-related factors (health status) as being associated with health care use. In the predisposing characteristics- Respondents provided information on sex, age, immigration status, and marital status. Four age groups were deﬁned: 15 to 24; 25 to 44; 45 to 64; and 65 or older, Marital status was grouped into three categories: married or common-law; divorced, separated or widowed; and single, never married. Moreover, Education, household income, employment status, and geographic location were considered to be enabling resources. Needs-related factors is the assessment of mental or substance disorder. Six mental disorders (lifetime and past year) were included: depression, bipolar disorder, generalized anxiety disorder, alcohol abuse and dependence, cannabis abuse and dependence, and substance abuse and dependence.

In this study they use descriptive statistics to determine the percentage of Canadians aged 15 or older who perceived MHC needs (any and by type). Needs were explored based on the presence of risk factors for MHC: a mental or substance disorder, distress, and chronic physical conditions. Logistic regression analysis was used to examine independent associations between these risk factors and having any MHC need (versus no need). Predisposing (sex, age group, immigration status, and marital status) and enabling (education, household income, employment status, and population centre/rural) factors were included as covariates.

As a result, they found that One in six has MHC need. In 2012, an estimated 17% of the population aged 15 or older reported having an MHC need in the past 12 months. Two-thirds (67%) reported that their need was met; for another 21%, the need was partially met; and for 12%, the need was unmet. The most reported need was for counselling, which was also the least likely to be met. Distress was identiﬁed as a predictor of perceived MHC need status. Many Canadians are estimated to have MHC needs, 12% reported a need for counselling; 10% reported a need for medication; 7% reported a need for information; and 1% reported another type of need. The presence of a mental disorder, higher distress, and chronic physical conditions were positively associated with perceiving an MHC need, many of which were unmet or only partially met. As well, higher levels of distress predicted a greater likelihood that needs would be unmet or partially met.

# **Our Project: Prediction of Mental Health based on Severity**

We will be using data from Statistics Canada for the year 2015 – 2016. Our results and analysis differ conceptually from above literatures. Above literatures have a definition of mental illness that includes depression and distress, while our focus will be on diagnosed and undiagnosed mental illness. More than one-fourth of the total burden was attributed to undiagnosed mental illness population, and they accounted for about 30% of the direct medical cost. Data covered several self-reported indicators of mental health on the positive dimension, including sense of coherence, self-esteem, mastery and happiness/interest in life, and on the negative side, depression, level of distress, impact of distress and cognitive impairment. Data also have information on a wide range of demographic attributes, and on psychosocial and physical health factors that are plausibly related to mental health. The demographic factors analysed here were age, sex, province of residence, education, income adequacy and household type.

Based on all data provided, our target is to consider all related factors to design descriptive analytics which shows analytics of diagnosed mental illness and design predictive model which predicts mental health of undiagnosed illness. In addition, we will design definitive appropriate model that predicts the different forms of future data recorded in the platform (website) by making use of the available tools and technologies. We will make the website readily available for public to use and creating an awareness to make use of it.

**References**

1. TheEconomicBurdenofMentalHealthProblemsinCanada. (2020).

Retrieved 23 February 2020, from <https://www.researchgate.net/profile/Michel_Lavoie/publication/11942928_The_storage_of_household_long_guns_The_situation_in_Quebec/links/54cabb8e0cf2517b756002eb.pdf#page=20>

1. MentalHealthoftheCanadianPopulation: AComprehensiveAnalysis. (2020).

Retrieved 23 February 2020, from <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.110.7477&rep=rep1&type=pdf#page=16>

1. Machine learning in mental health: a scoping review of methods and applications

(2020). Retrieved 24 February 2020, from <https://www.cambridge.org/core/services/aop-cambridge-core/content/view/0B70B1C827B3A4604C1C01026049F7D9/S0033291719000151a.pdf/machine_learning_in_mental_health_a_scoping_review_of_methods_and_applications.pdf>

**4. Machine learning for precision psychiatry**

(2020). Retrieved 24 February 2020, from <https://arxiv.org/ftp/arxiv/papers/1705/1705.10553.pdf>

**5. Perceived need for mental health care in Canada: Results from the 2012 Canadian Community Health Survey–Mental Health. (2020).**

Retrieved 24 February 2020, from https://pdfs.semanticscholar.org/23c8/97b7a04a68e51c2177a05b8429c59e817e9e.pdf