# MODELLING CO-OCCURRING AND CO-VARYING REPORTED HEALTH BEHAVIOURS:
# APPLICATIONS OF MACHINE LEARNING AND NETWORK PSYCHOMETRICS

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The International COVID-19 Awareness and Responses Evaluation (iCARE) Study is an international multi-wave cross-sectional observational cohort study of public awareness, attitudes, and responses to public health policies implemented to reduce the spread of COVID-19 on people around the world (www.mbmc-cmcm.ca/covid19). The study was led by the Montreal Behavioural Medicine Centre (MBMC: www.mbmc-cmcm.ca) in collaboration with a team of 200 international collaborators from 42 countries. I obtained access to the iCARE convenience and longitudinal samples through a summer scholarship. I thank the MBMC for access to their data and for financial support accompanying the summer scholarship.

**Open Science Statement**

Preprints, post-prints, and analysis code for each chapter are available on the following Open Science Framework project: https://osf.io/xgdbq/.

## ABSTRACT

**Background**: Health behaviours play a central role in health status and quality of life, and engaging in behaviours such as physical inactivity, unhealthy eating, smoking tobacco, and alcohol use are leading risk factors for chronic disease. However, most literature in health psychology focuses on each health behaviour in isolation, whilst everyday life experience is characterized by engaging in multiple different behaviours. The proportions of Canadians engaging in multiple sub-optimal health impacting behaviours concurrently is not well understood, nor are the interactive relationships between multiple health behaviours and health outcomes. Moving from a single behaviour to a multiple behaviour paradigm can enable a new set of questions to be answered about which health behavioural combinations people tend to engage in, and what are the strengths and directions of associations between health behaviours, questions for which we do not yet have robust answers. This dissertation aimed to advance the basic science of 'multiple health behaviours' by examining the co-occurrence and covariation of health impacting behaviours.

**Methods:** The thesis presents four studies that draw upon two large datasets: Studies 1, 2, and 3 use cross-sectional and longitudinal data (n = 40,268) from the Canadian Longitudinal Study of Aging (CLSA) while Study 3 and 4 use cross-sectional and longitudinal data from the international COVID-19 awareness, responses, and evaluation (iCARE) study (n = 85,861). Study 1 examines the co-occurrence of health impacting behaviours assessed with unsupervised machine learning methods, while Study 2 investigates the predictive utility of cluster analysis using multiple supervised machine learning methods. Study 3 investigates the interconnectedness of health behaviours, and

their sociodemographic patterns, via network psychometrics (i.e., recursive partitioning-based network trees and network comparison tests) using cross-sectional data. Finally, Study 4 models the temporal associations between traditionally studied health behaviours and COVID-19 pandemic protective behaviours using temporal, contemporaneous, and between-subject network analysis.

**Results:** Cluster analysis performed with data from the Canadian Longitudinal Study of Aging revealed seven groups of people based on similarity of behaviours (Study 1). These groups demonstrated sociodemographic variation but were not stronger predictors of health outcomes than individual behaviours. This pattern was consistent across several machine learning models (Study 2). Network psychometric analysis of national and international datasets explored correlations between health behaviours and revealed generally small associations with the exception of a larger relationship between physical activity and healthy diet, while the relationship between mask use and social distancing was stronger for males then women. (Study 3). The temporal dynamics of health behaviours (e.g., physical activity, alcohol consumption) and pandemic related health behaviours (e.g., hand washing, physical distancing) were modelled with items within the iCARE survey which identified bidirectional temporal effects between outdoor mask wearing and vaping behaviour as well as a temporal relationship between outdoor mask use and healthy eating (Study 4).

**Discussion:** This dissertation aimed to advance the basic science of multiple health behaviours through an examination of the co-occurrence and co-variation of health impacting behaviours. Using cross-sectional and longitudinal data from the CLSA and the iCARE study, I identified seven clusters of commonly co-occurring health behaviours and their sociodemographic characteristics (Study 1), compared these clusters against individual behaviours for classifying and prediction health outcomes using machine learning (Study 2), explored the interconnectedness of traditionally studied behaviours and pandemic specific behaviours and identified sociodemographic patterning (Study 3), and modelled the temporal relationships between health behaviours over time during the Covid-19 pandemic (Study 4). In the multiple health behaviour change literature, it is assumed that health behaviours covary; however, findings from this dissertation call into question this assumption. Additionally, the lack of alignment between covariation and co-occurrence approaches for modelling the interconnectedness of health behaviours call into question the validity of cluster analysis for determining which behavioural combinations co-occur in the population.  Before behavioural science can explain and predict health behaviour *change*, we must establish the basic science of multiple health behaviours.

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# CHAPTER 1

# INTRODUCTION

## 1.0 Overview

Health behaviours such as physical inactivity, unhealthy eating, smoking tobacco, and alcohol use are leading risk factors for chronic disease and play a central role in health status and quality of life (Fisher et al., 2011). However, most people do not meet the recommended standards outlined in national guidelines for these health behaviours (Reeves & Rafferty, 2005). In Canada, 17% of adults meet the guidelines for moderate-to-vigorous physical activity (Colley et al., 2018), less than 25% adhere to Canada's Food Guide recommendation (Brassard et al., 2018), while 27% exceed the maximum recommended number of weekly alcoholic beverages (Zhao et al., 2015), and 15% of Canadians are current tobacco smokers (Government of Canada, 2018). Unfortunately, the proportions of Canadians engaging in multiple sub-optimal health impacting behaviours concurrently is not known and the interactive causal relationships between health behaviours and health outcomes are not well understood.

Simple questions such as 'which health behavioural combination do people tend to engage in' and 'what are the strengths and directions of associations between health behaviours' are do not yet have robust answers. For example, although many analyses have been conducted to describe the combinations of risky health behaviours that tend to be enacted (e.g., Conry et al., 2011; Buck & Frosini, 2012; Noble, Paul, Turon, & Oldmeadow, 2015; Schneider, Huy, Scheussler, Diehl, & Schwarz, 2009) the clusters (i.e., groups of people) these studies identify are highly heterogenous, use a variety of statistical methods, and are difficult to amalgamate (e.g., Noble, Paul, Turon, & Oldmeadow, 2015; Whitaker et al., 2021). Further, while clustering studies often state that clusters can be used for public health intervention targeting, it is not known whether behavioural combinations have predictive utility (e.g., do clusters of multiple behaviours better predict health outcomes than individual behaviours). Additionally, while correlations between health behaviours are often reported there are few examples of research that incorporate the interconnectedness between multiple health behaviours (c.f., Nudelman, Kalish, & Shiloh, 2019) and meta-analyses have not yet been performed to ascertain the strength and direction of multivariate relationships between health behaviours (although research is underway; Silva, Presseau, Dinsmore, van Allen, & Marques, 2022). Further complicating matters, the 'minimal effect sizes of interest' have not been established to determine what strength of relationships between health behaviours are clinically meaningful.

At a fundamental level we do not have robust information regarding which behavioural combinations are prevalent or how behaviours are related to one another and their underlying mechanisms. In contribution to addressing these questions this dissertation focuses on advancing the *basic behavioural science* of our understanding of engaging in multiple health behaviours. At a basic level behavioural science is concerned with *predicting,* and *explaining,* behaviour. Prediction here refers to predicting the engagement of a behaviour or the outcome of a behaviour while explanations are focused on understanding the underlying mechanisms involved in behavioural activation. In the case of multiple health behaviours, researchers are interested in predicting engagement in the multiple behaviours pursued concurrently in daily life, the future health outcomes associated with given combinations of behaviours, and predicting when behaviour change will occur. Accurate explanations for and why health behaviours are enacted are also essential for behavioural science.

In this dissertation I incorporate two broad methodological frameworks that have thus-far been underutilized in the study of health behaviours but are well-suited for prediction (i.e., machine learning) and explanation (i.e., network psychometrics). For example, questions such as ‘which health behaviours and demographic factors predict future chronic conditions or general health as accurately as possible’ or ‘what health behaviours tend to cluster together’ are well suited to machine learning theory and methodology (e.g., Yarkoni & Westfall, 2017). Additionally, conceptualizing and modelling health behaviours and their underlying mechanisms as interconnected networks which vary over time may enable the observation of previously unknown associations between behaviours and underlying mechanisms.

The overarching aims of this dissertation are to 1) *predict* health outcomes based on commonly co-occurring health behaviours, and 2) provide *descriptive explanations* of how behaviours co-vary (i.e., are interconnected and interact over time).

## 1.1 Behavioural science theory informing our understanding of multiple health behaviours

The central task of basic behavioural science is to predict and explain behaviour to develop a cumulative evidence base of its correlates, causes, antecedents, and consequences, as a foundation for informing downstream application. In the context of health behaviour this refers to the ability to predict when behavioural activation will occur and to explain how this activation occurs. When applied to multiple health behaviours the scope of the research questions broadens to also include inquiries into 1) which sets of behaviours are relevant to health outcomes, 2) how are multiple behaviours or goals prioritized, 3) how do competing behavioural goals interact with one another, and 4) how can we intervene upon multiple behaviours to promote health and wellness.

**Relevant health behaviours.** Identifying the scope of behaviours relevant to health outcomes is essential for the study of health behaviours; however, no consensus exists regarding an agreed upon set of behaviours. In one effort to create a taxonomy of health relevant behaviours, researchers identified 25 health behaviours from interviews and focused groups with laypersons and health professionals (McHachan, Lawton, & Conner, 2010) and employed principal component analysis to identify three dimensions underpinning health behaviours: ‘‘important routines’ versus ‘unimportant one-offs’, ‘easy immediate pay-offs’ versus ‘effortful long-term pay-offs’, and ‘private unproblematic’ versus ‘public and problematic’. In another example, Nudelman and Shiloh (2015) derived a list of 66 healthy behaviours from a literature review and eliciting the views of health professionals and lay people.  Health impacting behaviours include those most associated with chronic disease (e.g., exercise, smoking) but also include less commonly studies behaviours such as teeth brushing, road safety behaviours, and laughter. These examples illustrate the variability in what is considered a ‘health behaviour’.

**Behaviour priorities.** Although the aforementioned efforts to create health behaviour taxonomies identified a broad array of health behaviours research has also found that the number of behaviours one engages in tends to decrease over the lifespan (Freund &

Baltes, 1998). Nonetheless, people often pursue multiple health and non-health related goals and must prioritize among competing demands. Much of the behavioural science work on multiple behaviours has been conducted in the context of multiple goal pursuit (e.g., Conner et al., 2022; Vancouver, Weinhardt, & Schmidt, 2010; Schmidt & DeShon, 2007; Louro, Pieters, & Zeelenberg, 2007). For example, in a series of experiments and observational studies Louro and colleagues (2007) found that, when a behavioural goal is distant, positive emotions from previously successful goals lead to an increase in effort towards the goal at the expense of other goals while negative emotions from prior failure promote a decrease in effort and a relocation of effort to other goals. In contrast, when goal attainment is close positive emotions can lead to coasting of effort and a reprioritization of other goals while negative emotions lead to an increase in effort to obtaining the goal.

In addition to affect and the relative distance of obtaining a behavioural goal, incentives also play a role in determining prioritisation among multiple goals. For example, Schmidt and DeShon (2007) have found that goals framed from an avoidance-incentive perspective were stronger predictors of goal prioritization than goals frames from an approach-incentive perspective. Additionally, when incentives for two goals are equal people tend to prioritize the goal which is furthest from completion while when incentives are only available for one goal people tend to prioritize the incentivized goal (Schmidt & DeShon, 2007). Building on the work of Schmidt & DeShon (2007), Vancouver et al (2010) developed a computational model of multiple goal pursuit which expanded upon and formalized the parameters of a multiple goal pursuit theory. In a simulation study this computation model replicated findings from Schmidt & DeShon (2007) while also accounting for individual variability in goal prioritization.

**Synergistic effects.** In addition to theories of multiple goal pursuit, behavioural theory has also investigated the potential for synergistic effects of multiple health impacting behaviours. To this end, some theories have focused on the role of cognitive processes in mediating conflicting behavioural objectives. For example, compensatory health beliefs refer to beliefs that the adverse consequences of unhealthy behaviours can be compensated for by performing healthy behaviours (Forestier et al., 2020; Knäuper et al., 2004). For instance, a person may engage in strenuous exercise to compensate for their smoking behaviour. The inverse of this relationship, where a person will engage in unhealthy behaviours following the completion of healthy behaviours, is conceptually similar to the moral licencing effect (Blanken, Van De Ven, & Zeelenberg, 2015). Although few studies in the health behaviour literature have drawn upon this theory (c.f., Sumnall, Montgomery, Atkinson, Gage, & Boardley, 2021) it provides a complementary perspective to compensatory health beliefs through the incorporation of cognitive processes and moral reasoning. Other behavioural phenomena which involve the interactions between multiple behaviours and their underlying mechanisms include preparatory behaviours (Barz et al., 2016; Cooke et al., 2020) which refer to behaviours performed in preparation for initiating the target behaviour, and conflicting health behaviour goals (Boudreaux & Ozer, 2012; Presseau et al., 2011; Presseau et al., 2015) which occur when the pursuit of one health goals conflicts with another due to competing demands for limited resources (e.g., motivation, environmental restraints).

**Multiple health behaviour change.** Finally, researchers and behaviour change practitioners have advocated for behaviour change interventions that focus on more than one behaviour (Geller et al., 2017; Noar et al., 2008; Prochaska et al., 2008). Multiple health behaviour change interventions target two or more behaviours sequentially or simultaneously within a specified time frame (Prochaska et al., 2008). The objective of these interventions is to improve the prevention of non-communicable diseases (Geller et al., 2017) through a more efficient use of health care and research resources (Prochaska et al., 2008). However, despite the potential benefits of multiple behaviour change interventions, early evidence for the effectiveness of these interventions were generally null (for reviews see Prochaska et al., 2008; Prochaska & Prochaska, 2011) while more recent evidence has been mixed (Alageel et al., 2017; Duan et al., 2021; King et al., 2015; Conner et al., 2022). Behavioural trial development is a complex multi-step process involving basic behavioural science, intervention development, intervention testing, and implementation science (Bacon et al., 2020). This research pipeline has been formalized in the ORBIT model of behavioural clinical trials (Figure 1; Bacon et al., 2020).

One contributing factor to the mixed success of multiple health behaviour change interventions is that at a fundamental level we do not have robust information regarding which behavioural combinations are prevalent (co-occurrence) or how behaviours are related to one another and underlying mechanisms (co-variation). Before behavioural science can explain and predict health behaviour *change*, we must establish the basic science of multiple health behaviours.

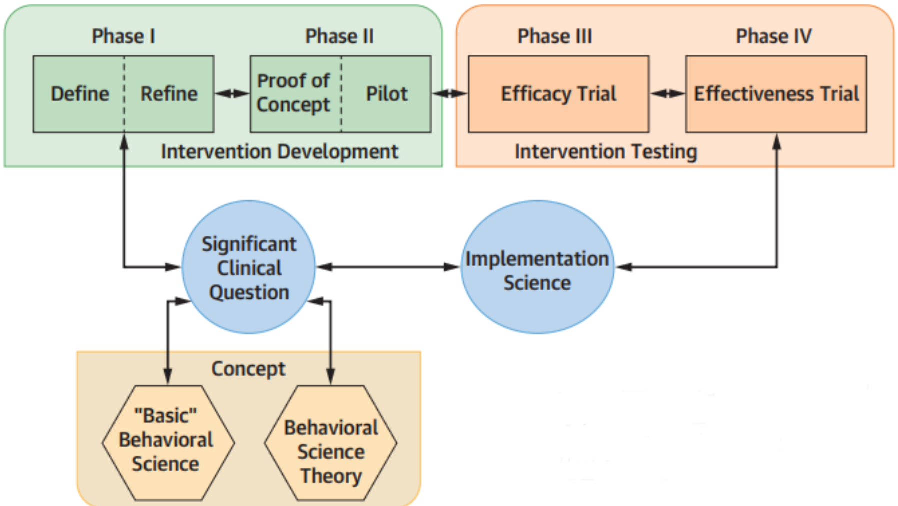


**Figure 3**. Adapted Behavioral Intervention Development and Testing Framework (ORBIT model; Bacon et al., 2020)

## 1.2 Co-Occurrence & Co-Variation

Two concepts central to the multiple health behaviour literature are co-occurrence (i.e., person focused analysis where people are placed into groups) and co-variation (i.e., variable focused analysis where correlations between variables are assessed). Co-occurring health behaviours are typically determined through the use of statistical methods such as cluster analysis and latent class analysis (Kwan et al., 2016; Schneider et al., 2009). Alternatively, co-occurring behaviours can be identified with 'behavioural profile' approaches based on the frequencies of different combinations of behaviours in a population or derived from guideline adherence (Shaw & Agahi, 2012). However, consensus on which behaviours co-occur is difficult due in part to behavioural heterogeneity across populations, variability in behaviours included in analyses, and also due to a lack of consistency within and between methodological approaches. Nonetheless, the ability to accurately identify sub-groups in the population based on health behaviour combinations is an important goal for public health research and multiple health behaviour scholarship.

Although accurately capturing co-occurrence is necessary for understanding multiple behaviour dynamics, it is not sufficient. An arguably more important component of multiple behaviour science is understanding how behaviours and their underlying mechanisms interact. Importantly, multiple health behaviours are hypothesized to manifest through shared co-variation of underlying mechanisms, yet these mechanisms are unclear (Geller et al., 2017). One possible reason why and understanding of the mechanisms remain elusive is a disconnect between the nature of health behaviour (i.e., they occur over time and at an individual level) and the common approaches to the study of multiple behaviours (i.e., cross-sectional between-subjects analysis). In response to this disconnect, recent years have seen a proliferation in the use of time series data in the behavioural science literature made possible by data collected via ecological momentary assessment studies and panel data (e.g., Shiffman et al., 2008; Tikkanen, Gustafsson, & Ingelsson, 2018). This trend has coincided with a resurgence of interest in idiographic methods in health psychology (Kwasnicka & Naughton, 2020) and psychology at large (Piccirillo & Rodebaugh, 2019). Yet, the methods employed in idiographic behaviour change research are not well suited for capturing the interconnected multivariate relationships between behaviours and their interactions over time. Arguably, network psychometrics (Epskamp, 2020) are an appropriate method, however, these approaches have been underutilized in the study of behaviour change (c.f., Heino et al., 2020). Figure 2 depicts how each dissertation chapter assesses co-occurrence and co-variation for the purposes of either prediction/classification or descriptive modelling.

## 1.2 Machine Learning for advancing our understanding of the dynamics of engaging in multiple behaviours

One analytical approach for predicting, classifying, and descriptively modelling health behaviours is machine learning. Broadly, machine learning refers to a "set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data" (Murphy, 2012, pp 1). Traditionally, machine learning algorithms are classified into four categories: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. This dissertation will focus on the use of supervised and unsupervised machine learning approaches.

| | Co-Occurrence | Co-Variation |
|---|---|---|
| Prediction / Classification | ○ Predicting and classifying health outcomes with clusters of health behaviours (Ch 2)<br>○ Predicting and classifying health outcomes with machine learning (Ch 3) | ○ Classifying chronic conditions from health behaviours (Ch 2) |
| Descriptive Modelling | ○ Identifying clusters of health behaviours (Ch 2)<br>○ Health behaviour profiles (Appendix 1) | ○ Cross-sectional networks of health behaviours (Ch 2)<br>○ Networks and network trees of health behaviours (Ch 4)<br>○ Temporal dynamics of health behaviour networks (Ch 5) |

**Figure 4.** Research objectives in relation to analytical objectives

In supervised learning, the relationships between the input and target variables are known. An algorithm is 'supervised' in that it can be trained on a dataset that contains the outcomes that are being classified (categorical outcome) or predicted (continuous outcome). Datasets containing these known outcomes are referred to as ‘labeled data’ in contrast to ‘unlabeled data’ in which the outcomes are not known. In the context of health behaviour research, supervised machine learning can be used to predict and classify health outcomes from a range of theoretically or data-determined predictors. For example, machine learning can be used to predict which risk factors are most strongly associated with obesity (Chatterjee, Gerdes, & Martinez, 2020) or to classify whether people are complying or not complying with public health measures (Roma et al., 2020).

In contrast to supervised learning, unsupervised learning works on its own do discover patterns in unlabeled data (Fung, 2001). The two central tasks which fall under the unsupervised umbrella of machine learning are clustering and dimensionality reduction. The overarching purpose of clustering is to group individual entities (e.g., people) into similar groups based on a pre-specified set of features (e.g., health behaviours) while dimensionality reduction techniques such as principal component analysis are used to reduce large number of predictor variables into a smaller set of predictors which retain the information contained in the original predictor set. In the context of multiple health behaviour research, unsupervised learning is commonly used for identifying clusters of co-occurring health behaviours (e.g., van Allen et al., 2021; van Allen et al., 2023; Kwan et al., 2016; Schneider et al., 2009). However, few studies in this area have focused on Canadians making generalizability to Canadian contexts difficult.

In this dissertation, I applied supervised and unsupervised machine learning techniques to large cohort datasets to identify patterns of co-occurring health behaviours and predicted/classified health outcomes from behavioural and contextual predictors. The purpose of this analysis is to identify the population sub-groups which may benefit from multiple health behaviour interventions and to determine the factors which most strongly predict desirable health outcomes. In contrast to data-driven machine learning approaches, this analysis does not seek to maximize the predictive utility of the dependent variable but to compare the predictive utility of clusters relative to individual health behaviours.

### 1.3 Network Psychometrics

Complex systems, such as the biopsychosocial systems involved in human behaviour, contain heterogenous component parts that mutually interact with one another. Systems are said to be 'complex' when the relationships between component parts are nonlinear, the system is inherently self-organizing, and emergent properties arise from the system that are not reducible to the sum of the systems parts (Richardson, Dale, & Marsh, 2014). Approaches to multiple health behaviours that incorporate complexity include formal models of multiple behaviours (Vancouver et al., 2010), recurrence analysis based methods for idiographic behaviours (Heino et al., 2020), qualitative techniques for understanding behaviour change (Gomersall, 2018), quantitative methods for incorporating dyads in supporting behaviour change (Gainforth et al., 2019), and the mapping of interconnected behavioural, social, and economic systems in public health (Bagnall et al., 2019). Increasingly, researchers have begun to call for the incorporation of complex systems approaches to the study of behavioural science and behaviour change (Chevance, Perski, & Hekler, 2021; Gomersall, 2018; Heino, Knittle, Noone, Hasselman, & Hankonen, 2020; Olthof, Hasselman, Maatman, Bosman, & Lichtwarck-Aschoff, 2020; Fried & Robinaugh, 2020).

One way to understand and model these interconnected systems is through the lens of network science. Networks have been used to study a broad range of phenomenon including technological networks, social networks, information networks, biological networks (Newman, 2018), and psychological networks (Fried & Cramer, 2017; Fried et al., 2017; Borsboom, 2017). Networks consist of nodes (e.g., measures of observed variables) and edges (relationships between nodes). Edges may be weighted or un-weighted (the former accounting for the strength of a relationship, the latter merely the presence of an association) or directed (indicating the direction from one node to another) or undirected. In psychological networks, nodes represent psychological attributes (e.g., emotions, affect, behaviours, symptoms) and edges represent relationships between nodes (e.g., correlations) and can indicate the presence of a positive or negative relationship and the direction of the effect. An example of a network approach to model multiple behaviours is goal systems theory (Kruglanski, 1996; Kruglanski et al., 2002; Zhang, Fishbach, & Kruglanski, 2007; Anderson et al., 2004). According to this theory, goals and the behavioural means of attaining goals (nodes) are connected (via edges) in an associative network where each goal can be associated with multiple behaviours. This interconnectedness allows for a 'spreading activation' effect to occur (Higgins, 1996; Shah & Kruglanski, 2000) wherein activation of one goal, or behaviour associated with the means of attaining the goal, can spread to activate other goals or behaviours.

Recently, statistical techniques such as network analysis have been adapted for use in psychology (Fried & Cramer, 2017; Fried et al., 2017; Borsboom, 2017). In this dissertation I applied network psychometrics to model the interconnectedness of multiple health behaviours from cross-sectional and longitudinal data. The purpose of this analysis is to 1) better understand how relationships between health behaviours vary across sociodemographic parameters to further the basic descriptive science of multiple behaviours, and 2) develop hypothesis generating models describing how health impacting behaviours interact with one-another over time.

### 1.4 Dissertation Outline

This dissertation aims to advance the basic behavioural science of multiple health behaviour change by addressing two overarching and interrelated research questions:

1. Which health behaviours co-occur and how are different combinations of behaviours predictive of health outcomes?
2. How do multiple health behaviours co-vary (over time)?

These questions are addressed across six chapters (see Table 1 for an overview). Chapters 2-4 make use of cross-sectional and longitudinal data (n = 40,268) from the Canadian Longitudinal Study of Aging (CLSA; Raina et al., 2009) while Chapters 4-5 use cross-sectional and longitudinal data from the international COVID-19 awareness, responses, and evaluation (iCARE) study (n = 85,861; Bacon et al., 2021). A brief summary of each chapter follows:

**Chapter 2** compared the utility of co-occurrence vs co-variation based approaches for understanding the interconnectedness between health impacting behaviours (van Allen et al., 2021; van Alen et al, 2023). Cluster analysis identified seven distinct groups of people based on co-occurring health behaviours while network analysis revealed patterns of co-variation between health behaviours. Sociodemographic variation was evident across behavioural clusters while associations between health behaviours were generally small. Clusters and individual behaviours were included as predictors in linear and logistic regressions predicting chronic condition status, life satisfaction, and general health measured at follow-up time point 1. Individual behaviours accounted for more variance in health outcomes than clusters.

**Chapter 3** extended the regression analysis from Chapter 2 by comparing machine learning algorithms for classifying chronic condition and Type II Diabetes status and predicting self-reported general health. Clusters and individual health behaviours were again included as predictor variables. For the prediction of continuous health outcomes (i.e., general health) from cluster membership six models were compared: ordinary least-squares regression, LASSO regression, ridge regression, model trees, neural networks, and support vector machines~~.~~ For the classification of categorical health outcomes (i.e., chronic condition status and Type II Diabetes) from cluster membership six models were compared including: XGBoost, random forest, k-nearest neighbours, naïve bayes, and logistic regression. Individual behaviours outperformed clusters for classifying chronic condition status with XGBoost outperforming other models. In contrast, clusters were the stronger predictors of general health with artificial neural networks narrowly outperforming competing algorithms.

**Chapter 4** furthers the network analysis presented in Chapter 2 with additional methods (i.e., network community detection, recursive partitioning-based network trees, and network comparison tests) while extending the analysis to include cross-sectional data from both the CLSA and iCARE study data.  Analysis of national (CLSA) and international (iCARE) datasets revealed known associations between some behaviours (e.g., physical activity and healthy eating), while identifying other mostly small relationships between health behaviours. Sociodemographic heterogeneity was evident in terms of statistically significant differences across age groups, sex, and income levels; however, effect sizes were small. Network comparison tests and network trees were useful tools for identifying patterns of interconnectedness and sociodemographic variability while network community detection did not produce actionable insights in this instance.

**Chapter 5** moved beyond cross-sectional data to model the temporal dynamics of health behaviours (e.g., physical activity, alcohol consumption) and pandemic related health behaviours (e.g., hand washing, physical distancing) using network psychometrics. This hypothesis generating analysis used temporal network models to fit temporal networks, contemporaneous networks, and between-subject networks from items within the iCARE survey. Abrupt mean level changes in several health behaviours (smoking, recreational drug use, and vaping) lead to violation of statistical assumptions and a poor fit between model and data. However, the application of temporal network analysis to the study of multiple health behaviours is well suited to address key research questions in the field such as 'how two multiple health behaviours co-vary with one another over time'.

**Chapter 6** concludes the dissertation with a discussion of the following themes: co-occurrence, co-variation, behavioural science theory, network psychometrics, and machine learning.

**Table 2.**Overview of Dissertation Chapters

| | | | | | |
|---|---|---|---|---|---|
| Ch 1 | Introduction | | An overview of underlying rationale and chapter structure for the proposed dissertation | | |
| | **Title** | **Data** | **Research Question(s)** | **Primary Methods** | **Results / Conclusions** |
| Ch 2 | Clustering of health behaviours in Canadians | CLSA | How do health behaviours cluster? Do sociodemographic, health indicators, non-health behaviours, and health care use predict cluster membership? Do clusters predict outcomes better then individual behaviours? | Agglomerative hierarchical cluster analysis; OLS/ logistic/ multinomial logistic regression | Seven clusters identified with sociodemographic patterning evident across clusters. Clusters outperformed by individual behaviours as predictors of health outcomes. |
| Ch 3 | Predicting healthy aging and classifying chronic condition status from multiple health behaviours | CLSA | Are clusters or behaviours at baseline better predictors of health at follow-up? Are clusters or behaviours at baseline better classifiers of chronic condition status at follow-up? Which machine learning method is best for prediction? | Ordinary least-squares regression, LASSO regression, ridge regression, neural networks, support vector machines, XGBoost, random forest, k-nearest neighbours, naïve bayes, and logistic regression | Individual behaviours outperformed clusters for classifying chronic condition status with XGBoost outperforming other models. In contrast, clusters were the stronger predictors of general health with neural networks narrowly outperforming competing algorithms. |
| Ch 4 | Network community detection of co-occurring health behaviours | CLSA & iCARE | Are communities/clusters evident in networks of health behaviours? Is there heterogeneity in these networks based on demographic factors and/or health indicators? | Mixed graphical model; clique percolation community detection; recursive network partitioning; network comparison tests | The strength and direction of interconnected associations between behaviours were modelled. Effect sizes were generally small. Community detection algorithm was not helpful for identifying clusters while recursive partitioning was useful exploratory technique. |
| Ch 5 | Multiple behaviour analysis for COVID | iCARE | How do health behaviours and pandemic specific behaviours interact over time? | lag-1 dynamic latent variable model for panel data (dlvml) | Temporal, contemporaneous, between-subject networks were modelled. A mismatch between data features and statistical assumptions resulted in poor model fit. Methodology is promising. |
| Ch 6 | Discussion | | Summary of dissertation findings, strengths, limitations, and areas for future research | | |

CHAPTER 2

## CLUSTERING OF (UN)HEALTHY BEHAVIOURS IN CANADIANS

### Abstract

**Background:** Health behaviours such as physical inactivity, unhealthy eating, smoking tobacco, and alcohol use are each leading risk factors for non-communicable chronic disease. Better understanding which behaviours tend to co-occur (i.e., cluster together) and co-vary (i.e., are correlated) may provide novel opportunities to develop more comprehensive interventions to promote multiple health behaviour change. However, whether co-occurrence or co-variation based approaches are better suited for this task remains relatively unknown.

**Purpose**: To compare the utility of co-occurrence vs co-variation based approaches for understanding the interconnectedness between multiple health impacting behaviours.

**Methods:** Using baseline and follow-up data (N=40,268) from the Canadian Longitudinal Study of Aging, we examined the co-occurrence and co-variation of health behaviours. I used cluster analysis to group individuals based on their behavioural tendencies across multiple behaviours and to examine how these clusters are associated with demographic characteristics and health indicators. We compared outputs from cluster analysis to behavioural correlations and compared regression analyses of clusters and individual behaviours predicting future health outcomes.

**Results:** Seven clusters were identified, with clusters differentiated by six of the seven health behaviours included in the analysis. Sociodemographic characteristics varied across several clusters. Correlations between behaviours were generally small. In regression analyses individual behaviours accounted for more variance in health outcomes than clusters.

This paper has been published at the *Annals of Behaviour Medicine*.

**van Allen, Z. M.**, Bacon, S., Bernard, P., Brown, H., Desroches, S., Kastner, M., … Presseau, J. (2023). Clustering of health behaviours in Canadians: A multiple behaviour analysis of data from the Canadian Longitudinal Study on Aging. *Annals of Behavioural Medicine.* kaad008, https://doi.org/10.1093/abm/kaad008

A protocol paper has been published in *JMIR: Research Protocols*.

**van Allen, Z. M**., Bacon, S., Bernard, P., Brown, H., Desroches, S., Kastner, M., … Presseau, J. (2021). Clustering of healthy behaviours in Canadians - Protocol for a multiple behaviour analysis of data from the CLSA. *JMIR: Research Protocols*, 10(6), e24887. https://doi.org/10.2196/24887

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## 2.1 Introduction

Non-communicable chronic diseases such as chronic respiratory disease, diabetes, cardiovascular disease, and cancer cause two thirds of annual deaths in Canada and worldwide (Public Health Agency of Canada, 2016; Who Health Organization, 2021; GBD Risk Factors Collaborators, 2016). Furthermore, nearly 12% of people aged 65 or older have lived with two or more chronic conditions during their lifetime (Public Health Agency of Canada, 2017). Health behaviours such as smoking, excessive alcohol consumption, physical inactivity, and unhealthy eating are strongly associated with quality of life and are leading risk factors for chronic diseases (Fisher et al., 2011). With approximately four in five adult Canadians engaging in at least one of the health impacting behaviours associated with non-communicable chronic diseases, the prevalence of risky health behaviours is high (Public Health Agency of Canada, 2017).

The consequences and risk factors of multimorbidity (living with 2 or more chronic conditions) has been studied extensively (Marengoni et al., 2011; Nunes, Flores, Mieke, Thume, & Facchini, 2016; Prados-Tores, Calderón-Larrañaga, Hancco-Saavedra, Poblador-Plou, & van den Akker, 2014); however, research seeking to understand the relationships between life satisfaction, general health, and different combinations of health behaviours has received comparably little attention. Our daily lives are characterized by multiple interconnected social, personal, family, health, and work-related behaviours, each contesting for the limited energy, motivation, and time available (Presseau, Tait, Johnston, Francis, & Sniehotta, 2013). Despite this, health risk behaviours are generally promoted and studied in isolation resulting in interventions and guidelines for healthy living siloed by individual behaviours. For example, historically Canada has had separate guidelines for alcohol consumption (Butt, Beirness, Gliksman, Paradis, & Stockwell, 2011; Canadian Center on Substance Abuse and Addition, 2018), and physical activity and sleep (Tremblay et al., 2011), although recent guidelines are beginning to incorporate multiple health behaviours (e.g., guidelines for movement behaviours including sleep, sedentary activity, and physical activity; Ross et al., 2020). The move towards guidelines that cover multiple health behaviours provide an opportunity to develop an evidence base to reflect an understanding of which health behaviours are interconnected, and how these patterns of interconnectedness are associated with health care utilization, life satisfaction, physical health, and mental health. This in turn may provide new opportunities to promote multiple health behaviour change in guidelines and beyond. Indeed, interventions could be tailored to reflect the real-world complexities of health behaviours through an understanding of which behaviours are interconnected and for whom.

When investigating the interconnectedness of multiple health behaviours there are two general approaches: *person-centered approaches* which assess co-occurrence of behaviours and group people into categories, and *variable centered approaches* which assess co-variation of behaviours through the strength and direction of relationships between behaviours. Person-centered approaches include but are not limited to agglomerative cluster analysis, k-means, latent class analysis, behavioural profiles, and Gaussian mixture models. Applied to multiple health behaviours, person-centered approaches aim to segment people into categories based on similarity of behavioural features to identify focused intervention targets (behavioural combinations) and the sociodemographic patterns associated with each group (Conry et al., 2011; Buck & Frosini, 2012; Noble, Paul, Turon, & Oldmeadow, 2015; Schneider, Huy, Schuessler, Diehl, & Schwarz, 2009).

However, to date research in this area often assesses different combinations of behaviours with heterogeneous measurements which result a wide array of behavioural clusters (Conry et al., 2011; Buck & Frosini, 2012; Noble et al., 2015; Schneider, et al., 2009). For example, Conry et al (2011) investigated the clustering of alcohol use, physical activity, smoking, and unhealthy eating in a sample of Irish adults obtained from the 2007 National Survey of Lifestyle, Attitudes, and Nutrition. Six clusters were identified in this cross-sectional analysis which were labelled as: 1) '*multiple risk factor*' (moderate physical activity, moderate to high alcohol use, variable healthy eating); 2) '*mixed lifestyle*' (those who had never smoked, reported moderate physical activity, and variable alcohol consumption); 3) '*physically inactive'* (people with low levels of physical activity, poor eating, who reporting some smoking and high alcohol use); 4) '*temperate*' (moderately active and moderate drinkers who had never smoked); 5) '*former smokers'* (former smokers who reported high physical activity, moderate alcohol use, and healthy eating); and 6) '*healthy lifestyle'* (characterized by people who had never smoked, high physical activity, highest healthy eating, moderate alcohol use). In another example, Buck and Frosini (2012) examined the clustering of unhealthy eating, alcohol use, smoking, and physical inactivity among adults aged 16-74 using 2003-2008 data from the Health Survey of England. Findings indicated that in 2008, 63% of the sample engaged in one or two unhealthy behaviours, 25% engaged in three or more risky health behaviours, and 5% reported engaging in all four measured health behaviours. Only 7% of the sample did not engage in any measured risky health behaviours. Finally, in contrast to these data-driven approached for clustering, Shaw and Agahi (2012) used a descriptive approach called ‘health behaviour profiles’ to assess all possible combinations of co-occurring health risk behaviours in American adults 50 years or older using baseline data from the Health and Retirement study (Heeringa & Connor, 1995). Overall, twelve health behaviour profiles were created using all combinations of physically active vs inactive, smokers vs non-smokers, and those who reported no vs moderate vs heavy alcohol consumption. The percentage of people represented in each profile varied widely with the six most prevalent profiles including: 1) ‘physically active, non-drinkers, who smoke’ (4.2%); 2) ‘physically inactive, non-drinkers, who smoke’ (6.5%); 3) ‘physically inactive, moderate drinkers, who do not smoke’ (8.6%); 4) ‘physically active, moderate drinkers, who do not smoke’ (10.1%); 5) ‘physically active, non-drinkers, who do not smoke (23.7%); and 6) ‘physically inactive, non-drinkers, who do not smoke’ (34.1%).

The second approach for modelling the relationships between health behaviours are *variable centered approaches*. The purpose of these types of analyses is to identify the associations between health behaviours to determine the strength and direction of the (usually linear) associations. Examples of variable-centered approaches include (but are not limited to) correlations, multiple regression, network psychometrics, structural equation modelling, and lag-1 temporal time series analysis. The variable-centered approach can help to identify important associations between health behaviours such as the strong positive relationship between healthy eating and exercise (Sallis, Prochaska, & Taylor, 2000). Additionally, revealing the absence of linear relationships, as is the case with the relative independence of sedentary behaviours and physical activity (Santos et al., 2012), can inform research, policy and interventions to consider these behaviours as independent from one another.

Although the person- and variable-centred approaches are used in the multiple health behaviour literature, to our knowledge there have been no direct comparisons between them. It remains unknown whether person- and variable-centered approaches produce complimentary or divergent insights in the context of multiple health behaviours. It is also unknown whether person or variable analysis is more suitable for understanding the relationships between behaviours and health outcomes (e.g., life satisfaction and general health, onset of chronic conditions, BMI). To this end, we analyzed baseline and follow-up data from the Canadian Longitudinal Study on Aging (CLSA; Raina et al., 2009), to 1) identify patterns of co-occurring and co-varying behaviours and assess how sociodemographic and health indicators are associated with these patterns; 2) compare outputs from these two methods; and 3) compare the ability of clusters vs individual behaviours to predict future health indicators.

## 2.2 Methods

The Canadian Longitudinal Study of Aging (CLSA) is a longitudinal, nationally representative study designed to measure societal, biological, physical, and psychosocial factors related to healthy aging (Raina et al., 2009). Baseline data collection for the CLSA was collected between 2010-2015 comprising two approaches. First, the 'tracking' cohort (n = 21,241) completed data collected via an hour-long computer assisted phone interviews. Second, the 'comprehensive' cohort (n=30,097) completed an in-person interview lasting 90-minutes as well as a data collection site visit. Additionally, a 'maintaining contact questionnaire' was administered over the phone for the comprehensive and tracking cohorts. The maintaining contact questionnaire, tracking cohort, and comprehensive cohort form the baseline data collected used in this analysis. Detailed methodological information is shown in the published protocol (van Allen et al., 2021). With follow-up CLSA data subsequently made available, additional analysis was also performed using follow-up data. In the follow-up wave of data collection participants again completed the ‘tracking’ cohort (n = 17,050) and the ‘comprehensive’ cohort (n = 27,765) packages. A total of n = 6,523 participants who completed baseline data collection did not provide follow-up data. Data are available from the Canadian Longitudinal Study on Aging (www.clsa-elcv.ca) for researchers who meet the criteria for access to de-identified CLSA data

### 2.2.1 Participants

Participants were recruited through random-digit dialing, provincial health registries, and the Canadian Community Health Survey on Healthy Aging (Raina et al., Wolfson et al., 2009). Exclusion criteria for the CLSA included: residents living in three territories and First Nations reserves, full time members of the Canadian Armed Forces, people living with cognitive impairments, and individuals living in institutions (including 24-hour nursing homes; Raina et al., 2009). Participants included in the study were n=51,338 French and English-speaking Canadians (51% female) between the ages of 45-85 at time of enrollment. The average participant age is 62.98 years (SD = 10.4) with 26% between 45-54 years, 32% between 55-64 years, 23% between 65-74 years, and 18% between 75-85 years of age. A full description of demographic characteristics of the sample, as well as summary data across all measured variables is available in the CLSA baseline data report (Raina, Wolfson, Kirkland, & Griffith, 2018). A total of n = 6.523 participants who completed baseline data collection did not provide follow-up data.  Thus, we have a sample size of n = 44,815 participants who completed follow-up data collection.

### 2.2.2 Variable Selection

The CLSA baseline dataset contains approximately 1800 variables. One of the most important decisions in cluster analysis is selecting a parsimonious set of variables, or features, to include in the model. Variable selection can be performed by objective or subjective approaches. Our approach is the latter. Objective methods rely on data-driven techniques (e.g., forward/backward selection) and techniques such as factor analysis and principal components analysis for dimension reduction (Deliu et al., 2016). Subjective approaches are generally driven by expert opinion and/or theory-driven research questions. Based on our research objectives, and the data collected by CLSA, we identified an initial set of variables assessing health behaviours, non-health behaviours, sociodemographic indicators, general health and well-being, and health care service utilization. Our decisions were also shaped by issues of survey design (e.g., skip-questions), knowledge of basic summary statistics for baseline CLSA data (Raina et al., 2018), and our own supplementary summary statistics on the baseline data[1]. See Appendix 1 for a description of each variable to be used in analyses and example items.

**Health Behaviours.** *Physical activity* and *sedentary behaviour* were measured as independent behaviours with the Physical Activity Scale for the Elderly (PASE; Washburn, Smith, Jette, & Janney, 1993) which assesses the frequency of sedentary behaviour, walking, light physical activity, moderate physical activity, strenuous physical activity, and exercise. Items asked participants to report on their activity levels over the previous 7 days on a 1 (never) to 4 (often, 5-7 days) scale. A Statistics Canada report focusing on the relationship between physical activity and lung functioning (Dogra et al., 2019) merged light and moderate physical activity together and also merged strenuous physical activity and exercise together based on issues with question prompts and conceptual overlap between question items. To

[1] The research team received access to the CLSA datasets prior to the publication of the protocol. We computed means and standard deviations for the variables used in this study in order to inform our analytical choices. None of the analyses were conducted prior to submission of the protocol.

facilitate dimension reduction, we opted for a similar approach in which the PASE subscale items were merged to represent: sitting, walking, light/moderate physical activity (renamed ‘light sports’ to avoid confusion with ‘light-to-moderate physical activity’; Saint-Maurice, Troiano, Berrigan, Kraus, & Matthews, 2018), and strenuous physical activity/ exercise. *Fruit and vegetable consumption* was assessed with one item from the Seniors in the Community Risk Evaluation for Eating and Nutrition questionnaire (Keller, Goy, & Kane, 2005). The item asks respondents how many servings of fruits and vegetables they eat in a day. The original scale was scored 1 (seven or more) to 7 (less than two); however, items were reverse coded such that higher scores indicate more fruit and vegetable consumption. *Smoking behaviour* was measured using a skip-question framework in the CLSA. We assigned a value of 0 to each respondent who responded ‘no’ to the question ‘have you ever smoked a whole cigarette’. A similar approach has been applied to skip structure data when missing data represent the absence of a behaviour or psychological feature (Borsboom & Cramer, 2013). Participants who answered ‘yes’ to the question ‘have you ever smoked a whole cigarette’ were subsequently asked whether they smoke not at all, occasionally, or daily, in the past 30 days. Ultimately, this created four levels distinguishing between people who have never smoked (coded 0), those who have not smoked within 30 days (1), those who smoke occasionally (2), and those who smoke daily (3). *Alcohol use* was assessed with a single item asking participants how often they drank alcohol in the past 12 months on a scale from 1 (almost every day) to 7 (less than once a week). Responses were reverse coded so that higher values indicate greater alcohol consumption. Finally, *sleep* was measured with a single item. Participants were asked how many hours of sleep they get, on average, during the past month and could respond with any value between 0-24. This variable was originally included in the analysis plan (van Allen et al., 2021) but was subsequently removed due to high (41.5%) prevalence of missingness.

**Sociodemographic Indicators.** We included age, as grouped in the CLSA dataset (45-54; 55-64; 65-74; 75-85), sex (male/female), marital status (single, married or common-law, widowed, divorced, separated), household income (<$20k, $20-$49k, $50-$99k, $100-$149k, $150k+), retirement status (completely retired, partly retired, not retired), and working status (yes/no to ‘are you currently working at a job or business’).

**Social Support.** Participants responded to 19 questions from the Medical Outcomes Study (MOS) Social Support Survey (Sherbourne & Stewart, 1991). The MOS is scored on 5 subscales: tangible social support, affection, positive social interaction, and emotional and informational support. A MOS ‘overall support index’ is also scored in the CLSA baseline dataset. To reduce the number of constructs in our analyses, we used the overall support index, scored from 0 (low support available) to 100 (high support available).

**General Health and Life Satisfaction.** Three single item measures were selected from the CLSA’s general health module: an indicator of general health (‘in general, would you say your health is excellent, very good, good, fair, or poor?’), mental health (‘in general, would you say your mental health is excellent, very good, good, fair, or poor?’), and perceptions of healthy aging (in terms of your own healthy aging, would you say it is excellent, very good, good, fair, or poor?’). Items were originally scored on a 1 (excellent) to 5 (poor) but were reverse coded. Additionally, a composite score from the Satisfaction with Life Questionnaire (SWLS; Diener, Emmons, Larsen, & Griffin, 1985) was used. The SWLS is scored from 1 (extremely dissatisfied) to 7 (extremely satisfied). A measure of body mass index (BMI) was used as an indicator of physical health.

**Chronic Conditions.** Participants reported any diagnosed chronic conditions during baseline and follow-up data collection (e.g., chronic respiratory disease, diabetes, cardiovascular disease, cancer). A summary variable which classifies people into those living with at least one chronic condition at follow-up (1) and those not living with any chronic conditions (0) was used as an indicator of health.

### 2.2.3 Cluster Analysis Overview

Classifying data through the assignment of classes to objects in a dataset is a common application of machine learning (i.e., "set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data" (Murphy, 2012)). Classification algorithms fall into three categories: supervised learning, semi-supervised learning, and unsupervised learning. In supervised learning, the relationship between the input and target variables are known. An algorithm is 'supervised' in that it can be trained on a dataset that contains correct classifications. Datasets containing these correct classifications are referred to as 'labeled data' in contrast to 'unlabeled data' in which the correct classifications are not known. In semi-supervised learning a combination of labeled and unlabeled data is used to model the data, while in unsupervised learning the model works on its own to discover patterns in unlabeled data (Fung, 2001).

Cluster analysis is a type of unsupervised machine learning that comprises a set of methods for identifying distinct characteristics in heterogenous samples and clustering them into homogenous groups (Rapkin & Luke, 1993). When the target number of clusters (*k*) is known, partitioning based clustering arguments such as *k*-means, *k*-medoids, or model-based clustering approaches are appropriate. However, when *k* is unknown, as is the case with clusters of Canadians based on health and non-health behaviours, hierarchical clustering is a suitable method (Rapkin & Luke, 1993).

The hierarchical structure of the data can be obtained through clustering individual data points in a bottom-up approach (i.e., agglomerative clustering) or by partitioning a single cluster into smaller clusters until each cluster is a single observation through a top-down approach (i.e., divisive clustering). Divisive methods are rarely used in practice due to heavy computational requirements (Xu & Wunsch, 2005). In agglomerative hierarchical clustering, each individual data point is initially treated as its own cluster. The methodological process is as follows (Alashwal et al., 2019): 1) each data point is assigned to its own cluster; 2) the distance between each cluster is calculated; 3) the pair of clusters with the shortest distance between them is selected and merged into a single cluster; 4) the distances between the new cluster and all other clusters are recalculated; and 5) these steps are repeated until only one cluster remains. However, a single cluster ($k$ = 1) is unlikely to be informative; researchers can identify the number of clusters that best describe the data (e.g., $k$ = 5) through subjective criteria and/or with the aid of statistical tests that have been developed for this purpose (see methods section below).

Several measures of ‘distance’ are widely used in practice, though the Gower distance (Gower, 1971) is appropriate for mixed data (binary, ordinal, continuous). In addition to selecting a measure of distance, hierarchical agglomerative clustering also requires a linkage method to be specified to define how the distance between clusters is calculated. Different methods exist for specifying the anchor points used to calculate the distance between clusters (i.e., how the distances between clusters are ‘linked’). For example, ‘single/minimum linkage’ calculates the minimum distance between data points in each cluster while ‘centroid linkage’ calculates the distance between the center of each cluster (Fung, 2001). No consensus exists as to which linkage method is superior, though it is recognised that final clustering solutions may differ based on the linkage method selected (Xu & Wunsch, 2005).

## 2.3 Analysis

### 2.3.1 Cluster Analysis

Prior to performing cluster analysis, all health behaviour variables (walking, sitting, light sports, exercise, smoking, alcohol) were standardized (i.e., mean centered) using the scale function in base R. Listwise deletion was applied to missing data in health behaviour variables resulting in a remaining total sample of n = 40,268 for baseline behaviours. I then performed hierarchical agglomerative cluster analysis with five linkage methods (e.g., complete-linkage, single-linkage, average-linkage, centroid-linkage, and Ward’s method) using ‘hclust’ function supported by the package ‘fastcluster’ (Mullner, 2013) to optimize performance. Gower distance was computed using the ‘daisy’ function in the ‘cluster’ package (Maechler, Rousseeuw, Struyf, Hubert, & Hornik, 2012).

I examined cluster analysis outputs by looking at summary statistics for health behaviour variables for each linkage method. Two of the five linkage methods produced interpretable and useful clustering solutions (i.e., Ward and complete-linkage) while the other methods resulted in clusters with nearly all participants forming a single cluster with a small number of participants (often one per cluster) forming the remaining groups. Next, I employed a data-driven approach to determine the optimal number of clusters using complete linkage and Ward’s method. We used the NbClust package (Charrad, Ghazzali, Boiteau, & Niknafs, 2014) to provide the top three clustering solutions for both linkage methods, resulting in six options for combinations of linkage measures and *k.* Four of six options produced clustering solutions with 2-3 clusters with minimal variability across behaviours. Of the remaining two options (Ward k=4 and k=7) the research team opted for the clustering solution with 7 clusters as this option produced more behavioural variability (i.e., more clusters defined by higher/lower scores on a given behaviour). For more details on the decision making process with co-authors see https://osf.io/xgdbq/.

### 2.3.2 Multinomial Logistic Regressions (Baseline)

I conducted four multinomial logistic regressions predicting cluster membership with baseline data to determine whether clusters are associated with 1) sociodemographic factors, 2) indicators of physical and mental health, 3) non-health behaviours, and 4) health care utilization. Analysis was performed using the 'multinom' function from the 'nnet' package (Ripley, Venables, & Ripley, 2020). Results are presented in appendix II.

### 2.3.3 Comparing Person and Variable Approaches

Comparisons between person- and variable-based approaches were conducted in two ways. First, baseline behaviours associated with one another via clusters are descriptively compared with associations assessed with partial polychoric correlations. Partial polychoric correlations (ρ) were computed using the same baseline (n= 40,268) sample used for cluster analysis and visualized as a network (Figure 2). Polychoric correlations are appropriate for ordered categorical data (Olson, 1979). Secondly, individual health behaviours and clusters were used as predictors in separate regression analyses to predict health outcomes (general health, healthy aging, and the presence of chronic conditions). Ordinary Least Squares (OLS) regression was used to predict general health and mental health while logistic regression was used to predict the presence of chronic conditions. The reference group for the regression analysis was Cluster 4 (‘frequent alcohol use and infrequent walkers’) due to most of that cluster’s health behaviours being close to the final sample average. Variance explained ($R^2$) values are used to compare OLS models while AIC is used to compare model fit for logistic regression. Age and sex were included as covariates in each model.

## 2.3 Results

### 2.3.1 Descriptive Analysis of Clusters

Standardized means and standard deviations for health behaviours in each cluster are presented in Table 1. Demographic information for each cluster is presented in Table 2. Ridge plots illustrating the density distributions of responses for each health behaviour across clusters are presented in Figure 1. Descriptive summaries highlighting the characteristics of the final sample and each cluster, interpreted using unstandardized scales, are provided below and are accompanied by radar charts using standardized scales in Figure 2.

**Final sample.** Following listwise deletion for missing values in health behaviour variables there were 40,268 people included in the final sample. On average, people engaged in walking activities 3-4 days a week (M = 3.1; SD = 1.1), sitting activities close to 4-5 days a week (M = 3.9; SD = 0.4), light sports were mostly performed between ‘never’ and ‘seldom (1-2 days per week; M = 1.3; SD = 0.5), people engaged in strenuous exercise approximately 1 day per week (M = 1.6; SD = .8), ate 4 servings of fruits and vegetables per day (M = 4.0; SD = 1.8), were non-smokers (M = 0.9; SD = 0.8), and consumed alcohol near the middle of a 7 point scale ranging from monthly to daily (M = 4.2; SD = 2.0). The overall sample was balanced by sex (50.2% Female). The majority were in married or common law relationships (70.8%) with household incomes between $50.000-$99,000 per year (35.6%). The distribution of age groups was 27.1% (age 45-54), 32.8% (age 55-64), 23.5% (age 65-74), and 16.6% (age 75-85).

**Table 1.**Standardized means and standard deviations for health behaviours and clusters

| | | Walking | | Sitting | | Light Sports | | Exercise | | Fruit/Veg | | Smoking | | Alcohol | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cluster | n | M | SD | M | SD | M | SD | M | SD | M | SD | M | SD | M | SD |
| 1 | 7703 | 0.81 | 0.18 | 0.17 | 0.53 | 0.38 | 1.28 | 1.09 | 0.94 | 0.37 | 0.96 | -0.17 | 0.62 | 0.03 | 0.95 |
| 2 | 7223 | 0.62 | 0.38 | 0.24 | 0.25 | -0.25 | 0.71 | -0.52 | 0.49 | -0.12 | 0.99 | -0.42 | 0.68 | -0.77 | 0.77 |
| 3 | 4094 | -1.53 | 0.41 | 0.22 | 0.34 | -0.19 | 0.83 | -0.33 | 0.82 | -0.35 | 0.93 | -0.38 | 0.68 | -0.97 | 0.75 |
| 4 | 10723 | -0.80 | 0.69 | 0.23 | 0.32 | 0.02 | 1.00 | 0.07 | 1.01 | 0.05 | 0.99 | -0.15 | 0.60 | 0.51 | 0.69 |
| 5 | 5212 | 0.83 | 0.11 | 0.20 | 0.47 | 0.04 | 0.96 | -0.55 | 0.40 | 0.15 | 0.95 | -0.03 | 0.65 | 0.86 | 0.48 |
| 6 | 3079 | -0.15 | 1.05 | -0.04 | 1.07 | -0.16 | 0.87 | -0.33 | 0.80 | -0.56 | 0.93 | 2.68 | 0.42 | -0.08 | 1.07 |
| 7 | 2234 | 0.08 | 0.91 | -3.32 | 1.52 | -0.11 | 0.84 | -0.05 | 0.90 | -0.05 | 0.95 | -0.26 | 0.65 | -0.14 | 0.96 |
| Full Sample | 40268 | 0.00 | 1.00 | 0.00 | 1.00 | 0.00 | 1.00 | 0.00 | 1.00 | 0.00 | 1.00 | 0.00 | 1.00 | 0.00 | 1.00 |

Notes: Standardized means are colorized to highlight the size (color intensity) and direction (green = positive, red = nedative) of mean differences. Cluster labels are as follows: Cluster 1 = Physically Active Healthy Eaters; Cluster 2 = Frequent Walkers with Infrequent Strenuous Exercise and Infrequent Alcohol Use; Cluster 3 = Infrequent Alcohol Use, Walking, Light Sports, and Exercise; Cluster 4 = Frequent Alcohol Use and Infrequent Walkers; Cluster 5 = Frequent Walkers with Infrequent Strenuous Exercise but Higher Alcohol Use; Cluster 6 = Occasional and Daily Smokers who Infrequently Eat Fruits and Vegetables and Exercise; Cluster 7 = Infrequent Sedentary Activities

**Cluster 1: Physically Active Healthy Eaters.** People assigned to this cluster comprised 19% of all participants and engaged in more walking activities and exercise than the final sample and ate slightly more daily servings of fruits and vegetables[2]. Specifically, people in Cluster 1 engaged in walking activities, on average, closer to 6-7 days a week than the 3-4 days overall average (M = 4.0; SD = 0.2) and strenuous exercise between 1-2 days a week and 3-4 days a week (M = 2.4; SD = 0.7). Average daily fruit and vegetable consumption was closer to 5 servings per day (M = 4.7; SD = 1.7) compared to the overall average of 4

2 We conducted one-way ANOVAs and follow-up multiple comparison tests as planned in our protocol. All one-way ANOVAs were statistically significant. Twenty-one follow-up tests using Tukey HSD were conducted per health behaviour resulting in 147 follow-up comparisons. Overall, 93.2% of comparisons were statistically significant. Given that most differences were statistically significant, we omit the reporting of p-values and interpret the clusters descriptively (although all mean level differences presented descriptively are also statistically significant).

servings per day. When compared to the proportion of people earning $150,000 or more annually in the final sample (15.4%), more people in this cluster earned $150,000 or more (20.5%).

**Cluster 2: Frequent Walkers with Infrequent Strenuous Exercise and Infrequent Alcohol Use.** People in this cluster represented 18% of participants and engaged in more frequent walking activities but less frequent strenuous exercise and alcohol consumption when compared to the overall sample. Walking activities were closer to 6-7 days a week than 3-4 days (M = 3.8; SD = 0.4) while the weekly average for strenuous exercise was closer to 'never' than 'seldom' (M = 1.2; SD = .4) and alcohol consumption was closer to monthly than daily (M = 2.7; SD = 1.6). Demographically, there were 5.6% fewer males in this group than the final sample and 5% more people earning $20,000-$49,000 annually.

**Figure 1.** Health behaviour ridge (density) plots across clusters.

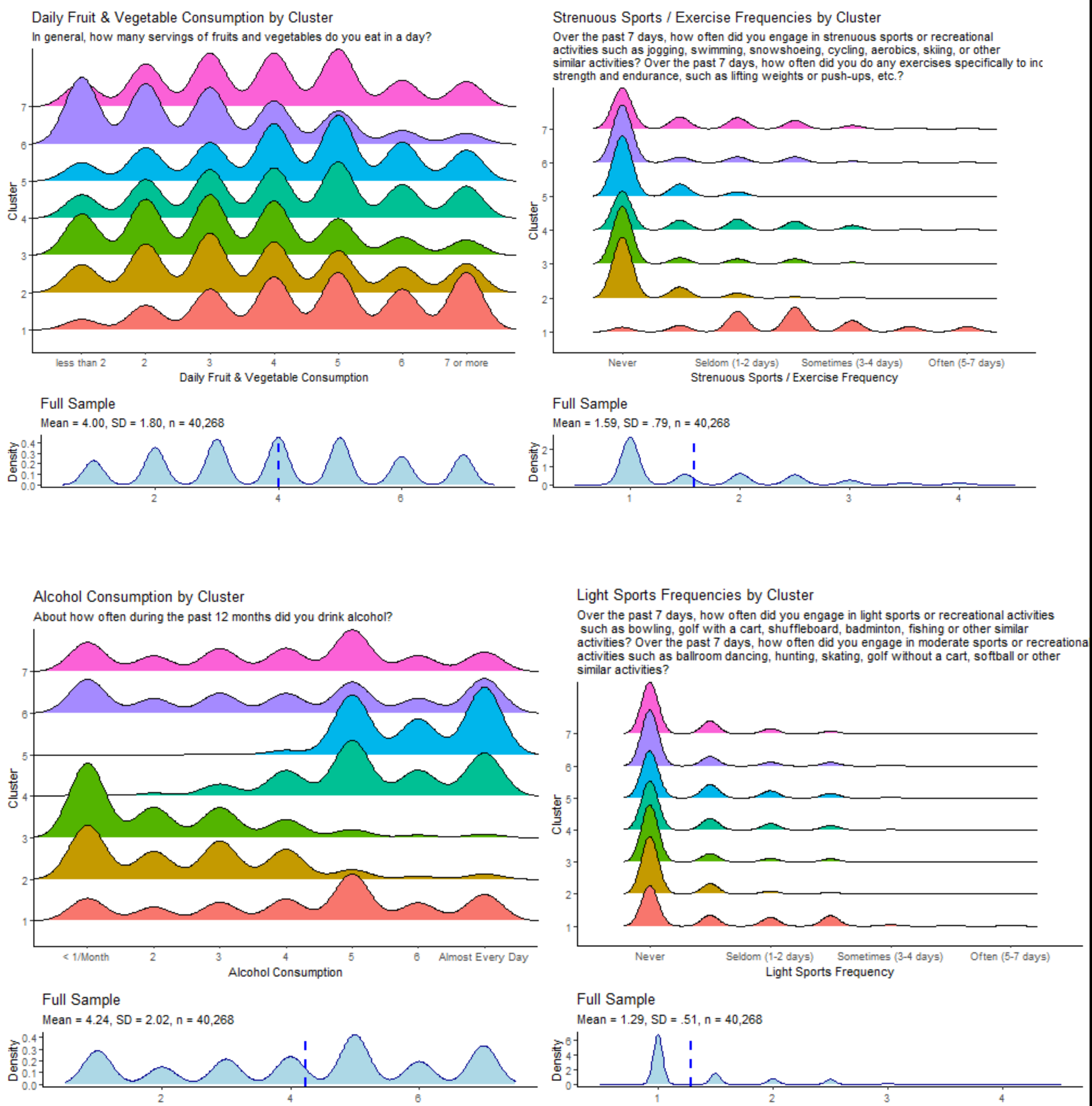


**Figure 1 Cont.** Ridge (density) plots for each health behaviour across clusters.

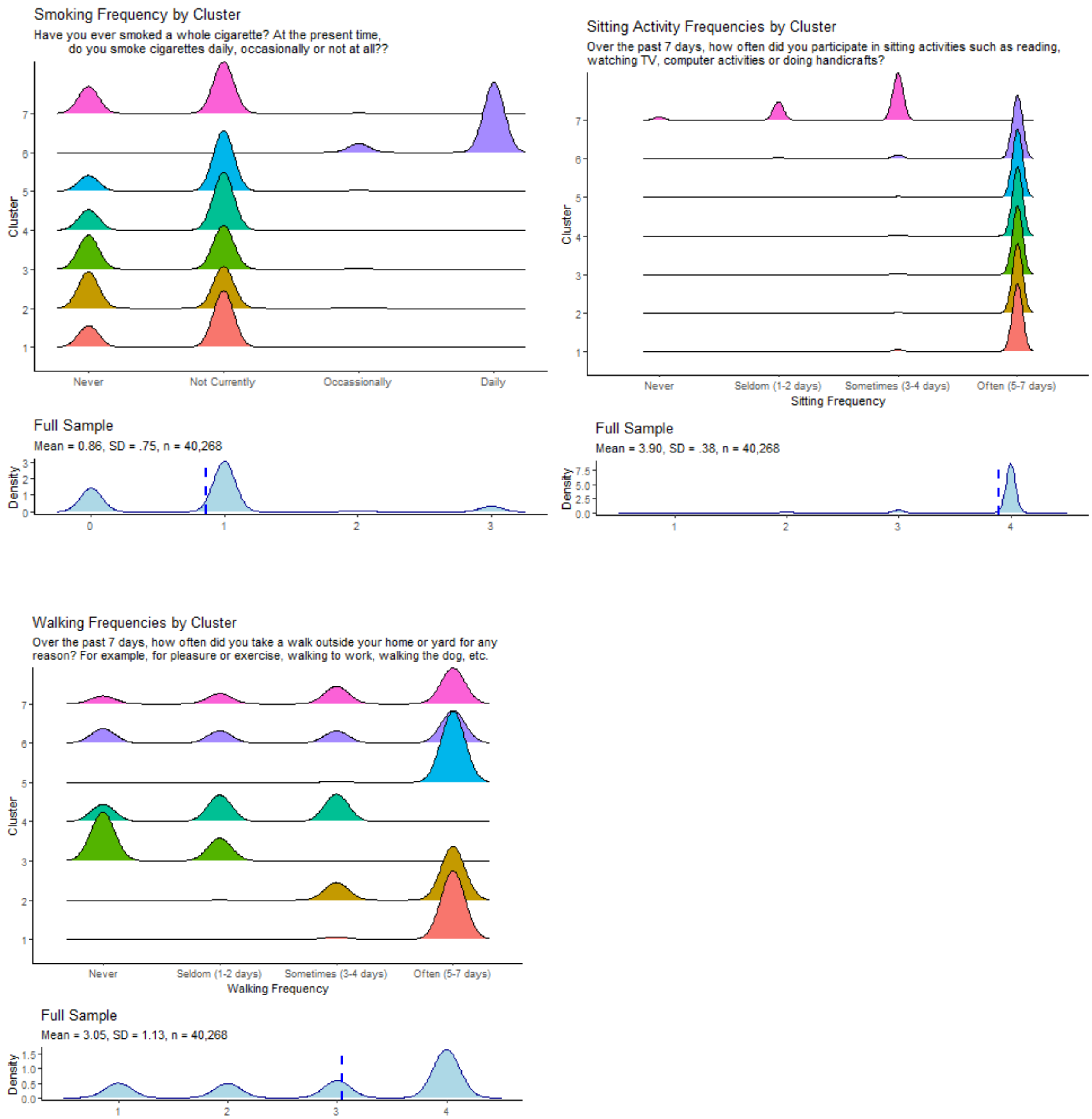



**Figure note:** Cluster labels are as follows: Cluster 1 = Physically Active Healthy Eaters; Cluster 2 = Frequent Walkers with Infrequent Strenuous Exercise and Infrequent Alcohol Use; Cluster 3 = Infrequent Alcohol Use, Walking, Light Sports, and Exercise; Cluster 4 = Frequent Alcohol Use and Infrequent Walkers; Cluster 5 = Frequent Walkers with Infrequent

Strenuous Exercise but Higher Alcohol Use; Cluster 6 = Occasional and Daily Smokers who Infrequently Eat Fruits and Vegetables and Exercise; Cluster 7 = Infrequent Sedentary Activities.

**Table 2.** Counts and percentages of sociodemographic variables for final sample and each cluster.

| | Full Sample | | Cluster 1 | | | Cluster 2 | | | Cluster 3 | | | Cluster 4 | | | Cluster 5 | | | Cluster 6 | | | Cluster 7 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | N | % | N | % | %-% | N | % | %-% | N | % | %-% | N | % | %-% | N | % | %-% | N | % | %-% | N | % | %-% |
| **Age Group** | | | | | | | | | | | | | | | | | | | | | | | |
| 45-54 | 10923 | 27.1 | 2274 | 29.5 | 2.4 | 1852 | 25.6 | −1.5 | 1013 | 24.7 | −2.4 | 2760 | 25.7 | −1.4 | 1040 | 20.0 | −7.2 | 1147 | 37.3 | 10.1 | 837 | 37.5 | 10.3 |
| 55-64 | 13186 | 32.7 | 2613 | 33.9 | 1.2 | 2300 | 31.8 | −0.9 | 1237 | 30.2 | −2.5 | 3451 | 32.2 | −0.6 | 1731 | 33.2 | 0.5 | 1182 | 38.4 | 5.6 | 672 | 30.1 | −2.7 |
| 65-74 | 9461 | 23.5 | 1772 | 23.0 | −0.5 | 1733 | 24.0 | 0.5 | 979 | 23.9 | 0.4 | 2591 | 24.2 | 0.7 | 1434 | 27.5 | 4.0 | 527 | 17.1 | −6.4 | 425 | 19.0 | −4.5 |
| 75-85 | 6698 | 16.6 | 1044 | 13.6 | −3.1 | 1338 | 18.5 | 1.9 | 865 | 21.1 | 4.5 | 1921 | 17.9 | 1.3 | 1007 | 19.3 | 2.7 | 223 | 7.2 | −9.4 | 300 | 13.4 | −3.2 |
| NA | 0 | 0.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| **Employment Status** | | | | | | | | | | | | | | | | | | | | | | | |
| Yes | 16401 | 40.7 | 3375 | 43.8 | 3.1 | 2843 | 39.4 | −1.4 | 1524 | 37.2 | −3.5 | 4310 | 40.2 | −0.5 | 1794 | 34.4 | −6.3 | 1411 | 45.8 | 5.1 | 1144 | 51.2 | 10.5 |
| No | 1609 | 4.0 | 236 | 3.1 | −0.9 | 325 | 4.5 | 0.5 | 204 | 5.0 | 1.0 | 327 | 3.0 | −0.9 | 158 | 3.0 | −1.0 | 267 | 8.7 | 4.7 | 92 | 4.1 | 0.1 |
| NA | 22258 | 55.3 | 4092 | 53.1 | −2.2 | 4055 | 56.1 | 0.9 | 2366 | 57.8 | 2.5 | 6086 | 56.8 | 1.5 | 3260 | 62.5 | 7.3 | 1401 | 45.5 | −9.8 | 998 | 44.7 | −10.6 |
| **Sex** | | | | | | | | | | | | | | | | | | | | | | | |
| F | 20220 | 50.2 | 3729 | 48.4 | −1.8 | 4029 | 55.8 | 5.6 | 2409 | 58.8 | 8.6 | 5025 | 46.9 | −3.4 | 2310 | 44.3 | −5.9 | 1563 | 50.8 | 0.6 | 1155 | 51.7 | 1.5 |
| M | 20048 | 49.8 | 3974 | 51.6 | 1.8 | 3194 | 44.2 | −5.6 | 1685 | 41.2 | −8.6 | 5698 | 53.1 | 3.4 | 2902 | 55.7 | 5.9 | 1516 | 49.2 | −0.5 | 1079 | 48.3 | −1.5 |
| NA | 0 | 0.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| **Annual Income** | | | | | | | | | | | | | | | | | | | | | | | |
| <$20k | 1669 | 4.1 | 208 | 2.7 | −1.4 | 409 | 5.7 | 1.5 | 280 | 6.8 | 2.7 | 229 | 2.1 | −2.0 | 122 | 2.3 | −1.8 | 326 | 10.6 | 6.4 | 95 | 4.3 | 0.1 |
| $20-$49k | 8663 | 21.5 | 1360 | 17.7 | −3.9 | 1912 | 26.5 | 5.0 | 1144 | 27.9 | 6.4 | 1973 | 18.4 | −3.1 | 931 | 17.9 | −3.7 | 865 | 28.1 | 6.6 | 478 | 21.4 | −0.1 |
| $50-$99k | 13928 | 34.6 | 2526 | 32.8 | −1.8 | 2464 | 34.1 | −0.5 | 1407 | 34.4 | −0.2 | 3823 | 35.7 | 1.1 | 1941 | 37.2 | 2.7 | 999 | 32.4 | −2.1 | 768 | 34.4 | −0.2 |
| $100-$149k | 7439 | 18.5 | 1636 | 21.2 | 2.8 | 1117 | 15.5 | −3.0 | 600 | 14.7 | −3.8 | 2195 | 20.5 | 2.0 | 1038 | 19.9 | 1.4 | 440 | 14.3 | −4.2 | 413 | 18.5 | 0.0 |
| $150k+ | 6214 | 15.4 | 1578 | 20.5 | 5.1 | 841 | 11.6 | −3.8 | 375 | 9.2 | −6.3 | 1886 | 17.6 | 2.2 | 912 | 17.5 | 2.1 | 260 | 8.4 | −7.0 | 362 | 16.2 | 0.8 |
| NA | 2355 | 5.8 | 395 | 5.1 | −0.7 | 480 | 6.6 | 0.8 | 288 | 7.0 | 1.2 | 617 | 5.8 | −0.1 | 268 | 5.1 | −0.7 | 189 | 6.1 | 0.3 | 118 | 5.3 | −0.6 |
| **Marital Status** | | | | | | | | | | | | | | | | | | | | | | | |
| Single | 3230 | 8.0 | 580 | 7.5 | −0.5 | 685 | 9.5 | 1.5 | 355 | 8.7 | 0.7 | 681 | 6.4 | −1.7 | 292 | 5.6 | −2.4 | 465 | 15.1 | 7.1 | 172 | 7.7 | −0.3 |
| Married/CL | 28520 | 70.8 | 5692 | 73.9 | 3.1 | 4843 | 67.0 | −3.8 | 2673 | 65.3 | −5.5 | 8076 | 75.3 | 4.5 | 3972 | 76.2 | 5.4 | 1697 | 55.1 | −15.7 | 1567 | 70.1 | −0.7 |
| Widowed | 3600 | 8.9 | 568 | 7.4 | −1.6 | 765 | 10.6 | 1.7 | 501 | 12.2 | 3.3 | 868 | 8.1 | −0.8 | 428 | 8.2 | −0.7 | 274 | 8.9 | −0.0 | 196 | 8.8 | −0.2 |
| Divorced | 3879 | 9.6 | 684 | 8.9 | −0.8 | 753 | 10.4 | 0.8 | 458 | 11.2 | 1.6 | 871 | 8.1 | −1.5 | 413 | 7.9 | −1.7 | 476 | 15.5 | 5.8 | 224 | 10.0 | 0.4 |
| Separated | 1027 | 2.6 | 175 | 2.3 | −0.3 | 177 | 2.5 | −0.1 | 105 | 2.6 | 0.0 | 225 | 2.1 | −0.5 | 107 | 2.1 | −0.5 | 165 | 5.4 | 2.8 | 73 | 3.3 | 0.7 |
| NA | 12 | 0.0 | 4 | 0.1 | 0.0 | 0 | 0.0 | −0.0 | 2 | 0.0 | 0.0 | 2 | 0.0 | −0.0 | 0 | 0.0 | −0.0 | 2 | 0.1 | 0.0 | 2 | 0.1 | 0.1 |

Notes: %-% denotes the % difference between final sample and a given cluster and are colorized to highlight the size (color intensity) and direction (green = positive, red = negative) of the differences. Cluster labels are as follows: Cluster 1 = Physically Active Healthy Eaters; Cluster 2 = Frequent Walkers with Infrequent Strenuous Exercise and Infrequent Alcohol Use; Cluster 3 = Infrequent Alcohol Use, Walking, Light Sports, and Exercise; Cluster 4 = Frequent Alcohol Use and Infrequent Walkers; Cluster 5 = Frequent Walkers with Infrequent Strenuous Exercise but Higher Alcohol Use; Cluster 6 = Occasional and Daily Smokers who Infrequently Eat Fruits and Vegetables and Exercise; Cluster 7 = Infrequent Sedentary Activities. NA = Missing data.

**Cluster 3: Infrequent Alcohol Users, Walkers, Fruit/Vegetable Consumption, Light Sports, and Exercise.** In this group (10% of participants), all health behaviours were performed less frequently than the group average except for slightly more sitting activities. Notably, the frequencies of walking, light physically activity, and strenuous exercise were each closer to ‘never’ than ‘seldom (1-2 days)’ (M = 1.3, 1.2, 1.3; SD = 0.5, 0.4, 0.6). Alcohol consumption was lower than average (M = 2.3; SD = 1.5) indicating that people in this group consumed alcohol closer to monthly than daily. Daily fruit and vegetable servings were closer to 3 servings a week (M = 3.4; SD = 1.7) than the overall average of 4 servings (M = 4.0; SD = 1.8). Additionally, the group was comprised of non-smokers. Demographically, there are more people aged 78-85 in this group (21.1%) compared to overall (16.6%), less Males (41.2%) than overall (49.8%), and the distribution of annual income was skewed towards lower income brackets compared to the final sample with 6.4% more people in Cluster 3 than the final sample earning $20,000-$49,000 and 6.3% less people earning $150,000 per year or more.

**Cluster 4: Frequent Alcohol Users and Infrequent Walkers.** The largest of the seven clusters (27%) was defined by near average frequencies of health behaviours with two exceptions. First, the average frequency of walking activities was lower in this cluster with people engaging in walking activities 1-2 days per week (M = 2.1; SD = 0.8) compared to 3-4 days per week in the final sample (M = 3.1; SD = 1.1). Second, alcohol consumption was higher (M = 5.3; SD = 1.4) than the final sample average (M = 4.2; SD = 2.0) meaning that people in this cluster were closer to daily alcohol consumption than monthly consumption on the 1 (< once a month) to 7 (almost every day) scale. There were slightly more people in married or common law relationships in this cluster (75.3%) compared to the overall sample (70.8%).

**Cluster 5: Frequent Walkers with Infrequent Strenuous Exercisers with Higher Alcohol Use.** Comprised of 13% of participants, Cluster 5 is similar to Cluster 2 with higher than average walking frequencies (M = 4.0; SD = 0.1) and lower than average strenuous exercise (M = 1.2; SD = 0.3). However, these two clusters are differentiated by alcohol consumption with the average drinking frequency for this group being 1 point away from 'almost every day' on a 1-7 scale (M = 6.0; SD = 1.0). Differences in demographics also distinguish these two clusters: there were fewer people aged 45-54 in this cluster compared to overall (20.0% vs 27.1%), more Males (55.7% vs 49.8%), and more people in married or common law relationships (76.2% vs 70.8%).

**Cluster 6: Occasional and Daily Smokers who Infrequently Eat Fruits and Vegetables and Exercise.** Nearly all participants who smoked occasionally or daily were included in this cluster (8% of total). Participants in this cluster also ate, on average, 1 less serving of fruits and vegetables per week (M = 3.0; SD = 1.7) compared to the overall sample (M = 4.0; SD = 1.8). Additionally, the average level of strenuous exercise in this group was closer to 'never' (M = 1.3; SD = 0.6) than the overall sample whose average was closer to 'seldom (1-2 days per week'; M = 1.6; SD = 0.8). Demographically, this group was skewed towards younger age groups (e.g., 37.3% aged 45-54 vs 27.1% final sample) and lower income brackets (e.g., 10.6% with income <$20,000 vs 4.1% final sample). Lastly, this group was comprised of 15.7% less married or common law individuals, compared to overall, and 7.1% more single people and 5.8% more divorced participants.

**Cluster 7: Infrequent Sedentary Activities.** The smallest cluster by group membership (6%), people assigned to this cluster engaged in sitting activities, on average, between ‘seldom (1-2 days’ and ‘sometimes (2-4 days)’ (M = 2.6; SD = 0.6) compared to the overall sample who, on average, participated in sitting activities closer to ‘often (5-7 days)’ (M = 3.9; SD = 0.4). Demographically, this group contains 10.3% more people aged 45-54 than the overall sample.

### 2.3.2 Partial Correlations (Baseline)

Partial polychoric correlations are visualized as a network in Figure 3. Correlations ranges from $\rho = -.13$ for smoking and fruit/vegetable consumption and $\rho = .14$ for exercise and fruit/vegetable consumption. The average correlation was $\rho = +/- .06$.

**Figure 2.** Radar plots for each cluster (standardized means).

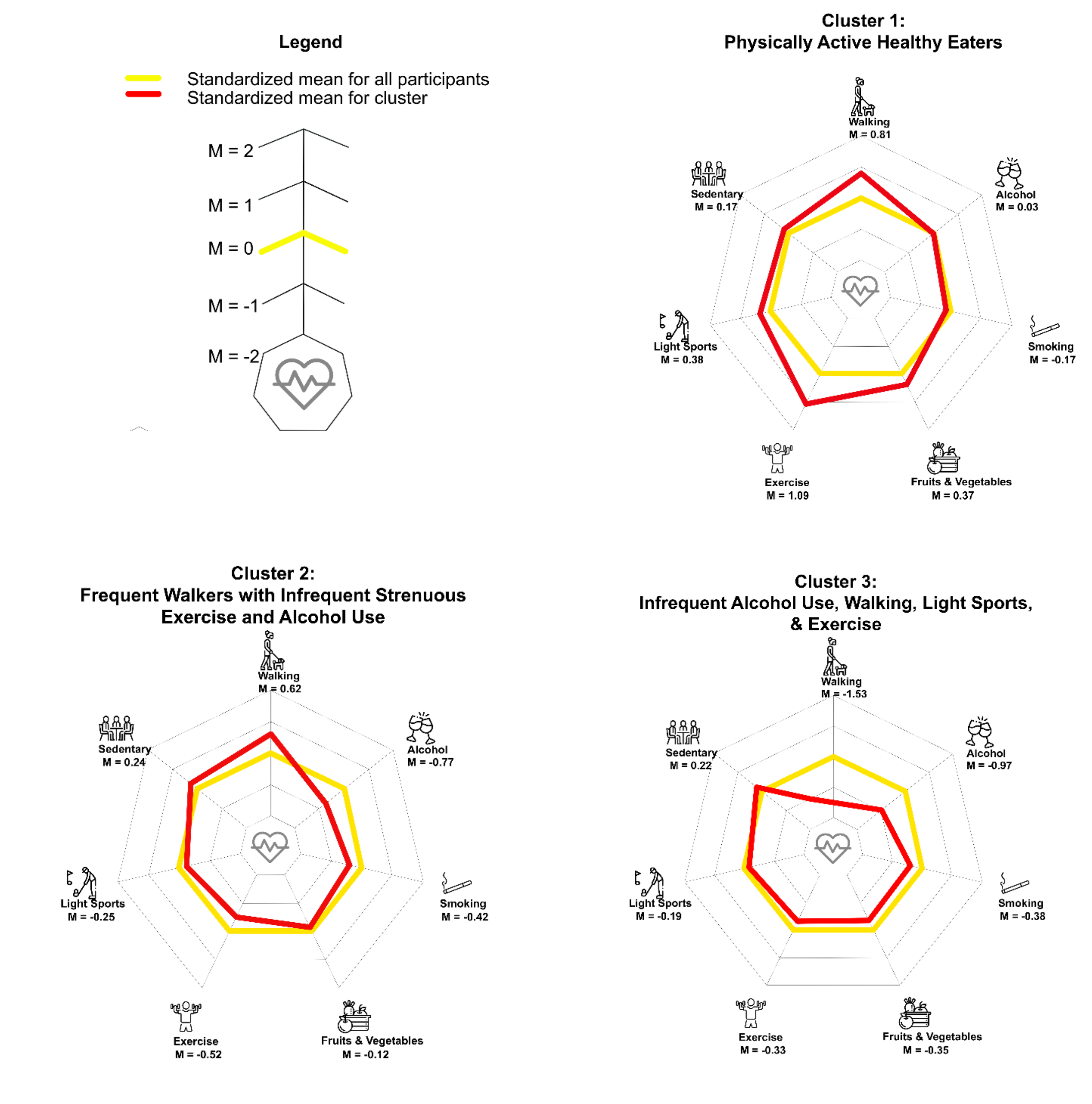
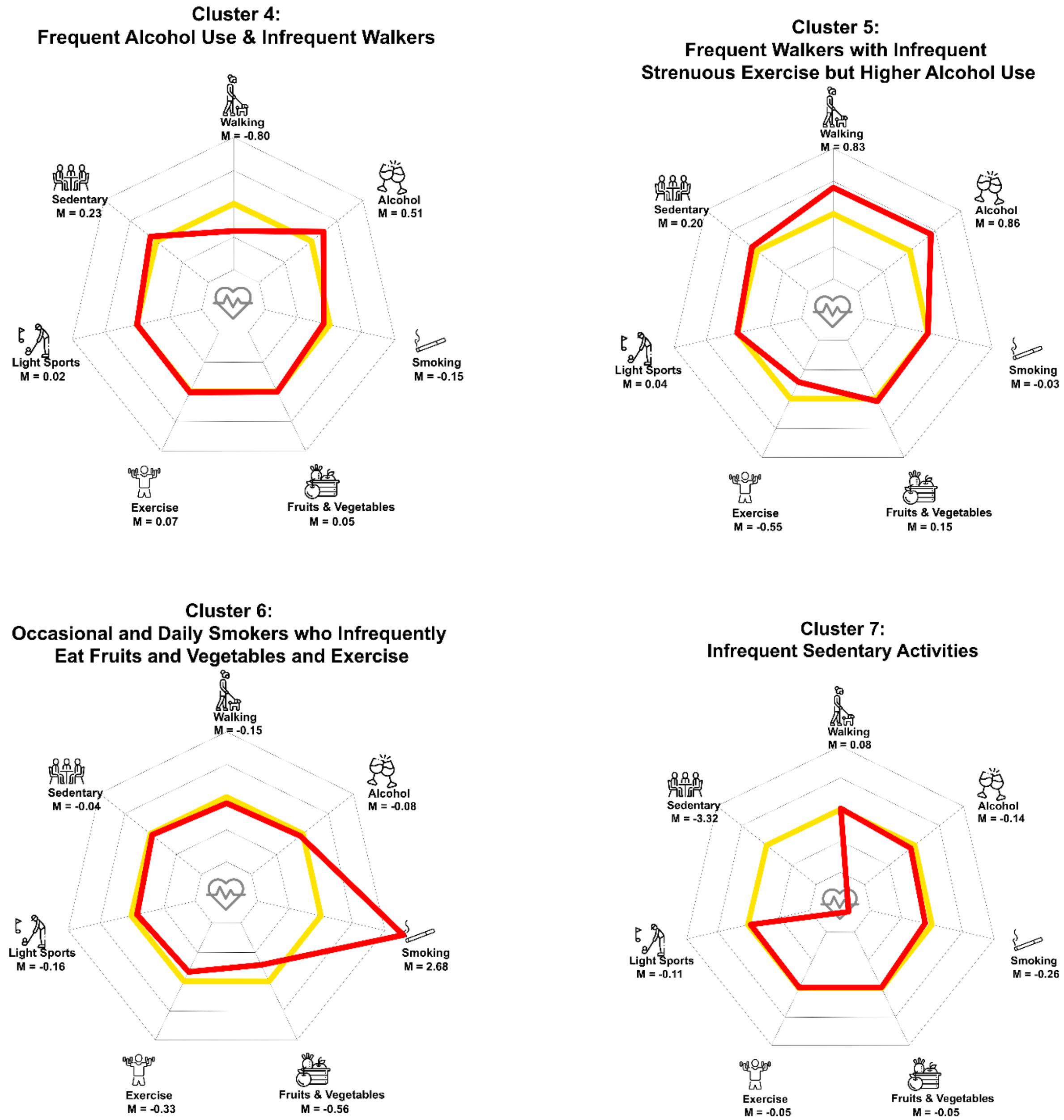


**Figure 2 Continued.** Radar plots for each cluster (standardized means).



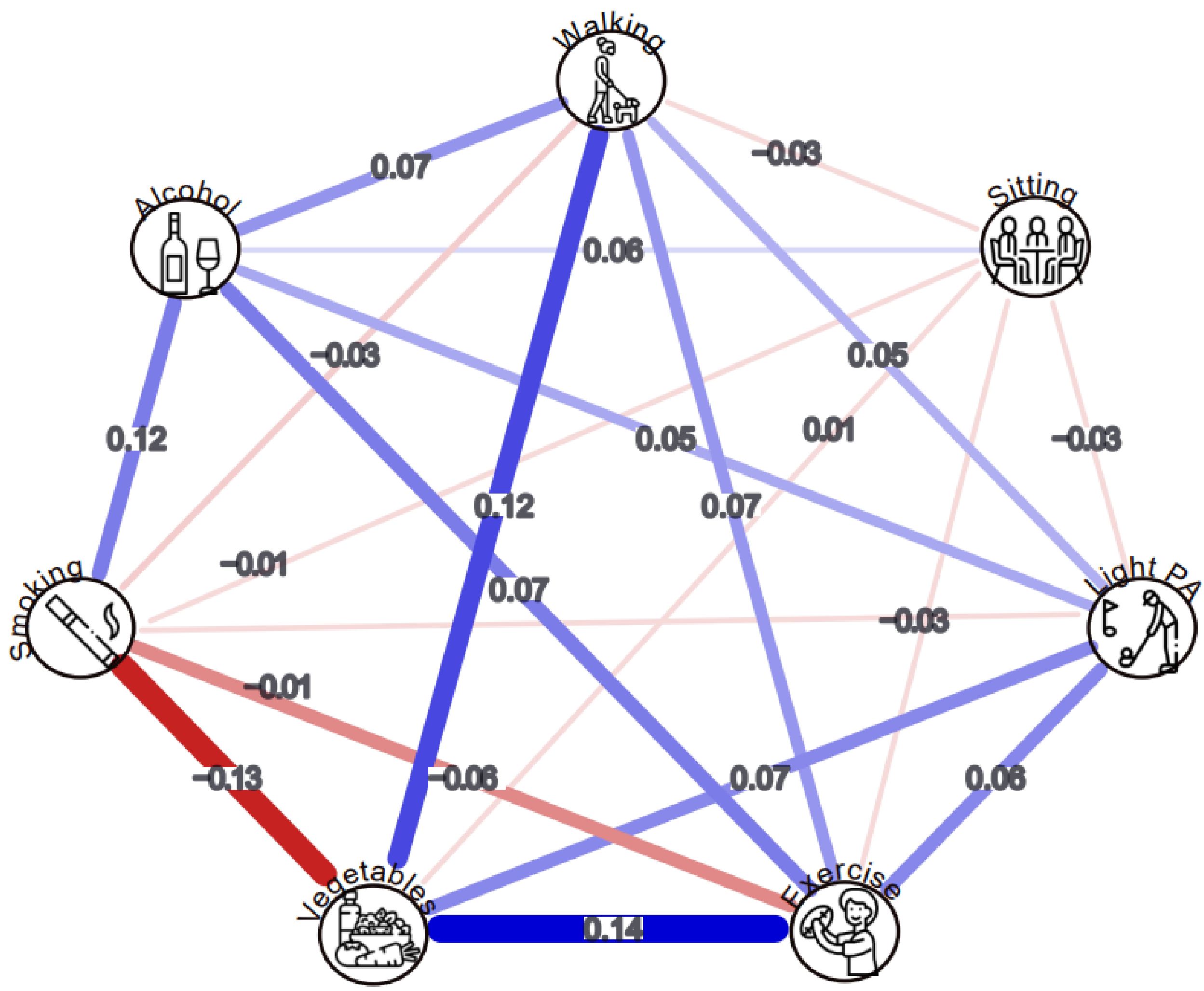



**Figure 3.** Partial polychoric correlation visualization of baseline health behaviours. Values represent partial polychoric correlations between variables. Red lines represent negative correlations and blue lines represent positive correlations. Line width corresponds to correlation strength.

**Table 3.** Regressions predicting follow-up health indicators from baseline behaviours and clusters

| | General Health | | Mental Health | | Chronic Conditions | |
|---|---|---|---|---|---|---|
| | β | *p* | β | *p* | β | *p* |
| Cluster 1 | .23 | <.001 | .10 | <.001 | -.24 | <.001 |
| Cluster 2 | -.12 | <.001 | -.10 | <.001 | .13 | .11 |
| Cluster 3 | -.31 | <.001 | -.19 | <.001 | .60 | <.001 |
| Cluster 5 | .09 | <.001 | .04 | .009 | .12 | .16 |
| Cluster 6 | -.42 | <.001 | -.29 | <.001 | -.07 | .50 |
| Cluster 7 | .03 | .18 | -.04 | .04 | -.26 | .01 |
| | $R^2$ = .04 | | $R^2$ = .02 | | AIC = 13,659 | |
| Walking | .07 | <.001 | .02 | <.001 | -.09 | <.001 |
| Sitting | -.04 | <.001 | -.01 | .63 | .26 | <.001 |
| Exercise | .16 | <.001 | .08 | <.001 | -.26 | <.001 |
| Light PA | .08 | <.001 | .05 | <.001 | -.01 | .90 |
| Fruit/Vegetable | .05 | <.001 | .03 | <.001 | .05 | <.001 |
| Smoking | -.13 | <.001 | -.08 | <.001 | .04 | .29 |
| Alcohol | .05 | <.001 | .03 | <.001 | -.03 | .03 |
| | $R^2$ = .08 | | $R^2$ = .03 | | AIC=13,606 | |

Cluster labels are as follows: Cluster 1 = Physically Active Healthy Eaters; Cluster 2 = Frequent Walkers with Infrequent Strenuous Exercise and Infrequent Alcohol Use; Cluster 3 = Infrequent Alcohol Use, Walking, Light Sports, and Exercise; Cluster 4 = Frequent Alcohol Use and Infrequent Walkers; Cluster 5 = Frequent Walkers with Infrequent Strenuous Exercise but Higher Alcohol Use; Cluster 6 = Occasional and Daily Smokers who Infrequently Eat Fruits and Vegetables and Exercise; Cluster 7 = Infrequent Sedentary Activities. All predictors listed in table 3 are those included in the model.

### 2.3.3 Predicting Follow-Up Indicators from Baseline Behaviours

Two sets of exploratory regression analyses were performed with baseline health behaviour clusters and individual health behaviours, predicting three health outcome indicators at follow-up. Summary statistics for health indicators are presented in Appendix III while regression outputs are summarized in Table 3.

## 2.4 Discussion

Multiple health behaviours are robustly associated with the development of preventable non-communicable diseases and people engage in different combinations of these behaviours to varying degrees. To identify which behaviours are associated with one another to support multiple health behaviour change interventions, it may help to first identify which behaviours co-occur and/or co-vary; co-occurrence and co-variation are assessed through person and variable centered approaches. In this study, we compared outputs from person centered (cluster analysis) and variable centered (partial correlation) approaches. Using representative data from the Canadian Longitudinal Study of Aging (CLSA), our cluster analysis produced seven groups of individuals based on similarities of frequencies they engage in key health behaviours (e.g., walking, sitting, light sports, exercise, fruit and vegetable consumption, smoking, and alcohol use). Overall, clusters were differentiated by six of the seven health behaviours included in the analysis with the most variability observed in weekly walking frequency, strenuous exercise, and alcohol consumption. Specifically, three clusters were partly characterized by walking frequency and two were characterized by strenuous exercise and alcohol consumption, respectively. Of the remaining health behaviours, there was little variability in weekly ‘light sports’ frequencies within the seven clusters, while one cluster was generally defined by a relative extreme of a single behaviour (infrequent sedentary activities). Sociodemographic characteristics varied across several clusters while associations between self-reported physical/mental health and cluster memberships were generally small.

In contrast, a partial correlation approach revealed small associations between health behaviours ranging from ranges from $\rho = -.13$ for smoking and fruit/vegetable consumption and $\rho = .14$ for exercise and fruit/vegetable consumption. Minimal effect sizes of interest are not well established in the multiple health behaviour change literature and it is unknown whether the small effect sizes observed in this study represent more than the 'crud factor', the idea that in the behavioral research everything correlates with everything else (Orben & Lakens, 2020). For example, in some fields within psychology a correlation less than $\rho = .10$ is not considered hypothesis supporting as the observed relationships between theoretically relevant and irrelevant constructs can reach this level of effect size (Ferguson & Heene, 2021).

A comparison between co-occurrence and co-variation approaches reveals strengths and limitations to each approach. Regarding limitations, neither approach modelled some known phenomena. For example, the combination of high physical activity and frequent sedentary behaviour is common in individuals who participate in sports and strenuous exercise [49]; this distinction was not captured in the cluster analysis which illustrates the trade-offs between parsimony and nuance using hierarchical cluster analysis to describe co-occurring health behaviours. Additionally, the clustering algorithm revealed associations that were overlooked with variable centered analyses. Specifically, three clusters were defined by varying combinations of walking frequency and alcohol consumption while correlations between the two variables were negligible. Taken together, these findings highlight the need for alignment between methods and research objectives with person centered approaches more suitable for identifying sub-groups for intervention targeting purposes and variable centered approaches more appropriate for understanding the strength and direction of relationships between interconnected behaviours.

In addition to comparing insights into health behaviour associations from person and variable centered approaches we also investigated the ability of these approaches to predict future health outcomes. Between 2%-8% of variability in general and mental health at follow-up were accounted for by baseline clusters or individual health behaviours. When classifying whether people reported any chronic conditions at follow-up, the baseline cluster of ‘infrequent alcohol use, walking, light sports, and exercise’ was the strongest predictor of having at least one condition while the individual behaviour of exercise was the strongest predictor of not having a chronic condition. To the best of our knowledge, no health behaviour clustering studies in adults have produced a grouping similar to the cluster we named ‘infrequent alcohol use, walking, light sports, and exercise’. Behaviourally, this cluster was defined by little to no physical activity of any kind, non-smoking, and less frequent alcohol and fruits/vegetable consumption than average. The only behaviour that was above the final sample average were sedentary behaviours. People in this group tended to be older, have lower annual incomes, have higher BMI’s, use healthcare services more frequently, not be employed, and be women. Taken together, the ‘infrequent alcohol use, walking, light sports, and exercise’ cluster may present a relatively homogenous behavioural sub-group to target for researchers and practitioners interested in conducting health behaviour interventions.

This research is subject to limitations worth noting when interpreting the findings. First, many of the items selected for planned analysis are self-report which have known and inherent strengths and weaknesses (Del Boca & Noll, 2000). Second, direct comparisons between multiple health behaviour studies is difficult due to variations in sample, measurement characteristics, and inconsistent naming conventions. Although heterogeneous samples and measurement variability may be useful for establishing the presence of robust phenomena in the form of co-occurring behaviours, we encourage future analysis to clearly label clusters to include each prominent health behaviour. For example, a cluster defined as ‘occasional and daily smokers who infrequently eat fruits and vegetables and exercise’ is more clearly defined than ‘smokers with other risk behaviours'. Third, the health behaviours included in the cluster analysis were not exhaustive (e.g., sleep hygiene, substance use, sexual risk behaviours were not included) and some behaviours were overrepresented such as physical activity. While grouping people based on the types of physical activities scored with the PACE scale (Washburn, Smith, Jette, Janney, 1993) enabled us to explore variability in walking activities, the way in which physical activity frequency was measured and the nature of the categories made it difficult to evaluate the health behaviours of this sample relative to behavioural guidelines.

Although a single comparisons between methods is not definitive, person centered approaches appear better suited than variable centered approaches or the purposes of identifying and prioritizing targets for multiple health behaviour change interventions. However, given the limitations of cluster analysis, we suggest that future person-centered research employ the 'behaviour profile approach' (Shaw & Agahi, 2012) with measures linked to behavioural guidelines in order to identify all possible combinations of 'meets guidelines/does not meet guidelines' for behaviours that contribute to negative health outcomes. Such approaches should ideally focus on datasets that include measures of health behaviour that provide an ability to directly link behaviour performance to thresholds recommended in guidelines. For variable centered approaches, the issue of measurement heterogeneity can be addressed through the use of meta-analysis. Although meta-analytic work on the associations between health behaviours has not yet conducted, some studies are planned for the future (Silva, PResseau, Dinsmore, van Allen, & Marques, 2023).

In conclusion, the scope, size, and rigour of the CLSA dataset provided an unprecedented opportunity to investigate how health behaviours are interconnected and to compare methods for modelling this interconnectivity. Our findings show how the population of older adults in Canada can be segmented by the multiple health behaviours that characterise people's lives and that these segmented clusters are socially patterned and associated with different health outcomes.

Comparing a person- and variable-centered approach can lead to insights about behaviours that may be overlooked with a single approach. Additionally, our analyses highlights opportunity for behavioural measures to be tied to national guidelines, which could lead to even more actionable analyses. The 'health behaviour profile' approach may be especially useful for future person-centered analysis, and a systematic review with meta-analysis could help establish associations between behaviours using a variable centered approach in future research. Understanding which behaviours co-occur and co-vary, and for whom, is an important first step towards developing tailored health behaviour change interventions. Future research will further develop our understanding of how interconnected health behaviours influence health outcomes over time using longitudinal data with multiple follow-up assessments.

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**Disclaimer**

The opinions expressed in this manuscript are the author's own and do not reflect the views of the Canadian Longitudinal Study on Aging

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## 2.6 Appendix I:
## Variables Included in Analysis

| Behaviour | CLSA Variable | Item Question & Response Scale |
|---|---|---|
| | | **Health Behaviours** |
| 1. **Sedentary Behaviour** | PA2_SIT | "Over the past 7 days, how often did you participate in sitting activities such as reading, watching TV, computer activities or doing handicrafts?" (*1 (never) to 4 (often, 5 to 7 days)*) |
| 2. **Walking** | PA2_WALK | "Over the past 7 days, how often did you take a walk outside your home or yard for any reason?" (*1 (never) to 4 (often, 5 to 7 days)*) |
| 3. **Light / Moderate Sports** | Combined: PA2_MSPRT, PA2_LSPRT | "Over the past 7 days, how often did you engage in moderate sports or recreational activities such as ballroom dancing, hunting, skating, golf without a cart, softball or other similar activities?" (*1 (never) to 4 (often, 5 to 7 days)*)<br>Over the past 7 days, how often did you engage in light sports or recreational activities such as bowling, golf with a cart, shuffleboard, badminton, fishing or other similar activities? (*1 (never) to 4 (often, 5 to 7 days)*) |
| 4. **Strenuous Physical Activity / Exercise** | Combined PA2_SSPRT, PA2_EXER | "Over the past 7 days, how often did you engage in strenuous sports or recreational activities such as jogging, swimming, snowshoeing, cycling, aerobics, skiing, or other similar activities?" (*1 (never) to 4 (often, 5 to 7 days)*)<br>"Over the past 7 days, how often did you do any exercises specifically to increase muscle strength and endurance, such as lifting weights or push-ups, etc.?" (*1 (never) to 4 (often, 5 to 7 days)*) |
| 5. **Fruit and Vegetable Consumption** | NUR_FRTVEG | "In general, how many servings of fruits and vegetables do you eat in a day?" (*1 (seven or more) to 7 (less than two)*) |
| 6. **Smoking** | SMK_CURRCG | "At the present time, do you smoke cigarettes daily, occasionally or not at all?" (*1 (daily) 2 (occasionally) 0 (not at all)*) |
| 7. **Alcohol Use** | ALC_FREQ | "About how often during the past 12 months did you drink alcohol?" (*1 (almost every day) to 7 (less than once a month)*) |
| 8. **Sleep** | SLE_HOUR_NB | "During the past month, on average, how many hours of actual sleep did you get at night?" (*continuous*) |

| | | |
|---|---|---|
| | **Sociodemographic Factors** | |
| 9. **Age** | AGE_DOB | "For some of the questions I'll be asking, I need to know your exact date of birth" and "What is your age?" (*grouped: 45-54; 55-64; 65-74; 75-85*) |
| 10. **Sex** | SEX_ASK | M (1) / F (0) |
| 11. **Marital status** | SDC_MRTL | "What is your current marital/partner status?" *(Single/Married or common-law/Widowed/Divorced/Separated*) |
| **12. Household income** | INC_TOT | "What is your best estimate of the total household income received by all household members, from all sources, before taxes and deductions, in the past 12 months?" (*<$20k/$20-$49k/$50-$99k/$100-$149k/$150k+*) |
| 13. **Social support availability** | SSA_DPALL | This derived variable measures the overall level of functional social support that is available to the respondent. It includes all aspects asked about in the MOS Social Support Survey. Higher scores indicate higher levels of functional social support (min = 0, max = 100) |
| **14. Retirement status** | RET_RTRD | "At this time, do you consider yourself to be completely retired, partly retired or not retired?" (*1 (completely retired), 2 (partly retired), 3 (not retired)*) |
| **15. Working** | LBF_CURR | "Are you currently working at a job or business?" (*1 (yes), 2 (no)*) |
| | **Health and Life Satisfaction Outcomes** | |
| **16. General health** | GEN_DHDI | This derived variable indicates the respondent's health status based on his/her own judgement. It is a recoded version of the questionnaire responses so that higher scores now indicate a more positively perceived health status. (1 – poor, 5 – excellent)APPEB |
| **17. Mental health** | GEN_DMHI | This derived variable indicates the respondent's mental health status based on his/her own judgement. It is a recoded version of the questionnaire responses so that higher scores now indicate a more positively perceived mental health status. (1 – poor, 5 – excellent) |
| **18. Healthy aging** | GEN_OWNAG | "In terms of your own healthy aging, would you say it is excellent, very good, good, fair, or poor?" (1 - Excellent to 5 - Poor) |
| **19. Life satisfaction** | SLS_DSCR | This variable describes participants' satisfaction with life and is an aggregate score of the responses to the five items of the SWLS. Individual responses to each item in the SWLS range from 1 – strongly disagree to 7 – strongly agree, and this score is a sum of those responses. Higher scores indicate a greater satisfaction with life. (min 5, max 35) |
| **20. BMI** | HWT_DBMI | Body Mass Index |

| Health Care Utilization | | |
|---|---|---|
| **21. Emergency Department** | HCU_EMEREG | "Have you been seen in an Emergency Department during the past 12 months?" (*yes/no*) |
| **22. Admitted to Hospital** | HCU_HLOVRNT | "Were you a patient in a hospital overnight during the past 12 months?" (*yes/no*) |
| **23. Nursing Home** | HCU_NRSHM | "Were you a patient in a nursing home or convalescent home during the past 12 months?" (*yes/no*) |

# 2.7 Appendix II:
# Multinomial Regressions

## Multinomial Logistic Regressions

I conducted four multinomial logistic regressions predicting cluster membership to determine whether clusters are associated with 1) sociodemographic factors, 2) indicators of physical and mental health, 3) non-health behaviours, and 4) health care utilization. Analysis was performed using the ‘multinom’ function from the ‘nnet’ package [38]. The reference group for the regression analysis was Cluster 4 (‘frequent alcohol use and infrequent walkers’) due to most health behaviours being close to the final sample average. Results are presented in Tables 3 (sociodemographics), 4 (heath indicators), and 5 (health care usage). These results are available in the appendix.

**Sociodemographics.** Several patterns of increasing or decreasing log of the odds ratios were observed for ordinal predictor variables (i.e., age and income). For age groups, the odds of being in Cluster 5 (‘frequent walkers with infrequent strenuous exercise but higher alcohol use”), relative to Cluster 4 (‘frequent alcohol use and infrequent walkers”), increased with older age. The odds of being assigned to Cluster 6 (‘occasional and daily smokers who infrequently eat fruits and vegetables and exercise‘) and Cluster 7 (“infrequent sitting activities”) decreased with older age, especially with the occasional and daily smokers group and those aged 75-85 ($OR$ = .04, $CI$ = .01, .07, $p$ <.001). For annual income, the odds of being assigned to Cluster 2 (“frequent walkers with infrequent strenuous exercise and alcohol use”), Cluster 3 (‘infrequent alcohol use, walking, light sports, and exercise”), Cluster 6 (“occasional and daily smokers who infrequently eat fruits and vegetables and exercise‘), and Cluster 7 (‘infrequent sitting activities‘) each decreased with higher levels of income. The strongest association was observed between those reporting an annual income of $150,000 or greater and membership in Cluster 6 ('occasional and daily smokers who infrequently eat fruits and vegetables and exercise'; *OR* = .09, *CI* = .06, .13, *p* <0.001).

**Table 5.** Multinomial logistic regression with sociodemographic variables predicting cluster membership

| | Cluster 1 | | | Cluster 2 | | | Cluster 3 | | | Cluster 5 | | | Cluster 6 | | | Cluster 7 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Characteristic** | **OR** | **95% CI†** | **p-value** | **OR** | **95% CI†** | **p-value** | **OR** | **95% CI†** | **p-value** | **OR** | **95% CI†** | **p-value** | **OR** | **95% CI†** | **p-value** | **OR** | **95% CI†** | **p-value** |
| **Age_Group** | | | | | | | | | | | | | | | | | | |
| 45-54 | — | — | | — | — | | — | — | | — | — | | — | — | | — | — | |
| 55-64 | 0.89 | 0.81, 1.0 | 0.021 | 1.0 | 0.90, 1.1 | 0.9 | 1.0 | 0.88, 1.1 | >0.9 | 1.3 | 1.1, 1.4 | <0.001 | 0.76 | 0.67, 0.87 | <0.001 | 0.70 | 0.61, 0.81 | <0.001 |
| 65-74 | 0.77 | 0.63, 0.94 | 0.011 | 0.95 | 0.77, 1.2 | 0.6 | 0.81 | 0.62, 1.0 | 0.10 | 1.5 | 1.2, 1.9 | <0.001 | 0.31 | 0.22, 0.43 | <0.001 | 0.56 | 0.41, 0.77 | <0.001 |
| 75-85 | 0.70 | 0.47, 1.0 | 0.075 | 0.85 | 0.58, 1.3 | 0.4 | 0.95 | 0.61, 1.5 | 0.8 | 1.7 | 1.2, 2.5 | 0.006 | 0.04 | 0.01, 0.17 | <0.001 | 0.48 | 0.26, 0.90 | 0.023 |
| **Sex** | | | | | | | | | | | | | | | | | | |
| Female | — | — | | — | — | | — | — | | — | — | | — | — | | — | — | |
| Male | 0.86 | 0.79, 0.95 | 0.002 | 0.74 | 0.67, 0.82 | <0.001 | 0.75 | 0.66, 0.84 | <0.001 | 0.87 | 0.77, 1.0 | 0.011 | 0.90 | 0.80, 1.0 | 0.085 | 0.82 | 0.72, 0.93 | 0.003 |
| **Marital_Status** | | | | | | | | | | | | | | | | | | |
| Single | — | — | | — | — | | — | — | | — | — | | — | — | | — | — | |
| Married/CommonLaw | 0.90 | 0.76, 1.1 | 0.2 | 0.95 | 0.80, 1.1 | 0.5 | 1.2 | 1.0, 1.5 | 0.088 | 1.0 | 0.84, 1.3 | 0.7 | 0.71 | 0.58, 0.86 | <0.001 | 1.0 | 0.76, 1.2 | 0.8 |
| Widowed | 1.2 | 0.83, 1.7 | 0.4 | 1.0 | 0.72, 1.4 | >0.9 | 1.0 | 0.69, 1.6 | 0.8 | 1.1 | 0.74, 1.7 | 0.6 | 1.0 | 0.67, 1.5 | >0.9 | 1.2 | 0.76, 2.0 | 0.4 |
| Divorced | 1.0 | 0.82, 1.3 | 0.8 | 0.87 | 0.70, 1.1 | 0.2 | 1.1 | 0.85, 1.4 | 0.5 | 1.0 | 0.79, 1.4 | 0.7 | 1.0 | 0.81, 1.3 | 0.9 | 1.0 | 0.71, 1.3 | 0.8 |
| Separated | 1.1 | 0.78, 1.4 | 0.7 | 1.0 | 0.70, 1.3 | 0.8 | 1.0 | 0.67, 1.4 | >0.9 | 1.1 | 0.73, 1.6 | 0.7 | 1.1 | 0.81, 1.5 | 0.5 | 1.4 | 0.95, 2.1 | 0.091 |
| **Income** | | | | | | | | | | | | | | | | | | |
| <$20k | — | — | | — | — | | — | — | | — | — | | — | — | | — | — | |
| $20-$49k | 0.67 | 0.44, 1.0 | 0.056 | 0.46 | 0.32, 0.66 | <0.001 | 0.49 | 0.33, 0.73 | <0.001 | 0.68 | 0.41, 1.1 | 0.13 | 0.48 | 0.33, 0.70 | <0.001 | 0.60 | 0.36, 1.0 | 0.048 |
| $50-$99k | 0.62 | 0.41, 0.92 | 0.019 | 0.35 | 0.25, 0.50 | <0.001 | 0.31 | 0.21, 0.47 | <0.001 | 0.75 | 0.46, 1.2 | 0.2 | 0.26 | 0.18, 0.37 | <0.001 | 0.50 | 0.31, 0.82 | 0.006 |
| $100-$149k | 0.64 | 0.43, 1.0 | 0.031 | 0.27 | 0.19, 0.38 | <0.001 | 0.23 | 0.15, 0.34 | <0.001 | 0.77 | 0.47, 1.3 | 0.3 | 0.15 | 0.10, 0.21 | <0.001 | 0.40 | 0.24, 0.66 | <0.001 |
| $150k+ | 0.75 | 0.50, 1.1 | 0.2 | 0.21 | 0.15, 0.31 | <0.001 | 0.15 | 0.10, 0.23 | <0.001 | 0.87 | 0.53, 1.4 | 0.6 | 0.09 | 0.06, 0.13 | <0.001 | 0.36 | 0.22, 0.60 | <0.001 |
| **Social_Support** | 1.0 | 1.0, 1.0 | >0.9 | 1.0 | 1.0, 1.0 | 0.6 | 1.0 | 1.0, 1.0 | <0.001 | 1.0 | 1.0, 1.0 | 0.9 | 1.0 | 1.0, 1.0 | 0.5 | 1.0 | 1.0, 1.0 | 0.8 |
| **Employed** | | | | | | | | | | | | | | | | | | |
| Yes | — | — | | — | — | | — | — | | — | — | | — | — | | — | — | |
| No | 0.89 | 0.74, 1.1 | 0.2 | 1.1 | 0.94, 1.3 | 0.2 | 1.3 | 1.0, 1.5 | 0.026 | 1.1 | 0.92, 1.4 | 0.2 | 1.6 | 1.3, 2.0 | <0.001 | 0.88 | 0.68, 1.1 | 0.3 |

† CI = Confidence Interval

Notes: Cluster 1 = Physically Active Healthy Eaters; Cluster 2 = Frequent Walkers with Infrequent Strenuous Exercise and Infrequent Alcohol Use; Cluster 3 = Infrequent Alcohol Use, Walking, Light Sports, and Exercise; Cluster 4 = Frequent Alcohol Use and Infrequent Walkers; Cluster 5 = Frequent Walkers with Infrequent Strenuous Exercise but Higher Alcohol Use; Cluster 6 = Occasional and Daily Smokers who Infrequently Eat Fruits and Vegetablesand Exercise; Cluster 7 = Infrequent Sedentary Activities

With the exception of Cluster 6 ("occasional and daily smokers who infrequently eat fruits and vegetables and exercise), the odds of being male were lower than the odds of being female in the reference group (Cluster 4; range = .74, .90). The odds of a person in a married or common law relationship being assigned to the 'occasional and daily smokers' group was lower than being assigned to the reference group (*OR* = .71, *CI* = .58, .56, *p* <0.001), however the remaining associations between relationship status and cluster memberships were not statistically significant or were associated with small log of the odds ratios. Similarly, social support was generally unrelated to cluster membership. Finally, for participants who are not employed the odds of being in Cluster 3 ("infrequent alcohol use, walking, light sports, and exercise"; *OR* = 1.3, *CI* = 1.0, 1.5, *p* = 0.026) and Cluster 6 ('occasional and daily smokers who infrequently eat fruits and vegetables and exercise'; *OR* = 1.6, *CI* = 1.3, 2.0, *p* <.001) were greater than for being in the reference group.

**Health Indicators.** For a one-unit increase in general health, scored on a scale from 0 to 4 (where higher scores indicated higher reported general health), the odds of being assigned to Cluster 1 ("physically active health eaters") was greater (*OR* = 1.20, *CI* = 1.2, 1.3, *p* <.001) than being assigned to the reference group. In contrast, for each one-unit increase in general health, the odds of membership in Cluster 3 ('infrequent alcohol use, walking, light sports, and exercise'; OR = .79, CI = .75, .83, p <.0001) and Cluster 6 ('occasional and daily smokers who infrequently eat fruits and vegetables and exercise'; *OR* = .79, *CI* = .74, .84, *p* <0.001) were lower relative to the reference group. For every one-unit increase in self-reported healthy aging, scored on a scale from 1-5, the odds of being assigned to Cluster 6 ('occasional and daily smokers who infrequently eat fruits and vegetables and exercise‘; *OR* = .75, *CI* = .71, .80, *p* <0.001) were lesser than being assigned to the reference group. Associations between mental health and cluster membership, and between life satisfaction and cluster membership, were generally negligible. Finally, for every one-unit increase in body mass index (range = 12.18, 70.46) the odds of cluster membership increase slightly (all *p*s <.001) for Cluster 2 (‘frequent walkers with infrequent strenuous exercise and alcohol use‘) and Cluster 3 (‘infrequent alcohol use, walking, light sports, and exercise‘), and decrease slightly for Clusters 1, 5, 6, and 7 (‘“physically active health eaters‘, “frequent walkers with infrequent strenuous exercise but higher alcohol use‘, ’occasional and daily smokers who infrequently eat fruits and vegetables and exercise‘, and “infrequent sitting activities‘, respectively).

**Healthcare Use.** Participants who had not visited an emergency department in the previous 12 months had higher odds of being assigned to Cluster 1 (‘physically active healthy eaters‘; *OR* - 1,2, *CI* = 1.1, 1.3, *p* <0.001) and lower odds of being assigned to Cluster 3 (‘infrequent alcohol use, walking, light sports, and exercise‘; *OR* = .77, *CI* = .70, .85, *p* <.001) or Cluster 6 (‘occasional and daily smokers who infrequently eat fruits and vegetables and exercise’; *OR* = .75, *CI* = .68, .83, *p* <0.001). People who had not had an overnight stay in a hospital in the past 12 months had lower odds of being in Cluster 3 (‘infrequent alcohol use, walking, light sports, and exercise’; *OR* = .80, *CI* = 0.70, .91, *p* <0.001). No statistically significant associations between nursing home usage and cluster membership.

**Table 6.** Multinomial logistic regression with health-indicator variables predicting cluster membership

| | Cluster 1 | | | Cluster 2 | | | Cluster 3 | | | Cluster 5 | | | Cluster 6 | | | Cluster 7 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Characteristic** | **OR** | **95% CI[1]** | **p-value** | **OR** | **95% CI[1]** | **p-value** | **OR** | **95% CI[1]** | **p-value** | **OR** | **95% CI[1]** | **p-value** | **OR** | **95% CI[1]** | **p-value** | **OR** | **95% CI[1]** | **p-value** |
| **General_Health** | 1.2 | 1.2, 1.3 | <0.001 | 0.93 | 0.89, 1.0 | 0.003 | 0.79 | 0.75, 0.83 | <0.001 | 1.1 | 1.0, 1.1 | 0.030 | 0.79 | 0.74, 0.84 | <0.001 | 1.0 | 1.0, 1.1 | 0.2 |
| **Mental_Health** | 0.94 | 0.90, 1.0 | 0.007 | 0.95 | 0.91, 1.0 | 0.016 | 1.0 | 1.0, 1.1 | 0.3 | 1.0 | 0.91, 1.0 | 0.082 | 1.0 | 0.95, 1.1 | >0.9 | 0.87 | 0.81, 0.93 | <0.001 |
| **Healthy_Aging** | 1.1 | 1.1, 1.2 | <0.001 | 1.0 | 0.95, 1.0 | 0.8 | 0.92 | 0.87, 1.0 | 0.005 | 1.0 | 1.0, 1.1 | 0.5 | 0.75 | 0.71, 0.80 | <0.001 | 1.0 | 1.0, 1.1 | 0.2 |
| **Life_Satisfaction** | 1.0 | 1.0, 1.0 | 0.028 | 1.0 | 1.0, 1.0 | 0.002 | 1.0 | 1.0, 1.0 | <0.001 | 1.0 | 1.0, 1.0 | <0.001 | 1.0 | 1.0, 1.0 | <0.001 | 1.0 | 1.0, 1.0 | 0.4 |
| **BMI** | 1.0 | 1.0, 1.0 | <0.001 | 1.0 | 1.0, 1.0 | <0.001 | 1.0 | 1.0, 1.1 | <0.001 | 1.0 | 1.0, 1.0 | <0.001 | 1.0 | 0.94, 1.0 | <0.001 | 1.0 | 1.0, 1.0 | <0.001 |

[1] CI = Confidence Interval

Notes: Cluster 1 = Physically Active Healthy Eaters; Cluster 2 = Frequent Walkers with Infrequent Strenuous Exercise and Infrequent Alcohol Use; Cluster 3 = Infrequent Alcohol Use, Walking, Light Sports, and Exercise; Cluster 4 = Frequent Alcohol Use and Infrequent Walkers; Cluster 5 = Frequent Walkers with Infrequent Strenuous Exercise but Higher Alcohol Use; Cluster 6 = Occasional and Daily Smokers who Infrequently Eat Fruits and Vegetablesand Exercise; Cluster 7 = Infrequent Sedentary Activities

**Table 7.** Multinomial logistic regression with healthcare-use variables predicting cluster membership

| | Cluster 1 | | | Cluster 2 | | | Cluster 3 | | | Cluster 5 | | | Cluster 6 | | | Cluster 7 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Characteristic** | **OR** | **95% CI[1]** | **p-value** | **OR** | **95% CI[1]** | **p-value** | **OR** | **95% CI[1]** | **p-value** | **OR** | **95% CI[1]** | **p-value** | **OR** | **95% CI[1]** | **p-value** | **OR** | **95% CI[1]** | **p-value** |
| **Emergency_Dept** | | | | | | | | | | | | | | | | | | |
| Yes | — | — | | — | — | | — | — | | — | — | | — | — | | — | — | |
| No | 1.2 | 1.1, 1.3 | <0.001 | 1.0 | 0.88, 1.0 | 0.3 | 0.77 | 0.70, 0.85 | <0.001 | 1.0 | 1.0, 1.1 | 0.4 | 0.75 | 0.68, 0.83 | <0.001 | 1.0 | 0.85, 1.1 | 0.5 |
| **Hospital_Overnight** | | | | | | | | | | | | | | | | | | |
| Yes | — | — | | — | — | | — | — | | — | — | | — | — | | — | — | |
| No | 1.1 | 1.0, 1.3 | 0.10 | 1.0 | 0.85, 1.1 | 0.5 | 0.80 | 0.70, 0.91 | <0.001 | 1.0 | 0.85, 1.1 | 0.7 | 1.0 | 0.84, 1.1 | 0.8 | 1.1 | 0.91, 1.3 | 0.3 |
| **Nursing_Home** | | | | | | | | | | | | | | | | | | |
| Yes | — | — | | — | — | | — | — | | — | — | | — | — | | — | — | |
| No | 1.5 | 0.92, 2.5 | 0.10 | 1.3 | 0.82, 2.0 | 0.3 | 0.80 | 0.52, 1.2 | 0.3 | 1.9 | 1.1, 3.5 | 0.027 | 1.1 | 0.62, 1.9 | 0.8 | 1.2 | 0.61, 2.5 | 0.6 |

[1] CI = Confidence Interval

Notes: Cluster 1 = Physically Active Healthy Eaters; Cluster 2 = Frequent Walkers with Infrequent Strenuous Exercise and Infrequent Alcohol Use; Cluster 3 = Infrequent Alcohol Use, Walking, Light Sports, and Exercise; Cluster 4 = Frequent Alcohol Use and Infrequent Walkers; Cluster 5 = Frequent Walkers with Infrequent Strenuous Exercise but Higher Alcohol Use; Cluster 6 = Occasional and Daily Smokers who Infrequently Eat Fruits and Vegetablesand Exercise; Cluster 7 = Infrequent Sedentary Activities

## 3.8 Appendix III:
## CLSA Health Indicators at Baseline and Follow-Up 1

| | | General Health | | | Mental Health | | | Healthy Aging | | | Life Satisfaction | | | Chronic Conditions | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cluster | n | Base | FU_1 | Δ | Base | FU_1 | Δ | Base | FU_1 | Δ | Base | FU_1 | Δ | Base | FU_1 | Δ |
| 1 | 7703 | 3.0 | 2.9 | -0.1 | 3.1 | 3.0 | -0.1 | 4.0 | 3.9 | -0.1 | 29.2 | 29.6 | 0.4 | 89.5% | 94.1% | 4.6% |
| 2 | 7223 | 2.6 | 2.6 | -0.1 | 2.9 | 2.8 | -0.1 | 3.7 | 3.7 | 0.0 | 27.9 | 28.4 | 0.5 | 92.4% | 95.8% | 3.4% |
| 3 | 4094 | 2.4 | 2.4 | 0.0 | 2.8 | 2.7 | -0.1 | 3.5 | 3.5 | 0.0 | 27.0 | 27.2 | 0.2 | 94.9% | 97.3% | 2.4% |
| 4 | 10723 | 2.8 | 2.7 | -0.1 | 3.0 | 2.9 | -0.1 | 3.8 | 3.7 | -0.1 | 28.6 | 28.8 | 0.3 | 91.8% | 95.3% | 3.5% |
| 5 | 5212 | 2.8 | 2.8 | -0.1 | 3.0 | 2.9 | -0.1 | 3.8 | 3.8 | 0.0 | 29.1 | 29.4 | 0.2 | 91.6% | 95.8% | 4.2% |
| 6 | 3079 | 2.4 | 2.3 | -0.1 | 2.7 | 2.6 | -0.1 | 3.4 | 3.3 | -.01 | 26.1 | 26.4 | 0.3 | 90.1% | 95.0% | 4.9% |
| 7 | 2234 | 2.8 | 2.7 | -0.1 | 2.9 | 2.9 | 0.0 | 3.8 | 3.8 | 0.0 | 28.6 | 28.9 | 0.3 | 88.9% | 93.9% | 5.0% |

**Note:** Δ denotes the changes from baseline (Base) to the first follow-up assessment (FU_1)

CHAPTER 3

# PREDICTING GENERAL HEALTH AND CLASSIFYING CHRONIC CONDITION STATUS FROM MULTIPLE HEALTH BEHAVIOURS AND CLUSTERS


## Abstract

**Background:** Excessive engagement in health impacting behaviours (e.g., physical inactivity, unhealthy eating, smoking, inadequate sleep, alcohol use) are leading risk factors for the development of chronic conditions. Commonly co-occurring health behaviours can be identified with cluster analysis; however, it is not known whether clusters capture clinically meaningful synergetic effects that are more predictive of health outcomes than are individual health behaviours. Additionally, there are few existing applications of machine learning to the multiple health behaviour literature from which to decide upon the most appropriate models for studying the relationship between behaviours and health outcomes. The present analysis compares the ability of clusters of behaviours and individual health behaviours to predict self-reported general health and to classify chronic condition status with multiple machine learning models.

**Methods:** Using baseline and follow-up data from the Canadian Longitudinal Study of Aging (n = 44, 815) several machine learning models were compared for their ability to predict general health and classify chronic condition status and Type II diabetes. For the prediction of continuous health outcomes from cluster membership and individual health behaviours, the following models were compared: ordinary least-squares regression, LASSO regression, ridge regression, random forests, neural networks, and support vector machines. For the classification of categorical health outcomes, the following models were tested: xgboost, random forest, k-nearest neighbours, naïve bayes, and logistic regression.

**Results:** Overall, using behaviours as predictor variables (c.f., clusters) resulted in greater classification accuracy of chronic condition status and accounted for more variability in general health scores. However, even the best performing classification models (xgboost) displayed a poor ability to identify people living without chronic conditions with clusters as predictors (AUC = 51.9%, accuracy = 95.7%, sensitivity = 0%, specificity = 100%) and with behaviours as predictors (AUC = 58.3%, accuracy = 95.5%, sensitivity = 0%, specificity = 100%). A similar pattern was observed with Type II diabetes status where neither behaviours (AUC = 64.3%, accuracy = 90.8%, sensitivity = 0%, specificity = 100%) nor clusters (AUC = 58.8%, accuracy = 91%, sensitivity = 0%, specificity = 100%) were able to correctly classify a positive case of Type II diabetes. Neural networks were the best performing model for predicting general health with behaviours as predictors ($R^2$ = .08, RMSE = .88) while random forests performed best with clusters as predictors ($R^2$ = .05, RMSE = .90).

**Conclusion:** The promise of clustering studies is that they can identify groups of people based on similar features. It is possible that synergistic effects of multiple co-occurring behaviours may lead to greater variability in health outcomes than single behaviours in isolation. However, in isolation, neither clusters nor individual behaviours were able to identify persons not living with chronic conditions or who were diagnosed with Type II Diabetes. Individual health behaviours explain approximately the same variance in self-reported general health as non-modifiable factors such as personality traits but are susceptible to modification. The XGBoost algorithm performed best for classification tasks while neural networks outperformed other models for prediction.

## 3.1 Introduction

Leading risk factors for the onset of chronic non-communicable diseases include health behaviours such as smoking, unhealthy eating, inadequate sleep, alcohol use, and physical inactivity. However, it remains unclear which combinations (and frequencies of behaviour) are associated with the highest risk for chronic conditions and life satisfaction (Shaw & Agahi, 2012). There is evidence to suggest that multiple health impacting behaviours may have compounding or synergistic effects on health outcomes. For example, people who smoke tobacco regularly and who also drink in excess are at a greater risk for developing cancer (Franceschi et al., 1990; Marrero et al., 2005) and heart and lung disease (Grucza & Beirut, 2007). However, research that considers the synergistic effects of health behaviours tend not to include more than two health behaviors.

Identifying high-risk combinations of risky health behaviours could guide behaviour change intervention developers and trialists towards targeting high impact co-occurring behaviours in multiple health behaviour change interventions. Multiple health behaviour change interventions target two or more behaviours sequentially or simultaneously within a specified time frame (Prochaska et al., 2008). The objective of these interventions is to improve the prevention of non-communicable diseases (Geller et al., 2017) through a more efficient use of health care and research resources (Prochaska et al., 2008). Additionally, such interventions have the potential to be more person-centered by tailoring approaches to the idiosyncratic set of health behaviours adopted by an individual. Identifying which combinations of health behaviours are associated with the greatest long-term risk will advance the basic science of multiple health behaviour change and potentially increase the efficiency of research resources by facilitating a more precise targeting of the most high-risk co-occurring health behaviours.

Previously Chapter 2 explored the clustering (co-occurrence) and associations (co-variation) between health behaviours. The central promise of clustering studies is that partitioning people into groups based on similarity of behavioural features (e.g., extent of engagement in health behaviours) can be used to segment the population to facilitate intervention targeting (Yan, Kwan, Tan, Thumboo, & Low, 2018; Nnoaham & Cann, 2020). However, beyond serving as a tool for informing intervention design, empirical questions remain regarding the predictive validity of a cluster-based approach to identifying co-occurring risk behaviours. For example, we currently do not know if clusters capture clinically meaningful combinations of behaviours which have predictive ability above and beyond modelling individual behaviours. Although co-occurring health behaviours are implicated in health outcomes, the extent to which cluster analysis can capture co-occurrence that impacts health outcomes is relatively unknown. Understanding whether behavioural clusters are predictive of health outcomes, when compared to predicting outcomes with individual health behaviours, could provide behavioural scientists and public health researchers with valuable insights into the strengths and limitations of cluster analysis as a tool for modelling co-occurring health behaviours and their impact on health.

Chapter 2 tested whether clusters or individual behaviours are better predictors of health outcomes using OLS and logistic regression to predict mental health, general health, and living with chronic conditions in Canadians adults 45 years old and over. This analysis revealed that between 2%-8% of variability in general and mental health at follow-up were accounted for by baseline clusters or individual health behaviours with individual behaviour accounting for slightly more explained variability. When classifying whether people reported any chronic conditions at follow-up, the baseline cluster of ‘infrequent alcohol use, walking, light sports, and exercise’ was the strongest predictor of having at least one condition while the individual behaviour of exercise was the strongest predictor of not having a chronic condition. Although these results provide one comparison of the predictive ability of individual behaviours vs behavioural clusters, it is possible that other methods and statistical models are better suited for prediction. When prediction is prioritized over casual explanation in psychological science, machine learning is an appropriate approach (Yarkoni & Westfall, 2017; Rosenbusch, Soldner, Evans, & Zeelenberg, 2021).

Broadly, machine learning refers to a "set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data" (Murphy, 2012, pp 1). Machine learning algorithms are considered 'supervised' or 'unsupervised' depending on whether outcome variables are labelled (e.g., chronic condition status is known). Datasets containing these known outcomes are referred to as 'labeled data' in contrast to 'unlabeled data' in which the outcomes are not known.

Unsupervised learning discovers patterns in unlabeled data (Fung, 2001). The two central tasks which fall under the unsupervised umbrella of machine learning are clustering and dimensionality reduction. The overarching purpose of clustering is to group individual entities (e.g., people) into similar groups based on a pre-specified set of features (e.g., health behaviours) while dimensionality reduction techniques such as principal component analysis are used to reduce large number of predictor variables into a smaller set of predictors which retain the information contained in the original predictor set. In the context of multiple health behaviour research, unsupervised learning is commonly used for identifying clusters of co-occurring health behaviours (e.g., van Allen et al., 2021; van Allen et al., 2023; Kwan et al., 2016; Schneider et al., 2009). However, few studies in this area have focused on Canadians making generalizability to Canadian contexts difficult and cluster analysis focusing on people most likely to have chronic conditions (i.e., older Canadians) is sparce.

In supervised learning, the relationship between the input and target variables are known. An algorithm is 'supervised' in that it can be trained on a dataset that contains the outcomes that are being classified (categorical outcome) or predicted (continuous outcome). In the context of health behaviour research, supervised machine learning can be used to predict and classify health outcomes from a range of theoretically or data-determined predictors. For example, machine learning can be used to predict which risk factors are most strongly associated with obesity (Chatterjee, Gerdes, & Martinez, 2020) or to classify whether people are complying or not complying with public health measures (Roma et al., 2020). Increasingly, machine learning has been applied to the prediction of chronic disease. In such studies, it is common to model multiple sets of predictor variables, several machine learning algorithms, and/or several difference chronic conditions (e.g., Khalilia, Chakraborty, & Popescu, 2011; Lu, Uddin, Hajati, Moni, & Khushi, 2022; Choudhury & Gupta, 2019; Demiaray et al., 2022; Bhola, Garg, & Kumari, 2021; Al-Jaishi et al., 2022).

Although these and other studies have compared the ability of machine learning models to predict health outcomes from health behaviours, there are few, if any, existing studies which have compared models and individual vs clustered health behaviours (c.f., van Allen et al., 2023). In such cases, where the optimal model for a given problem is unknown, it is common to perform a series of exploratory models and select the best performing models for subsequent interpretation (Szabelska et al., 2021). This chapter extends previous work (van Allen et al., 2023) by comparing 1) whether individual health behaviours or health behaviour clusters are better predictors/classifiers of health outcomes, and 2) which machine learning algorithm demonstrates the greatest performance.

## 3.2 Methods

The methods are divided into four sections. First, a description of the datasets used for training and testing the machine learning algorithms are presented. Second, the variables used in analysis are defined. Third, the machine learning algorithms and methodology are described. Finally, the processes involved in hyperparameter optimization and model evaluation are explained.

### 3.2.1 CLSA Data

This chapter used data collected from the Canadian Longitudinal Study of Aging (CLSA) described in previous chapters. The CLSA is a nationally representative longitudinal study aimed at measuring the biological, societal, psychosocial, and physical factors related to healthy aging (Raina et al., 2009). Data collected for the 'baseline' assessment of the CLSA was obtained between 2010 and 2015 using two approaches: 1) a 'tracking' cohort (n = 21,241) of participants provided data collected via hour-long computer assisted phone interviews, and; 2) a 'comprehensive' cohort (n=30,097) of participants completed an in-person interview lasting 90-minutes in addition to a data collection site visit. Additionally, a 'maintaining contact questionnaire' was administered over the phone for the comprehensive and tracking cohorts. The maintaining contact questionnaire, tracking cohort, and comprehensive cohort form the baseline data collected used in this analysis. Between 2015 and 2018 another wave of data was collected during the 'follow-up 1' assessment. In the follow-up wave of data collection, participants again completed the 'tracking' cohort (n = 17,050) and the 'comprehensive' cohort (n = 27,765) packages. A total of n = 6,523 participants who completed baseline data collection did not provide follow-up data. Data are available from the Canadian Longitudinal Study on Aging (www.clsa-elcv.ca) for researchers who meet the criteria for access to de-identified CLSA data.

Participants in the CLSA were recruited through provincial health registries, random-digit dialing, and the Canadian Community Health Survey on Healthy Aging (Raina et al., 2009; Wolfson et al., 2009). Exclusion criteria for the CLSA included: residents living in three territories and First Nations reserves, full time members of the Canadian Armed Forces, people living with cognitive impairments, and individuals living in institutions (including 24-hour nursing homes; Raina et al., 2009). Participants who enrolled in baseline data collection were n=51,338 French and English-speaking Canadians (51% female) between the ages of 45-85. The average participant at baseline was 62.98 years old (SD = 10.4) with 26% between 45-54 years, 32% between 55-64 years, 23% between 65-74 years, and 18% between 75-85 years of age. A full description of demographic characteristics of the sample, as well as summary data across all measured variables is available in the CLSA baseline data report (Raina, Wolfson, Kirkland, & Griffith, 2018). Data are available from the Canadian Longitudinal Study on Aging (www.clsa-elcv.ca) for researchers who meet the criteria for access to de-identified CLSA data.

### 3.2.2 Variables

**Health Behaviours.** *Physical activity* and *sedentary behaviour* were measured with the Physical Activity Scale for the Elderly (PASE; Washburn, Smith, Jette, & Janney, 1993). The PASE measures the frequency of sedentary behaviour, walking, light physical activity, moderate physical activity, strenuous physical activity, and exercise. Participants were asked to report on their activity levels over the previous 7 days, on a 1 (never) to 4 (often, 5-7 days) scale. Due to conceptual overlap between constructs in the PASE, light and moderate physical activity were merged to create a single mean score (renamed ‘light sports’) and the same transformation was applied to strenuous physical activity and exercise (Dogra et al., 2019; van Allen et al., 2023).

*Fruit and vegetable consumption* was measured with a single item from the Seniors in the Community Risk Evaluation for Eating and Nutrition questionnaire (Keller, Goy, & Kane, 2005) which asked participants how man servings of fruits and vegetables they eat in a day. Original response options were reverse scored to make higher scores indicate more fruit and vegetable consumption. Response options range from 1 (less than two fruits/vegetables) to 7 (seven or more fruits/vegetables).

*Smoking behaviour* was measured using a skip-question framework in the CLSA. We assigned a value of 0 to each respondent who responded ‘no’ to the question ‘have you ever smoked a whole cigarette’. A similar approach has been applied to skip structure data when missing data represent the absence of a behaviour or psychological feature (Borsboom & Cramer, 2013). Participants who answered ‘yes’ to the question ‘have you ever smoked a whole cigarette’ were subsequently asked whether they smoke not at all, occasionally, or daily, in the past 30 days. Ultimately, this created four levels distinguishing between people who have never smoked (coded 0), those who have not smoked within 30 days (1), those who smoke occasionally (2), and those who smoke daily (3). This approach has been employed in previous work with the CLSA (van Allen et al., 2023).

*Alcohol* consumption measured with one item asking respondents how often they drank alcohol in the past 12 months on a scale from 1 (almost every day) to 7 (less than once a week). Responses were reverse coded so that higher values indicate greater alcohol consumption. Finally, *sleep* was also measured with a single item but was not included in analysis due to high (41.5%) prevalence of missingness.

**General Health.** Three single-item measures were used to assess general health. These items included measures of general health (‘in general, would you say your health is excellent, very good, good, fair, or poor?'), mental health ('in general, would you say your mental health is excellent, very good, good, fair, or poor?'), and perceptions of healthy aging (in terms of your own healthy aging, would you say it is excellent, very good, good, fair, or poor?'). Originally, items were scored on a 1 (excellent) to 5 (poor) but were reverse coded so that higher scored indicate higher health. Only the general health item was used in this chapter.

**Chronic Conditions.** Participants reported any diagnosed chronic conditions during baseline and follow-up data collection (e.g., chronic respiratory disease, diabetes, cardiovascular disease, cancer). A summary variable which classifies people into those living with at least one chronic condition at follow-up (1) and those not living with any chronic conditions (0) was used as an indicator of health.

**Type II Diabetes**. Participants reported whether they had been diagnoses with Diabetes. A summary variable was computed which coded all persons with Type II Diabetes as (1) and all others as (0).

**Sociodemographic Indicators.** Age and sex (male/female) were measured but were not included as covariates in order to directly compare clusters and individual behaviours. A comparison of OLS regression models with and without age and sex as covariates (Chapter 2, not reported) produced identical $R^2$ values (.08).

**3.2.3 Clusters.** Participants who completed all health behaviour measures at baseline were grouped into one of seven clusters using hierarchical agglomerative clustering (van Allen et al., 2021; van Allen et al., 2023). Clusters were given descriptive labels based on the prominent behaviours which defined each group. The seven clusters (and % of sample) are: 1) physically active healthy eaters (19%); 2) frequent walkers with infrequent strenuous exercise and alcohol (18%); 3) frequent walkers with infrequent strenuous exercise but higher alcohol use (13%); 4) infrequent alcohol use, walking, light sports, and exercise (10%); 5) frequent alcohol use and infrequent walkers (27%); 6) occasional and daily smokers who infrequently eat fruits and vegetables and exercise (8%); and 7) infrequent sedentary activities (6%). Cluster membership at baseline was used to predict health outcomes at follow-up.

**3.3 Analysis**

Using the unique participant identifiers within the CLSA dataset, cluster memberships identified in previous analysis (van Allen et al., 2023) were linked to variables collected at follow-up 1. This enabled the prediction and classification of health indicators at follow-up 1 from health behaviour clusters at baseline. Health outcomes included self-report measures (general health) and objective measures of health (presence or absence of chronic conditions). Sociodemographic variables including age and biological sex were included as independent variables. Modelling was conducted with the *tidymodels* package (Kuhn & Silge, 2022), a meta-engine for machine learning models in the R programming language. The tidymodels package contains a collection of packages for modelling and machine learning in addition to workflow structures which can prevent common errors in machine learning such as data leakage (Kuhn & Silge, 2022). There are few existing applications of machine learning to the multiple health behaviour literature from which to decide upon the most appropriate models for studying the relationship between behaviour and health outcomes. Therefore, a series of exploratory models were performed from which the best performing models were selected for subsequent interpretation (Szabelska et al., 2021).

Modelling of health outcomes can be categorized as prediction for continuous health outcomes (i.e., general health) and classification for categorical outcomes (i.e., absence of chronic conditions, Type II Diabetes). For the prediction of continuous health outcomes from cluster membership and individual behaviours, the following models were compared: ordinary least-squares regression, LASSO regression, ridge regression, random forests, neural networks, and support vector machines. For the classification of categorical health outcomes from cluster membership and individual behaviours, the following models were tested: xgboost, random forest, k-nearest neighbours, naïve bayes, and logistic regression. Predictors for neural networks and support vector machines were normalized while cluster membership and smoking behaviour were dummy coded as categorical variables for neural networks, regression, and support vector machines. Hyperparameters for each model were determined with a grid search methodology (see hyperparameter optimization section). Hyperparameters control the learning process and determine the values of model parameters and are selected before the algorithm is trained. See Table 1 for a glossary of key terms.

Analysis was completed with two sets of predictor variables: 1) health behaviours, and 2) health behaviour clusters. Competing models were compared based on their ability to predict out-of-sample health outcomes (see ‘evaluating models’ section for more details).

### 3.3.1 Machine Learning Algorithms & Methodology

**3.3.2. Random Forests.** Random Forest (Breiman, 2001) models are ensembles of decision trees (Quinlan, 1986) used for both classification and prediction analysis. Decision trees partition data into subgroups of increasing homogeneity based on binary options defined by the predictor values (e.g., Male/Female or Alcohol values above/below a certain value; Rosenbusch, Soldner, Evans, & Zeelenberg, 2021). Random Forest models fit multiple decision trees to bootstrapped subsets of the training data to enhance model performance and reduce overfitting. Three hyperparameters were optimized for both classification and prediction models: the number of decision trees, the number of predictor variables considered at each split, and the minimal node size. See hyperparameter optimization section for further details.

**3.3.3. XGBoost.** Similar to Random Forest models, XGBoost (eXtreme Gradient Boosting) uses an ensemble of decision trees for classification and prediction. However, while Random Forest models use a 'bagging' technique which averages over many decision trees, XGBoost employs

**Table 1**. Glossary of Machine Learning Terminology.

| | |
|---|---|
| **Machine Learning** | A set of statistical methods used to learn/detect patterns in data and then use the learned patterns to predict future data. |
| **Training and Test Data** | Datasets are partitioned into data which is used to train statistical models (training set) and data used to test the predictive ability of the model (test set). |
| **Cross-Fold Validation** | A resampling method that allows for model evaluation on the training data without using the test data. |
| **Supervised Learning** | Machine learning where the relationship between input and target variables are known (e.g., predicting disease status when status is known). |
| **Unsupervised Learning** | Machine learning for discovering patterns in unlabelled data (e.g., assigning people to clusters based on similarity of health behaviours). |
| **Prediction** | Predicting the value of continuous outcomes. Also referred to as 'regression'. |
| **Classification** | Classifying the status of a binary or categorical outcome (e.g., disease status). |
| **Hyperparameters** | Hyperparameters control the learning process and determine the values of model parameters and are selected before the algorithm is trained. |
| **Grid Search** | A method for determining the optimal hyperparameters for a machine learning model. |
| **Confusion Matrix** | A matrix representing different combinations of predicted and actual values for classification algorithms which forms the basis of metrics for sensitivity, specificity, and accuracy, and is used to produce AUC-ROC curves |
| **AUC-ROC Curves** | A probability curve that represents performance of a classification models and which visualizes of how well the model can distinguish between classes. |
| **Accuracy, Specificity, Sensitivity** | Specificity refers to the percentage of negative case correctly identified as negative, sensitivity refers to the percentage of positive cases correctly identified as postive, and accuracy is the proportion of true results regardless of whether true positive or true negative. |
| **Class Imbalance** | When a categorical outcome measure is not equally balances (e.g., 10% of population has Type II Diabetes and 90% does not). |

a ‘boosting’ method wherein models with poor model performance are combined with other poor models to produce a better performing model. Gradient boosting extends this process by formalizing the process of boosting through a gradient descent algorithm over an objective function (Natekin & Knoll, 2013). The ‘xgboost’ package (Chen et al., 2015) was used for this analysis. A total of seven hyperparameters were tuned through grid search including: the number of predictor variables considered at each split, the number of decision trees, minimal node size, tree depth, learn rate, minimum loss reduction, and proportion of observations sampled.

**3.3.4 Neural Networks.** An artificial neural network model (McCulloch & Pitts, 1943), specifically a feed-forward perceptron, was fitted to training data to predict self-reported general health from clusters and individual health behaviours. Based on biological neural networks, artificial neural networks consist of several layers of ‘neurons’ and an output layer (Hasson, Nastase, & Goldstein, 2020). Through the process of learning via training data, the connections between artificial ‘neurons’ are assigned weights which are adjusted based on the successful classification of the labelled output data through the process of backpropagation (Rumelhart, Hilton, & Williams, 1986). Using the ‘nnet’ package (Venables & Ripley, 2002) four hyperparameters were optimized in grid search: penalty (specifying the amount of regularization), epochs (the number of training iterations), and the number of hidden layers included in the model. Following analysis from Kuhn and Johnson (2013) the number of hidden units in the neural network were set to range between 1 and 27 units.

**3.3.5. Regression.** Four regression models were used for predicting continuous outcomes (ordinary least squares, ridge regression, LASSO regression) and classifying binary outcomes (logistic regression). Ridge and LASSO regression were optimized through tuning the hyperparameter lambda which determines the penalty applied to predictor to reduce the likelihood of overfitting the data. Two hyperparameters representing the regularization penalty and the mixture or proportion of LASSO penalty were optimized for logistic regression analysis.

**3.3.6. Support Vector Machines.** Support Vector Machines (SVMs) are a supervised learning algorithm used for classification and prediction analysis (Cortes & Vapnik, 1995). A SVM model was fitted on training data to classify the presence or absence of chronic conditions, and to classify the Type II Diabetes status, from health behaviour clusters or individual health behaviours. SVMs aim to identify a hyperplane with the largest margin between classes (Boateng, Otoo, & Abaye, 2020). This algorithm uses a similarity function over al pairs of data points, referred to as kernel functions, for mapping input space into n-dimensional feature space so that it can be linearly separable (Hussain, Wajid, Elzaart, & Berbar, 2011). Models were trained using two types of kernels, radial and polynomial. Each SVM model contains hyperparameters which were tuned for optimal performance. For radial SVM models the hyperparameters for gamma and cost were tuned while for polynomial SVM models the hyperparameters for constant, and degree of the polynomial were optimized.

**3.3.7. Naïve Bayes.** The Naïve Bayes algorithm is a probabilistic supervised learning classification model based on Bayes theorem (Wickramasinghe & Kalutarage, 2021). The Naïve Bayes algorithm is 'naïve' in that it assumes independence among its predictors. Using the 'klar' package (Weihs, Ligges, Luebke, & Raabe, 2005) this algorithm computed the probability of a person not living with any chronic conditions from the predictor sets using labelled training data. Two hyperparameters were optimized using a grid search: smoothness (representing the relative smoothness or flexibility of the class boundary) and Laplace (a value determining the Laplace correction for smoothing low-frequency counts).

**3.3.8. K-Nearest Neighbors.** The K-Nearest Neighbours (k-NN; Fix & Hodges, 1952) algorithm is a supervised learning classification and prediction model. The k-NN algorithm seeks to classify data points by identifying their closest neighbor, or data point assigned to a classification (e.g., chronic condition status; Boateng, Otoo, Abaye, 2020). The 'kknn' package (Schliep & Hechenbichler, 2016), which used a measure of Minkowski distance to identify the nearest 'neighbor', was used to classify chronic conditions. Three hyperparameters were optimized for the k-NN models: 'neighbors' (the number of neighbors to consider), a weight function (defining the type of kernel function used to calculate weight distances between samples), and 'distance power' (defining the parameter used for calculating Minkowski distance).

**3.3.9. Hyperparameter Optimization.** A grid search methodology was employed to identify the optimal hyperparameters for each machine learning model specified above. The 'tune' package (Kuhn, 2022) from the tidymodels ecosystem (Kuhn & Wickham, 2020) was used for hyperparameter optimization. A total of 125 models for classification and 150 models for prediction were computed with varying hyperparameters (see Figures 1 and 2) and the best performing models were selected for further fitting and evaluation. See Tables for the optimized hyperparameters in the training data for each model.

**3.3.10. Evaluating Models.** For classification models performance was evaluated through the level of misclassification on out-of-sample data using a standard confusion matrix (Yarkoni & Westfall, 2017). A confusion matrix is a 2 x 2 matrix representing different combinations of predicted and actual values which forms the basis of metrics for precision, specificity, and accuracy, in addition to their use for computing AUC-ROC curves (Szabelska et al., 2021). Specificity refers to the proportion of true negative, sensitivity refers to the proportion of true positives, and accuracy is the proportion of true results regardless of whether true positive or true negative. For prediction models (i.e., predicting self-reported general health) RMSE (root mean squared error) values were assessed to determine the error between observed and predictive values.

**3.3.11. Training and Test Data**. Datasets were split between training data (80%) and testing data (20%) while data used for classification was stratified by chronic condition status so that equal proportions (~4.5%) of people living without chronic conditions were included in testing and training datasets. Datasets for Type II Diabetes were stratified by diagnosis status so that equal proportions (~10%) of diagnosed persons were in each dataset.

## 3.4 Results

A total of n = 6.523 participants who completed baseline data collection did not provide follow-up data. Thus, this chapter uses a sample size of n = 44,815 participants, prior to listwise deletion for missing data, who completed follow-up data collection. Following listwise deletion for missing data sample sizes ranges from n=36,352 for classification models and n=37,475 for prediction models.

All modelling on training data employed 10-fold cross-validation as is generally considered best practice with machine learning (Szabelska et al., 2021). Resampling methods such as cross-validation enables the determination how well a model works without using the test set. Using a grid search approach to optimizing hyperparameters, a total of 125 models with varying hyperparameters were tested for classifying chronic condition status while 150 models were tested for predicting general health. Table 1 displays the hyperparameters for the best performing models while Figure 1-3 display models comparisons for AUC and RMSE.

Overall, using behaviours as predictor variables resulted in better classification of chronic condition status and Type II diabetes status, and also accounted for more variability in general health scores. However, the best performing classification models were unable to identify people living without chronic conditions or people diagnoses with Type II Diabetes. For chronic condition, the XGBoost algorithm performed best on training data and was fitted to the test data with clusters as predictors (AUC = 51.9%, accuracy = 95.7%, sensitivity = 0%, specificity = 100%) and with behaviours as predictors (AUC = 58.3%, accuracy = 95.5%, sensitivity = 0%, specificity = 100%). The AUC value of 51.9% suggests that clusters have no discriminatory value for classifying chronic condition status while an AUC of 58.3% is bellow the standard of 70%-80% that is considered acceptable for diagnostic tests (Mandrekar, 2010). The high accuracy of values for both models were skewed due to the class imbalance of people living with vs without chronic conditions (i.e., the model predicted ‘has chronic condition’ for every case and was ~95% correct because ~95% of the cases were people living with chronic conditions). Neither model was able to correctly identify a single person who was not living with a chronic condition. The AUC ROC curves for both final models are presented in Figure 4 & 5 while performance metrics for classification and prediction models are presented in Tables 2 & 3. A similar pattern was observed with Type II diabetes status. Although this metric had a less pronounced class imbalance (9.47% in training data, 9.04% in test data), neither behaviours (AUC = 64.3%, accuracy = 90.8%, sensitivity = 0%, specificity = 100%) nor clusters (AUC = 58.8%, accuracy = 91%, sensitivity = 0%, specificity = 100%) were able to correctly classify a positive case of Type II diabetes.

For predicting general health with behaviours as predictors, neural networks outperformed other models on the training data and was fitted to the test data with clusters as predictors ($R^2$ = .08, RMSE = .88). For predicting general health with clusters, random forest models fractionally outperformed neural networks, OLS regression, ridge regression, and LASSO regression and was fitted to the test data ($R^2$ = .05, RMSE = .90). For all prediction models, the average distance between the values predicted by the models and actual values (RMSE) indicated a poor fit between model and data. Performance metrics for test and train data are presented in Tables 2 & 3.

**Table 2.** Optimized hyperparameters for final models

| | | | Chronic Conditions | | Type II Diabetes | |
|---|---|---|---|---|---|---|
| **Task** | **Model** | **Hyperparameter** | **Clusters** | **Behaviours** | **Clusters** | **Behaviours** |
| **Classify** | Random Forest | Number of trees | 17 | 550 | 363 | 550 |
| | | Predictors / split | 1 | 1 | 1 | 1 |
| | | Min node size | 26 | 31 | 40 | 31 |
| | XGBoost | Number of trees | 1902 | 1902 | 1604 | 1902 |
| | | Predictors / split | 5 | 5 | 5 | 5 |
| | | Min node size | 13 | 13 | 9 | 13 |
| | | Tree depth | 2 | 2 | 11 | 2 |
| | | Learn rate | .00582 | .00582 | .0805 | .00582 |
| | | Min loss reduction | .0000001 | .0000001 | .0000000 | .0000002 |
| | | Prop observation samples | .446 | .446 | .134 | .446 |
| | K Nearest Neighbor | Neighbors | 14 | 15 | 14 | 14 |
| | | Weight | Bi Weight | Rank | Bi Weight | Rectangular |
| | | Distance power | .844 | .523 | .844 | 1.29 |
| | Naïve Bayes | Smoothness | 1.46 | 1.07 | .685 | .563 |
| | | Laplace | 2.73 | 2.06 | .263 | .937 |
| | Logistic Regression | Penalty | .0005 | .0036 | .0000001 | .00000005 |
| | | Mixture | .535 | .472 | .171 | .056 |
| | | | **General Health** | | | |
| | | | **Clusters** | **Behaviours** | | |
| **Predict** | OLS Regression | n/a | | | - | - |
| | Ridge Regression | Penalty | .000 | .000 | - | - |
| | LASSO Regression | Penalty | .000 | .000 | - | - |
| | Random Forest | Predictors / split | 1 | 2 | - | - |

| | | | | | |
|---|---|---|---|---|---|
| | Min node size | 9 | 32 | - | - |
| Neural Network | Penalty | .128 | .0007 | - | - |
| | Epochs | 409 | 738 | - | - |
| | Hidden layers | 21 | 3 | - | - |
| Support Vector Machine (Polynomial) | Cost | 18.5 | 7.15 | - | - |
| | Polynomial degree | 2 | 2 | - | - |
| Support Vector Machine (Radial) | Gamma | .0007 | .013 | - | - |
| | Cost | .373 | .113 | - | - |

**Table 3.** Train and Test Datasets Classification Metrics

| | | Clusters Classifying Chronic Condition Status | | | | Behaviours Classifying Chronic Condition Status | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Dataset** | **Model** | **AUC (St Err)** | **Accuracy** | **Specificity** | **Sensitivity** | **AUC % (St Err)** | **Accuracy** | **Specificity** | **Sensitivity** |
| **Train** | Random Forest | .560 (.01) | .952 | 0 | 1 | .586 (.01) | .952 | 0 | 1 |
| | XGBoost | .561 (.01) | .952 | 0 | 1 | .601 (.01) | .953 | 0 | 1 |
| | K Nearest Neighbor | .520 (.01) | .952 | 0 | 1 | .524 (.01) | .953 | 0 | 1 |
| | Naïve Bayes | .560 (.01) | .952 | 0 | 1 | .597 (.01) | .953 | 0 | 1 |
| | Logistic Regression | .556 (.01) | .952 | 0 | 1 | .587 (.01) | .953 | 0 | 1 |
| **Test** | XGBoost | .519 | .957 | 0 | 1 | .583 | .955 | 0 | 1 |
| | | **Clusters Classifying Type II Diabetes Status** | | | | **Behaviours Classifying Type II Diabetes Status** | | | |
| **Train** | Random Forest | .597 (.01) | .905 | 0 | 1 | .648 (.00) | .906 | 0 | 1 |
| | XGBoost | .597 (.01) | .905 | 0 | 1 | .652 (.00) | .906 | 0 | 1 |
| | K Nearest Neighbor | .572 (.01) | .905 | 0 | 1 | .578 (.01) | .905 | 0 | 1 |
| | Naïve Bayes | .597 (.01) | .905 | 0 | 1 | .649 (.00) | .906 | 0 | 1 |
| | Logistic Regression | .597 (.01) | .905 | 0 | 1 | .640 (.00) | .906 | 0 | 1 |
| **Test** | XGBoost | .588 | .910 | 0 | 1 | .643 | .908 | 0 | 1 |

**Table 4.** Train and Test Datasets Prediction Metrics

| Dataset | Model | Behaviours Predicting General Health | | | Clusters Predicting General Health | | |
|---|---|---|---|---|---|---|---|
| | | **$R^2$** | **RMSE** | **Std. Error** | **$R^2$** | **RMSE** | **Std. Error** |
| **Train** | OLS Regression | .077 | .899 | .003 | .038 | .917 | .003 |
| | Ridge Regression | .077 | .899 | .003 | .039 | .917 | .003 |
| | LASSO Regression | .077 | .899 | .003 | .039 | .917 | .003 |
| | Random Forest | .074 | .900 | .003 | **.039** | **.917** | **.003** |
| | Neural Network | **.079** | **.898** | **.003** | .039 | .917 | .003 |
| | SVM (Polynomial) | .070 | .912 | .004 | .025 | .945 | .003 |
| | SVM (Radial) | .073 | .912 | .004 | .026 | .942 | .003 |
| **Test** | Neural Network | .078 | .888 | | | | |
| | Random Forest | | | | .047 | .902 | |

**Figure 1**. Model comparison for classifying chronic condition status

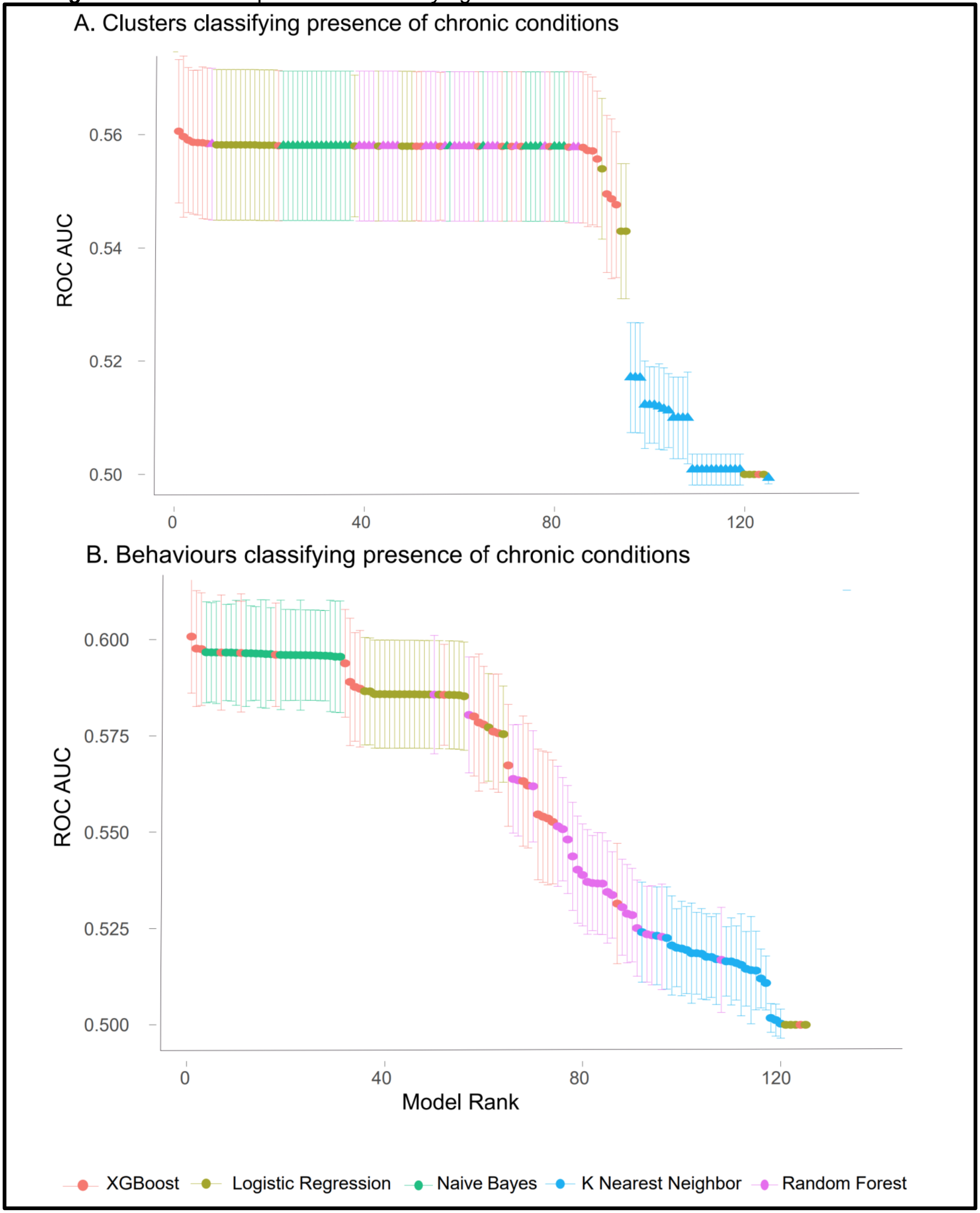


**Figure 2.** Model comparisons for predicting general health.

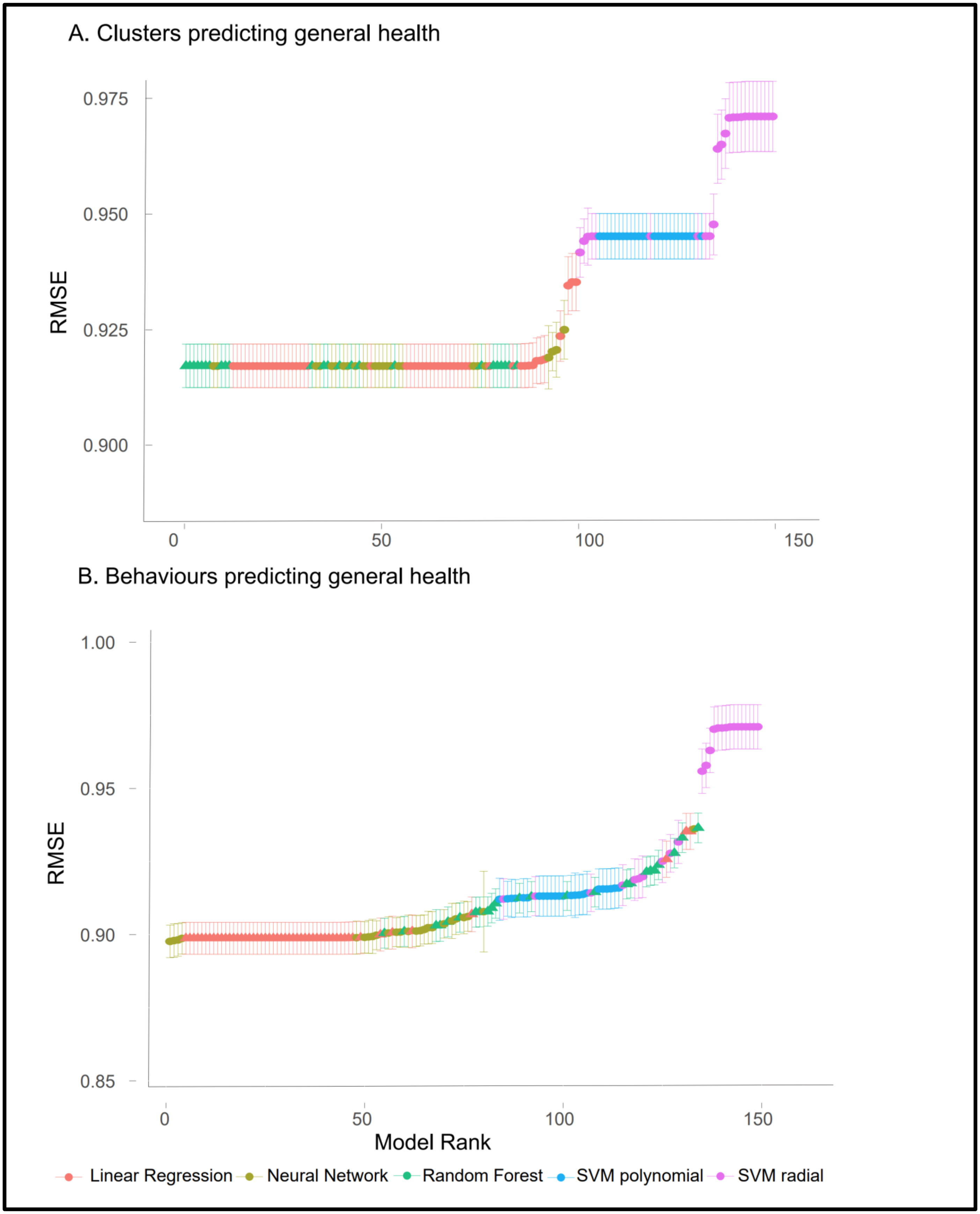


**Figure 3.** Model comparisons for classifying Type II Diabetes.

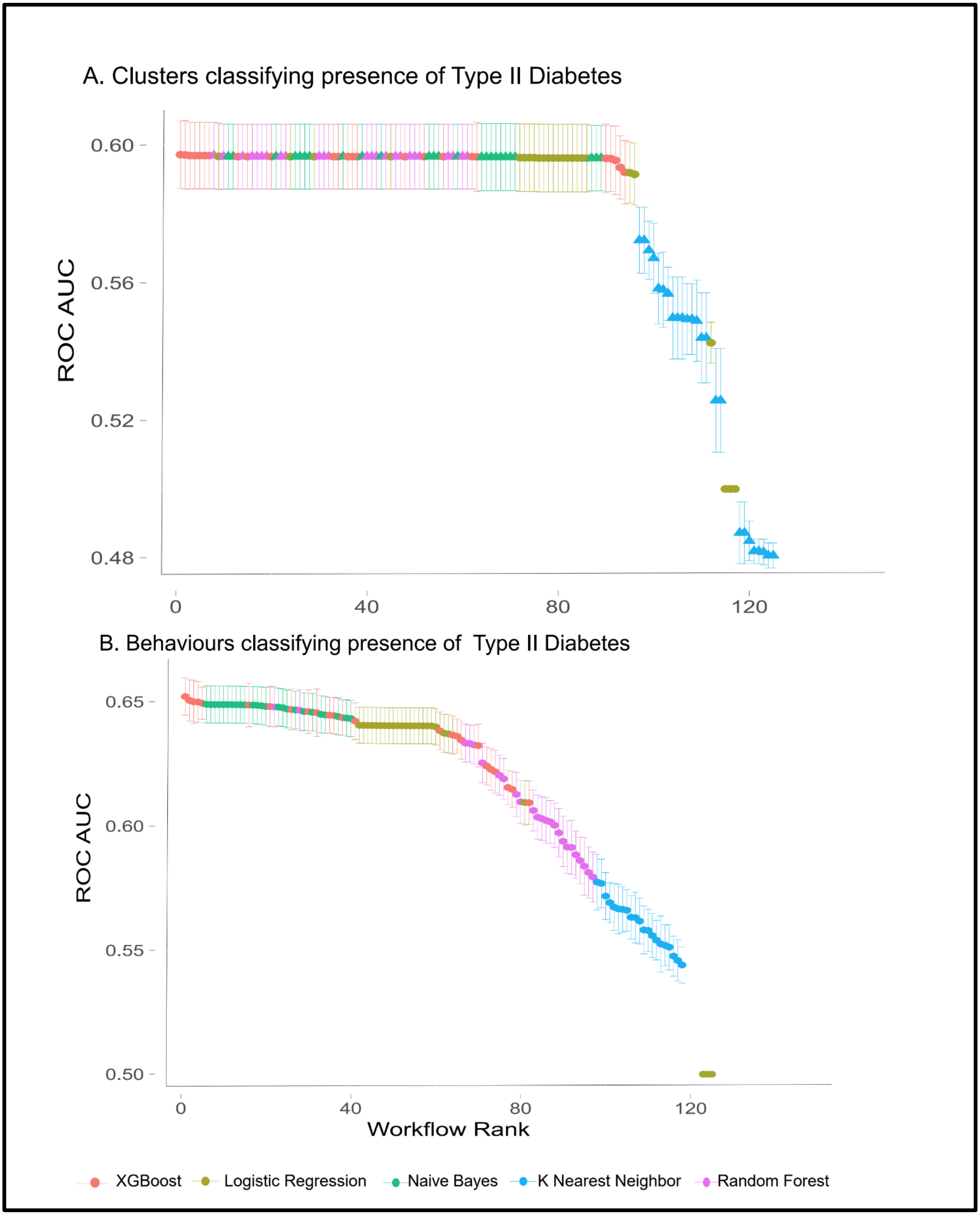


**Figure 4.** AUC ROC for final classification models

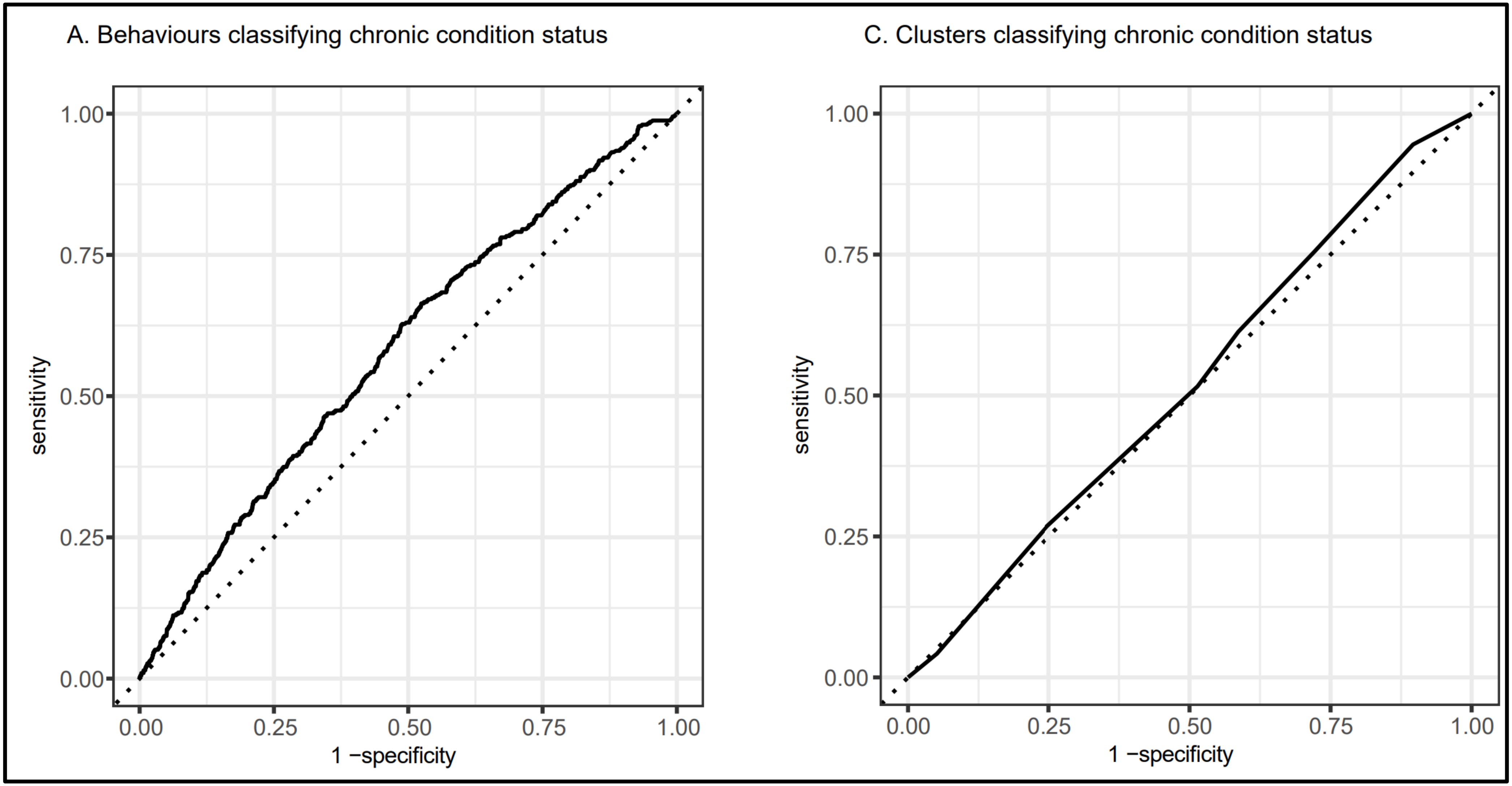
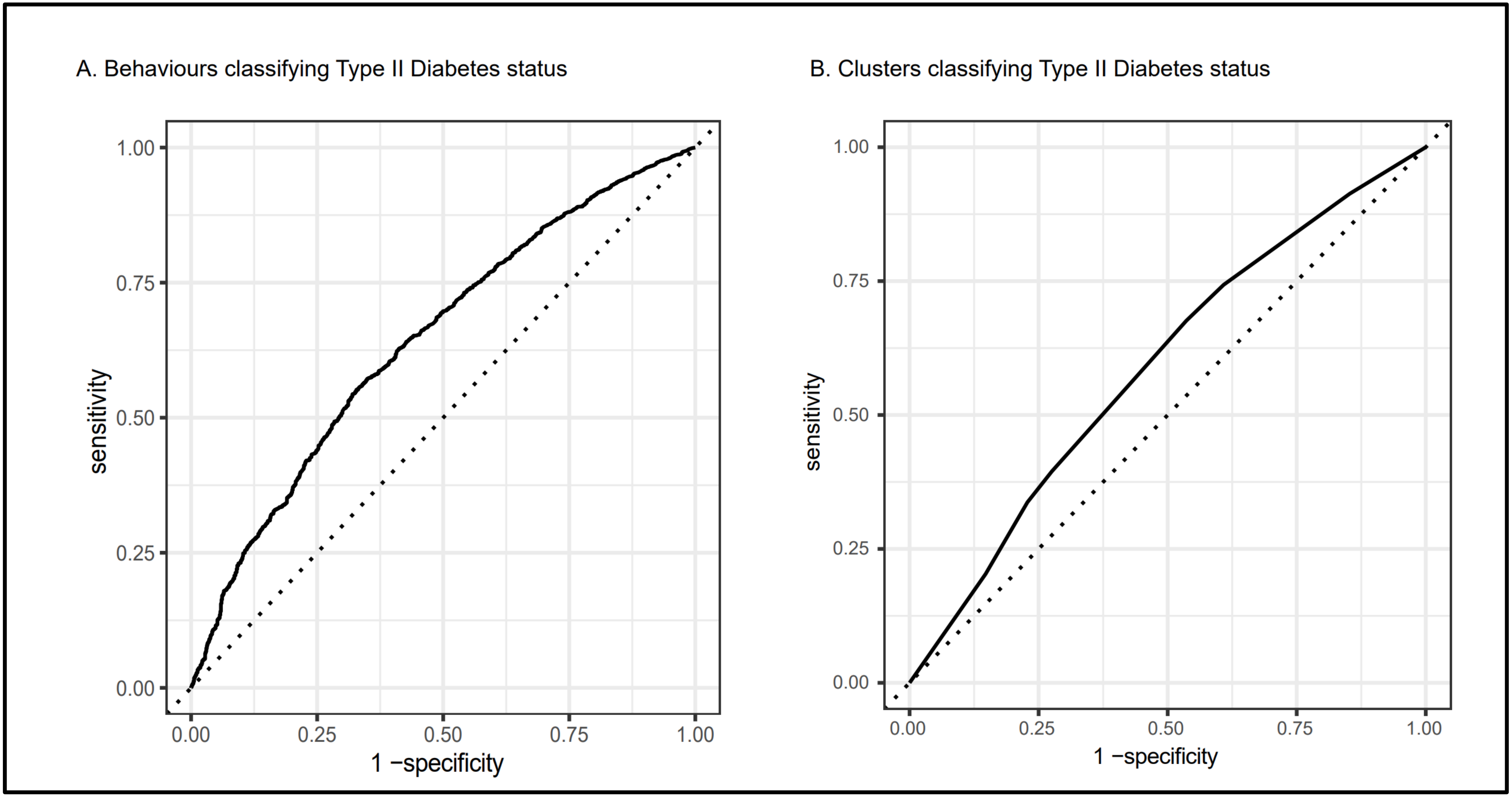


**Figure 5.** AUC ROC for final claddification models (Type II Diabetes)



## 3.5 Discussion

The ability to identify patterns of co-occurring health behaviours is an important task in health psychology and public health (e.g., Agrawal, Budney, & Lynskey, 2012; Anthony & Echeagarary-Wagner, 2000; Dusseldorp et al., 2014). Although many clustering have been performed in pursuit of distinguishing groups of people based on their health behaviours (e.g., Conry et al., 2011; Buck & Frosini, 2012; Noble, Paul, Turon, & Oldmeadow, 2015; Schneider, Huy, Scheussler, Diehl, & Schwarz, 2009; Noble, Paul, Turon, & Oldmeadow, 2015; Whitaker et al., 2021) fewer studies have investigated whether these combinations of commonly co-occurring behaviours have predictive utility beyond individual behaviours. The present study sought to address this research question by predicting and classifying health outcomes from health behaviours and clusters from 1-8 years earlier[3]. Additionally, several statistical models were compared to identify which machine learning algorithms performed best for the purpose of classification and prediction. Using data from the Canadian Longitudinal Study of Aging (Raina et al., 2009), health behaviours including smoking, alcohol consumption, walking, exercise, sedentary activities, and fruit and vegetable consumption, were used to derive seven health behaviour clusters (van Allen et all., 2023). Clusters and individual behaviours were used to predict general health and classify chronic condition and diabetes status using a variety of machine learning algorithms.

Overall, and irrespective of modelling approach, health behaviours and clusters were relatively poor classifiers of chronic condition status (AUC range = 51.9% - 60.1%; specificity range 0-0) and the explained variance in self-reported general health was small (R2 = .03 - .08). However, the purpose of this analysis was not to maximize prediction accuracy, but to compare predictor

[3] Baseline data was collected between 2010-2015 and follow-up data was collected between 2015-2018.

sets (behaviours vs clusters) across several models. Neither health behaviours nor behavioural clusters were able to correctly classify a person living without a chronic condition, or a person living with Type II Diabetes, while health behaviours accounted for less than 10% of variability in self-reported general health. For context, the big five personality factors account for 12% of variability in a similarly phrased single item of general health (Wasylkiw & Fekken, 2002) while being largely non-modifiable. The top performing models for prediction and classification (XGBoost, neural networks, random forests) outperformed simple regression-based models (e.g., OLS and logistic regression), however, these algorithms are considered each black box models meaning that information regarding internal processes are not extractable. The inability to understand the internal processes of these models represents a trade-off with machine learning in psychological science which favors the ability to predict future behaviour over the ability to explain the causal underpinnings of behaviour (Yarkoni & Westfall, 2017; Rosenbusch, Soldner, Evans, & Zeelenberg, 2019).

### 3.5.1 Limitations

There are at least three main reasons why models performed sub-optimally: the limited set of predictor variables, the selection of outcome variables, and the temporal distance between baseline and follow-up time points.

Although there is no consensus on the exact number of health impacting behaviours (e.g., Nudlebaum & Shiloh, 2015; McHachan, Lawton, & Conner, 2010), the number of health behaviours included in the present analysis was certainly not comprehensive. Some health behaviours, for example risky sex behaviour and recreational drug use, was not included in analysis as they were not assessed in the CLSA baseline assessment but have been shown to impact health (e.g., Cornish & O'Brien, 1996; Hall & Lynskey, 2020; Galvin & Cohen, 2004).

Other behaviours such as sleep, and sleep hygiene behaviours, were excluded from analysis due to high levels of missing data resulting from sleep being assessed for only a sub-sample of the CLSA cohort. Additionally, the present analysis constrained the predictor sets to health behaviours to address a specific research question regarding the ability of health behaviours to predict/classify future health outcomes. A more comprehensive set of predictor variables related to health outcomes would have increased model performance but was outside the scope of the present analysis.

Another potential limitation are the outcomes measures used in analysis. General health and chronic condition status were selected as outcome measures to provide a subjective and objective measure of health status. General health was measured via self-report measure which by its nature contains inherent strengths and weaknesses (Del Boca & Noll, 2000). Chronic condition status was broadly conceptualized as persons who are living with any chronic condition. It is possible that this measure was too broadly conceived and that a more focused measure would have led to greater model performance. Although chronic conditions could have been recoded to represent multimorbidity (living with more than one chronic condition concurrently) or change in chronic condition status, these approaches would likely exacerbate class imbalances in the data resulting in increased difficulty identifying true negatives (i.e., model specificity). For these reasons, Type II Diabetes was added as an outcome due to its higher prevalence in the dataset of approximately 10%. However, neither behaviours nor clusters were able to classify positive diagnoses. This is likely due to the limited number of predictor variables as other studies have achieved higher classification rates for Type II Diabetes even with cross-sectional data (e.g., Xie, Nikolayeva, & Li, 2019).

Finally, the temporal distance between timepoints may have been insufficient for health impacting behaviours to impact health in a discernable manner. To use the example of smoking and lung cancer, a person who smokes approximately 10,000 cigarettes over the course of 50 years has 1-in-6 odds of dying from lung cancer (Cokkinides, Albano, Samuels, Ward, & Thum, 2005). The dose dependent relationship between smoking and the development of a chronic condition illustrates that greater time periods between waves of data collection may be required to observe the effect of repeated behaviours over time. Although longitudinal data was used to estimate temporal associations, the limited time between data collection waves renders the analysis more akin to cross-sectional associations (i.e., the analysis answers ‘can behaviours/clusters characterize people living with a chronic condition’ rather than ‘do behaviours/clusters predict future incidence of chronic conditions’).

Taken together, model performance could be improved with a larger set of relevant predictor variables, more narrowly defined outcome variables, and a greater temporal distance between data collection waves.

### 3.5.2 Conclusion and Future Research

The promise of clustering studies is that they can identify groups of people based on similar features. These clusters can be used to tailor targeted intervention strategies at the public health level. Additionally, it is possible that synergistic effects of multiple co-occurring behaviours may lead to greater variability in health outcomes than single behaviours in isolation. Therefore, a relatively unexplored area of research is whether clusters have predictive utility beyond individual health behaviours. The results of the present study suggest that, in isolation, clusters and individual behaviour are both sub-optimal classifiers of chronic condition status and account for a proportion of explained variance in self-reported general health similar in magnitude to nonmodifiable factors such as personality traits. However, these findings are limited by the temporal distance between time points and class imbalances in chronic condition status and cannot answer this question definitively. Future research, utilizing more time points larger predictor sets, can build on this approach and develop models with greater sensitivity to identify chronic condition status.

CHAPTER 4

# MULTIPLE HEALTH BEHAVIOURS: INTERCONNECTEDNESS AND HETEROGENEITY FROM A NETWORK PERSPECTIVE ACROSS TWO LARGE DATASETS

## Abstract

**Background:** This chapter builds upon the network analysis reported in Chapter 2 using national and international data.

**Methods**: Secondary data analysis was performed on two cross-sectional data sources: 1) the Canadian Longitudinal Study of Aging and 2) the international COVID-19 awareness, responses, and evaluation (iCARE) study. Baseline data for the CLSA (n = 51,338) was collected prior to the COVID-19 pandemic (2010-2015) while iCARE (n = 66,522) data collection began in response to the pandemic (2020-2021). The interconnectedness of health behaviours was modelled with a network approach and sociodemographic heterogeneity was explored with network comparison tests and recursive partitioning-based network trees. Health behaviour clustering was assessed with the clique percolation method of community detection[4].

**Results**: Partial polychoric correlations (*ρ)* between seven health behaviours assessed in the CLSA were small (*ρ* range = -.13, .14; M = +/- .06) and a similar pattern was observed with iCARE data (*ρ* range = -.08, .19; M = +/- .09) except for a larger relationship between changes in physical activity and healthy diet since the beginning of the covid-19 pandemic (*ρ* = .48). Differences in edge weights between groups distinguished by age, sex, and income in the CLSA were present but small (β = .03-.07). Edge weight differences in the iCARE study were in a similar range with the largest observed difference reflecting a stronger association between

[4] A protocol for the analysis performed in the chapter has been published. Analysis outlined in the protocol was meant for the CLSA dataset and was later adapted to apply to the iCARE dataset as well:
**van Allen, Z. M**., Bacon, S., Bernard, P., Brown, H., Desroches, S., Kastner, M., … Presseau, J. (2021). Clustering of healthy behaviours in Canadians - Protocol for a multiple behaviour analysis of data from the CLSA. *JMIR: Research Protocols.*

indoor mask use and social distancing in males (β = .36) compared to females (β = .16). Differences in network communities were present in the iCARE sample but not in the CLSA. The Clique Percolation Algorithm for network community detection was of limited use in identifying clusters in the CLSA due to small associations between behaviours and many researcher degrees of freedom in the analysis.

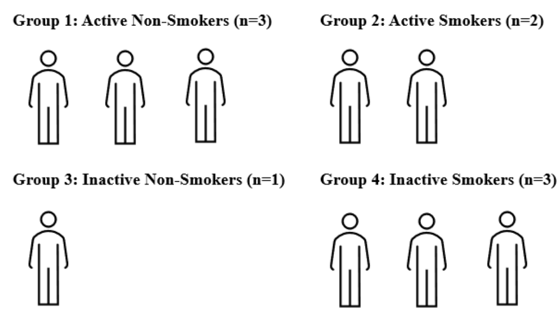
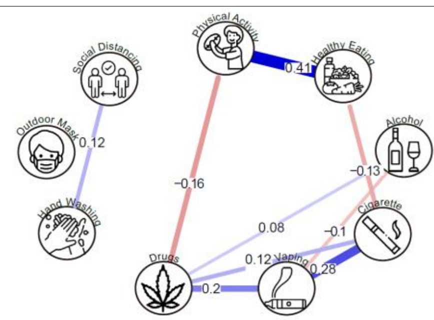
**Conclusions**: Analysis of national (CLSA) and international (iCARE) datasets showed associations between some behaviours (e.g., physical activity and healthy eating), while identifying other mostly small relationships between health behaviours. Sociodemographic heterogeneity was evident in terms of statistically significant associations across age groups, sex, and income levels; however, effect sizes were small.

## 4.1 Introduction

Health behaviours are self-directed activities which may influence one’s future physical health and quality of life. Health behaviours such as smoking, alcohol consumption, physical inactivity, sedentary activity, and unhealth eating are robustly associated with an increased likelihood of developing one or more chronic conditions (González, Fuentes, & Márquez, 2017; Godtfredsen, Prescott, & Osler, 2005; Shield, Parry, & Rehm, 2014), are also robustly associated with sociodemographics, environmental characteristics and life circumstances. Implementing behaviour change interventions to reduce preventable chronic conditions requires accurate phenomenon detection (Borsboom et al., 2021) and ‘basic’ behavioural science combined with behavioural theory (Czajkowski et al., 2015; Bacon et al., 2020). For example, prior to pilot testing an intervention researchers base their initial intervention design on basic behavioural science knowledge such as the relationships between behaviours and outcomes, heterogeneity of behaviours across sociodemographic factors, and theoretical associations between socio-cognitive variables and behaviours of interest. This chapter seeks to further refine knowledge of the interconnectedness of health behaviours and sociodemographic heterogeneity using recently developed tools from the network psychometrics literature.

Broadly, health behaviours can be interconnected in one of two ways: behaviours can co-occur and/or they can co-vary. Co-occurrence in this context refers to multiple health behaviours enacted by the same individual while co-variation refers to correlations between health behaviours. While some health behaviours will, to a greater or lesser extent, co-occur within all individuals (e.g., physical activity, sedentary behaviour, sleep) other behaviours will be performed by some but not by others and to varying degrees (e.g., alcohol consumption, drug use, risky sex behaviours). Additionally, the strength and direction of co-variation between behaviours will differ between behaviours with patterns of co-variation likely heterogeneous across persons. These two types of interconnectedness lend themselves to different approaches for analysis. For example, *person-centered analysis* such as cluster analysis (Chapter 2) or behavioural profiles (Appendix I) can be used to assign individuals into groups based on behavioural characteristics. In contrast, *variable-focused analysis* such as correlation and regression-based approaches seek to describe the co-variation between variables (see Table 1).

**Table 1.** Examples of person-centered co-occurrence and variable-centered co-variation

| Category | Central Task | Example Analysis | Visual Depiction |
|---|---|---|---|
| **Co-Occurrence** | Assign people into groups based on similar features | ▪ Hierarchical agglomerative cluster analysis<br>▪ K-means clustering<br>▪ Crosstabs / behavioural profiles<br>▪ Latent class analysis<br>▪ DBSCAN clustering<br>▪ Gaussian mixture models |  |
| **Co-Variation** | Determine direction and strength of associations between variables | ▪ Correlations<br>▪ Multiple regression<br>▪ Network analysis<br>▪ Structural equation modelling<br>▪ Lag-1 temporal analysis |  |

One promise of identifying co-varying behaviours is that if behaviour A and B are interrelated, intervening on A may have positive impacts on B, assuming a directional relationship between A and B. For example, engaging in physical activity and eating a healthy diet are often interconnected and an intervention on one could have positive knock-on effects in some cases. Additionally, the absence of co-variation is also informative; for example, the finding that physical activity and sedentary behaviour are generally unrelated has informed the development of interventions and guidelines which address each behaviour separately (Santos et al., 2012). Further, interventions which do not consider the interconnectedness of multiple behaviours may overlook relevant factors in the promotion or prevention of a behaviour (e.g., a smoking cessation intervention may not account for the interconnectedness between alcohol and smoking leading to reduced effectiveness for those who smoke when they consume alcohol).

In addition to understanding the relationships between health behaviours, it is also important to identify heterogeneity across groups of individuals. Identifying heterogeneity based on sociodemographic factors is a central challenge to the promise of tailored health behaviour interventions at the population level. Most research is univariate, focused on relationships between a single behaviour and outcome (e.g., physical activity and multimorbidity; Vancampfort et al., 2017; Chudasama et al., 2019). Identifying heterogeneity within the interconnectedness of health behaviours could enable further tailoring of support for behavioural trials. Although heterogeneity can be assessed by investigating co-occurrence and/or co-variation, the present chapter focuses on identifying heterogeneity using a co-variation approach.

One analytical approach for modelling the interconnectedness between variables is through network analysis. Network analysis graphically represents the conditional dependence relationships between observed and/or latent constructs (Hevey, 2018; Robinaugh, Hoekstra, Toner, & Borsboom, 2020; McNally, 2021). The most common form of network model the is the Graphical Gaussian Model (GGM) which is based on partial correlations between variables (Epskamp & Fried, 2018). In network psychometric models, all possible regressions between a set of variables are conducted and regularization penalties are applied to shrink small and potentially spurious relationships to zero (Epskamp, Borsboom, & Fried, 2018). Although somewhat novel, these networks provide little additional information to a correlation matrix beyond a graphical representation and modest regularization effects with large datasets (Williams, Rhemtulla, Wysocki, & Rast, 2019). However, the potential of networks for identifying heterogeneous patterns of interconnectivity in health behaviours is more salient when combined with methodology for identifying differences in interconnectivity across sociodemographic factors.

One such method is ‘network comparison tests’ which enable conducting exploratory identification of network invariance (i.e., different network structures) based on dichotomized demographic factors (von Borkulo, Epskamp, & Millner, 2016). For example, network comparison tests can determine if the patterns of associations between health behaviours differ between men and women. This test functions as an omnibus test of network invariance while additional tests can be performed to assess whether differences between edges (i.e., associations between behaviours) are statistically significant (von Borkulo, Epskamp, & Millner, 2016). Although network comparison tests provide a useful extension to the network psychometric framework they are limited to dichotomous comparisons. However, networks can be combined with decision tree algorithms to identify when statistically significant differences are present in network structure based on combinations of demographic factors.  For example, model-based recursive partitioning techniques can be combined with network analysis to produce ‘network trees’ which recursively splits a dataset based on covariates to detect subgroups based on a correlation or covariance matrix (Jones, Mair, Simon, & Zeilleis, 2020). This exploratory data technique has the potential to identify whether patterns of interconnected health behaviours vary across combinations of sociodemographic factors (e.g., low income males aged 45-54 vs high income females aged 75-84). This technique, which has not yet been applied in the health behaviour context, has the potential to identify patterns of sociodemographic heterogeneity within health behaviours.

Finally, network-based approaches can also be used to identify clusters of commonly associated health behaviours. Although clustering is usually performed through person centered/co-occurrence analysis, network community detection algorithms can also perform this function when employed with correlation-based networks. Many community detection algorithms can be used to identify which health behaviours cluster together including the clique percolation algorithm (Palla, Derenvi, Farkas, & Vicsek, 2005; Farkas, Abel, Palla, & Viscek, 2007), the spinglass algorithm (Reichardt & Bornholdt, 2006), leading eigenvector (Newman, 2006), exploratory graph analysis (Golino & Epskamp, 2017), and the walktrap algorithm (Pons & Latapy, 2005). However only the clique percolation algorithm can identify overlapping network communities (i.e., where a node may belong to more than one community). The ability to identify overlapping communities is a helpful feature for identifying 'bridge nodes' which connect two otherwise distinct clusters. The identification of bridge nodes is important theoretically and for hypothesis generation as targeting bridge nodes has the potential to sever the interconnectedness between otherwise unconnected sets of nodes and prevent the spreading activation of nodes across a behavioural system (e.g., Jones, Ma, & McNally, 2019). With the clique percolation method of community detection, the number of nodes ($k$) which must be connected can vary, with the smallest clique being $k = 3$ (a closed triangle). When more than one set of cliques are adjacent in a network, they are said to form a community. In psychological networks, where edges are weighted (e.g., representing correlations), only edges which surpass a certain threshold ($I$) are considered when identifying cliques (Palla, Derenvi, Farkas, & Vicsek, 2005; Farkas, Abel, Palla, & Viscek, 2007; Lange, 2019). To the best of my knowledge, this method for identifying clusters has neither been performed on health behaviour networks nor compared to person-centered methods using the same dataset (e.g., Chapter 2).

Psychometric networks combined with large datasets have the potential to be a helpful toolset for identifying the relationships between multiple health behaviours and patterns of heterogeneity at the population level. This chapter serves as both an exploration of conditional dependence relationships between health behaviours and a test of network methodology in the multiple health behaviour domain by addressing the following research questions: 1) what are the multivariate relationships between health behaviours (assessed with network analysis); 2) do these relationships vary by sociodemographic factors (assessed with network comparison tests and network trees) and; 3) which health behaviours form clusters/communities of interrelated behaviours (assessed through community detection)?

## 4.2 Methods

### 4.2.1 Data sources

Analysis was performed on two cross-sectional data sources: 1) the baseline Canadian Longitudinal Study of Aging (CLSA Raina et al., 2016; and 2) the international COVID-19 awareness, responses, and evaluation study (iCARE; Bacon, Lavoie, Boyle, Stojanovic, & Joyal-Desmarais, 2021). Baseline data for the CLSA (n = 51,338) was collected prior to the COVID-19 pandemic (2010-2015) while iCARE (n = 66,522) data collection began in response to the pandemic (2020-2021).

### 4.2.2 The Canadian Longitudinal Study of Aging (CLSA)

Participants in the CLSA were recruited through the Canadian Community Health Survey on Health Aging (Raina et al., 2009; Wolfson et al., 2009), provincial health registries, and random digit dialing. Baseline data collection (2010-2015) was comprised of two approaches: a ‘comprehensive’ cohort (n=30,097) in which participants completed a 90-minute in-person interview, and a ‘tracking’ cohort (n=21,241) where participants completed a 60-minute computer assisted telephone interview. Additionally, a 30-minute ‘maintaining contact questionnaire’ was provided to both cohorts 18 months following initial contact to collect supplementary data. Collectively, the comprehensive cohort, the tracking cohort, and the maintaining contact questionnaire, form the baseline data used in the present analysis.

Respondents to the CLSA baseline surveys were French and English-speaking Canadians who were between the ages of 45-85 at time of enrollment. Individuals living on a First Nations reserve or one of three Canadian territories, full time members of the Canadian Armed Forces, and individuals living in institutions or with cognitive impairments were excluded from the study (Raina et al., 2009).

#### 4.2.2.1 CLSA Variables
#### Sociodemographic Indicators

To provide base sample descriptions we used three sociodemographic indicators. These include age, as grouped in the CLSA dataset (45-54; 55-64; 65-74; 75-85), sex (male/female), and household income (<$20k, $20-$49k, $50-$99k, $100-$149k, $150k+).

#### Health Behaviours

*Physical activity* and *sedentary behaviour* were assessed with the Physical Activity Scale for the Elderly (PASE; Washburn et al., 1993). The PASE measures the frequency of exercise, strenuous physical activity, moderate physical activity, light physical activity, walking, and sedentary behaviour over the preceding seven days on a 1 (never) to 4 (often, 5-7 days) scale. All items were reverse scored so that higher values indicate higher frequencies. Based on previous research (Dogra et al., 2019; van Allen et al., 2021), conceptual overlap between items and highly similar responses, two sets of items were averaged into single items (light physical activity and moderate physical activity were combined; strenuous physical activity and exercise were combined). Ultimately, this produced four subscales representing: walking, sitting, strenuous physical activity/exercise, and light/moderate physical activity (henceforth renamed 'light sports' to avoid confusion with 'light-to-moderate physical activity'(e.g., Saint-Maurice et al., 2018).

*Fruit and vegetable consumption* was measured with a single item from the Seniors in the Community Risk Evaluation for Eating and Nutrition questionnaire (Keller et al., 2005). Specifically, participants were asked how many servings of fruits and vegetables they eat in a day. The original scale ranging from 1 (seven or more fruits/vegetables) to 7 (less than two fruits/vegetables) was reverse coded so that higher scores indicate more fruit and vegetable consumption.

*Smoking behaviour* was measured using a skip-question framework. Respondents who answered 'no' to the question 'have you smoked at least 100 cigarettes in your life' and responded 'yes' to the question 'have you ever smoked a whole cigarette' were subsequently asked whether they smoke occasionally, daily, or not at all in the past 30 days. Next, only those who reported smoking occasionally or daily were asked follow-up questions pertaining to frequency and types of tobacco products used. A value of 0 was assigned to each respondent who responded 'no' to the question 'have you ever smoked a whole cigarette' as these individuals also did not smoke in the past 30 days. A similar approach has been applied to skip structure data when missing data represent the absence of a behaviour or psychological feature (Borsboom & Cramer, 2013). Ultimately, this creates three levels distinguishing between people who smoked occasionally, daily, or not at all during a 30-day window.

*Alcohol use* was assessed with one item asking participants how often they consumed alcohol in the past 12 months. The original scale ranged from 1 (almost every day) to 7 (less than once a week) but was coded so higher values indicate greater alcohol consumption.

**Non-Health Behaviours**

*Participation in hobbies and musical activities* were assessed by asking participants to report their frequency of engagement in hobbies such as crossword puzzles, sodoku, jigsaw puzzles, or board games, and engagement in playing a musical instrument or singing in a choir. The original items were scored on a 1 (every day) to 5 (once a year) scale which was reverse coded for analysis.

*Community activity involvement* over the past twelve months was measured for each of nine activities: 1) participation in educational or cultural activities; 2) participation in sports or physical activities with others; 3) participation in family/ friends activities out of household; 4) volunteer or charity work; 5) community or professional association activities; 6) service club or fraternal organization activities; 7) attending concerts, plays, or visiting museums; 8) church or religious activities; and 9); participation in other recreational activities. A derived variables in the CLSA baseline data was used in analysis reflecting frequency of participation in any activity of the above activities on a 0-4 scale (0 = no activities, 1 = yearly, 2 = monthly, 3= weekly, 4 = daily).

*Social networking site usage* was assessed using several items within a skip-question framework. Preliminary descriptive analysis has shown that 44.7% reported using social networking sites while 38.0% were not social networking site users and 17.3% of responses either missing or non-responses. Although more detailed follow-up questions were subsequently posed to respondents, including these items would substantially reduce the sample size available for analysis. Given the skip-question structure of the CLSA social networking site module, we included a binary variable representing the use (1) or non-use (0) of social networking site.

*Respondent caregiving* to any persons in the previous twelve months, excluding rendering aid as part of volunteer or paid work, was assessed through the CLSA caregiving module which asked questions pertaining to assisting others, how many others were assisted, the type of assistance, the people who the respondents help most often, and the personal and professional impacts of providing care to others. A single item reflecting whether participants did (coded 1) or did not (coded 0) provide assistance to others in the previous twelve months was used in analysis.

### 4.2.3 The iCARE Study

The International COVID-19 Awareness and Responses Evaluation (iCARE) Study is an international multi-wave cross-sectional observational cohort study of public awareness, attitudes, and responses to public health policies implemented to reduce the spread of COVID-19 on people around the world (www.mbmc-cmcm.ca/covid19). Survey data collection began in March 2020 using convenience snowball sampling (globally) and parallel representative sampling in targeted countries. Survey data can be linked at the country/province-level with Oxford Government Policy Tracker data, Google Mobility data, and Johns Hopkins case/death/recovery data.

The study is led by the Montreal Behavioural Medicine Centre (MBMC: www.mbmc-cmcm.ca) in collaboration with a team of 200 international collaborators from 42 countries. It has received REB approval from the Comité d’éthique de recherche du CIUSSS-NIM (Centre intégré universitaire de santé et de services sociaux du Nord-de-l’île-de-Montréal), approval # : 2020-

2099 / 25-03-2020. Recruitment began on March 27th, 2020 and the survey is available in 34 languages.

#### 4.2.3.1 iCARE Variables

**Sociodemographic Indicators**

Three sociodemographic indicators were selected from the iCARE survey to provide basic sociodemographic information for the sample. These include age (grouped to match the 10-year age groups in the CLSA), sex (male/female/other), and household income (bottom third, middle third, top third), to align with the CLSA based analysis.

**iCARE Health Behaviours (Survey Waves 1-4)**

In surveys 1-4 the health behaviours of *physical activity, healthy diet, alcohol consumption* were assessed by asking respondents 'in general, <u>how would you rate your health behaviours compared to the average person in your country</u>' on a scale ranging from 1 (I do it a lot more than most) to 5 (I don't do this). Responses were reverse coded so that higher values reflect higher frequencies. Surveys 1-4 were collected between March 27$^{th}$ 2020 and September 15$^{th}$, 2020.

*Cigarette consumption* was measured via the question 'have you ever smoked regular tobacco cigarettes?'. Response options were never, in the past (ex-smoker), I smoke occasionally, and I smoke daily. Responses were coded on a scale from 1-4, respectively.

*Vaping or electronic cigarette consumption* employed a similar question prompt to cigarette consumption by asking participants if they "currently use any vaping or electronic cigarettes products?" using the following response options: no (1), yes occasionally (2), and yes daily (3).

Three health behaviours related to the COVID-19 pandemic were selected from the iCARE survey: *Hand washing with soap and water*, *wearing a face mask*, and *staying at least 1-2 meters away from other people* were assessed on a 1 (most of the time) to 4 (never) scale use the question prompt “Please indicate the frequency with which you have adopted each action/behaviour in the previous 7 days.” Items were reverse coded for analysis.

**iCARE Health Behaviours (Surveys 5-10)**

In surveys 5-10, all health behaviours were assessed with a common question stem and set of response options. Specifically, participants were asked “In general, how have the following behaviours changed since the start of COVID-19?” and responded on a 1 (I do this a lot more) to 6 (I don’t do this) scale which was reverse coded in analysis such that higher responses indicate greater frequencies. Each of the five health behaviours assessed in surveys 1-4 were also assessed during surveys 5-10 (i.e., *physical activity, healthy diet, alcohol consumption, cigarette consumption, vaping consumption*). In addition, during surveys 5-10 participants also reported the frequencies of their recreational drug use (marijuana, cocaine, opioids, hallucinogens, etc.). Data from surveys 5-10 was collected from Sept 15$^{th}$, 2020 to June 15$^{th}$, 2021.

Similar pandemic related health behaviours were assessed from surveys 5-10, albeit with slight modifications from earlier assessments. Specifically, participants were asked to “indicate the frequency with which you have adopted each action/behaviour in response to the COVID-19 pandemic” on a 1 (never) to 4 (most of the time) scale with an option to identify that a given behaviour was not applicable to one’s situation. The behaviours were: *hand washing with soap and water, wearing a face mask in indoor spaces (shops, restaurants, public transit, at work),* and *staying at least 1-2 metres / 3-6 feet away from other people.* All items were reverse coded for analysis so that higher scores reflect greater engagement in a behaviour.

**4.2.4 Analysis Plan**

For both datasets, the analysis steps were as follows: Step 1) descriptive analysis and partial correlations for health behaviours; Step 2a) when sociodemographic variables had two categories, separate networks were computed for each category or Step 2b) when sociodemographic variables had more than two categories data driven analyses (i.e., network trees) were used to identify statistically significant partitions in the data based on the sociodemographic variables; Step 3) network psychometrics were applied to the study data; Step 4) network comparison tests were used to test whether the relationships (i.e., edge weights) between variables were statistically different between sociodemographic groups; and Step 5) network community detection was performed on each computed network to identify co-occurring variables within the network. These steps are modified slightly from our published protocol (van Allen et al., 2021) to reflect an updated understanding of network analyses and the inclusion of a second dataset (iCARE data). These analyses answered the following questions: 1) what are the multivariate relationships between health behaviours (network analysis), 2) do these relationships vary by sociodemographic factors (network comparison tests, network trees), and 3) do any health behaviours form clusters/communities of interrelated behaviours?

Step 1: Given that all health behaviour variables in both the CLSA and iCARE datasets use Likert scale items with response options raging from four to seven, polychoric partial correlations were computed for all health behaviours. Polychoric correlations are appropriate for ordered categorical data (Olsson, 1979) and polychoric correlation matrixes are used as inputs for several network estimation methods. Bivariate polychoric correlations were computed with the cor_auto function from the qgraph package (Epskamp, Cramer, Waldorn, Schmittmann, & Borsboom, 2012) and converted to partial correlations with the cor_to_pcor function from the correlation package (Makowski, Ben-Scachar, Patil, & Lüdecke, 2020).

Step 2a: To explore heterogeneity in the conditional dependence structures of health behaviours, networks can be compared based on a covariate of interest. When multiple levels of a categorical covariate are present, and there are no priori hypotheses, model-based recursive partitioning can be applied to identify structural differences between sub-groups (Zeileis et al. 2008). Recently, model-based recursive partitioning has been extended to the network approach via ‘network trees’ (Jones, Mair, Simon, & Zeileis, 2020). This approach recursively splits a dataset based on specified covariates and detects variability in a correlation or covariance matrix with the goal of identifying meaningful subgroups within the dataset (Jones et al., 2020). Step 2b: In the present study, network trees are used to identify differences in sub-groups when covariates of interest have multiple levels or categories (i.e., age groups, income brackets).

Step 3: Network psychometrics are commonly estimated through Pairwise Markov Random Field (Van Borkulo et al., 2014; Epskamp, Borsboom, & Fried, 2018; PMRF). In a PMRF, nodes are variables connected by edges which represent conditional independence relationships. Variable analytical procedures are available to model networks with different data types (Borsboom et al., 2021). Gaussian Graphical Models (GGMs), for example, model continuous or ordinal data while Ising models (e.g., Van Borkulo et al., 2014) are used on binary data and Mixed Graphical Models (Haslebeck & Wldorp, 2020; MGMs) can be applied to mixed data containing a combination of continuous/ordinal and binary data.  Due to the large number of parameters often estimated in a PMRF, researchers often compute a regularized network by applying, for example, the Least Absolute Shrinkage and Selection Operator (LASSO; Tibshirani, 1996) to produce a sparse/conservative network that reduces weak connections between nodes to 0, resulting in a more interpretable network. However, recent work has questioned whether regularization is required for low dimensional data with large sample sizes (Williams & Rast, 2018). In response to this work, the ggmModSelect algorithm was developed in the bootnet package (Epskamp, Borsboom, & Fried, 2018). This algorithm produces a range of networks (default is 100) via varying the tuning parameters which control the LASSO (Isvoranu & Epskamp, 2021). Subsequently, each network is re-estimated through maximum likelihood estimation so that only non-zero edges in the regularized networks are estimated as non-regularized edges (Isvoranu & Epskamp, 2021). Non-regularized estimates are then used to optimize the Extended Bayesian Information Criteria (EBIC; Cehn & Chen, 2008) which are thought to lead to more accurate model selection than the standard graphical LASSO using EBIC. Given the low dimensional data and large sample sizes of both the CLSA and iCARE datasets, health behaviour analysis, ggModSelect will be used for network analysis. However, MGMs were fitted to model health and non-health behaviours using CLSA data in a set of secondary analysis (see Appendix).

Step 4: Network comparison tests are permutation-based tests that conduct comparisons between two networks to assess differences in edge weights, global structure, and global centrality strength. The 'NetworkComparisonTest' R package (Van Borkulo, Epskamp, Jones, Haslebeck, Millner, 2016) was used to detect statistically significant differences between individual edges. As these tests are exploratory in nature, Bonferroni corrections were applied to control for family wise error rate. Each test used 1000 permutations/iterations in analysis.

Step 5: Community detection analysis was performed on each network and sub-group analysis using the ‘CliquePercolation’ package (Lange, 2019). With the clique percolation method of community detection, the number of nodes (*k*) which must be connected can vary, with the smallest clique being *k = 3* (a closed triangle). When more than one set of cliques are adjacent in a network, they are said to form a community. The algorithm for weighted networks seeks to optimize combinations of k and I through two possible methods. For larger networks, the algorithm computes the ratio of the largest to second largest communities for each combination of k and I and identifies combinations which exceed a ratio value of 2 (Lange, 2019). However, this approach requires a minimum of two communities to be present in the data. An alternative approach for smaller networks is to use a measure of entropy to identify optimal combinations of k and I via a permutation test that determines whether entropy is greater than would be expected by chance (i.e., greater than the 95% confidence interval for each value of k; Lange, 2019). Given the small number of variables included in the health behaviour networks an entropy-based analysis was used with the range of i set from 0 to the value of the highest edge weight in the models (.50) by intervals of .005 and the range of k will be 3-4 to identify co-occurrence between a reasonable number of health behaviours that could be subject to a multiple behaviour change intervention. When multiple combinations are identified, I have opted to abide by the decision rule of selecting the combination with the highest intensity value.

## 4.3 Results

### 4.3.1 CLSA Participants

Following listwise deletion of cases with missing data on health behaviour variables, a total of n=40,268 participants from the CLSA baseline data collection were included in the analysis. Respondents were balanced by sex (50% Male; 50% Female). The average participant was 63 years old (SD = 10) with ages distributed across the following age groups: 45-54 (27%), 55-65

(33%), 65-74 (24%), 75-85 (17%). Annual income varied across the following categories: $150k+ (15%), $100-149k (19%), $50-99k (25%), $20-49k (%), <$20k (22%), missing (6%).

### 4.3.2 CLSA Correlations

Partial polychoric correlations ($\rho$) between seven measures of health behaviours are presented in Table 2. Correlations were small ($\rho$ range = -.13, .14; M = .06) with the strongest positive association observed between exercise and fruit/vegetable consumption ($\rho$ = .14) and the strongest negative association observed between smoking and fruit/vegetable consumption ($\rho$ = -.13).

### 4.3.3 CLSA Networks

A network model of CLSA health behaviours was computed using the ggModSelect algorithm from the bootnet package (Epskamp, Borsboom, & Fried, 2018). Edge weights from the full sample network (presented as βs) varied little from the partial correlations in Table 1. An exploration of sociodemographic heterogeneity followed.

For CLSA data, both annual income and age groups have multiple levels. Recursive partitioning was conducted with age group and income entered as covariates in separate analysis. Statistically significant differences were detected between the age groups 45-55/55-64 and 65-74/75-85 and annual incomes of <$20k/$20-49k and $50-99k/ $100-149k/ $150k+. The dichotomous measurement of sex did not require partitioning. Networks were then estimated based on these subgroups and the edge weights between the two networks were compared using network comparison tests.

**Table 2.** Demographic Information by sample

| CLSA Baseline | | | iCARE Surveys 1-4 | | | iCARE Surveys 5-10 | | |
|---|---|---|---|---|---|---|---|---|
| | n | % | | n | % | | n | % |
| **Sex** | | | | | | | | |
| Female | 20220 | 50.21 | Female | 22812 | 70.93 | Female | 6410 | 73.59 |
| Male | 20048 | 49.79 | Male | 9071 | 28.2 | Male | 2231 | 25.61 |
| | | | Other | 98 | 0.3 | Other | 26 | 0.3 |
| | | | NA | 181 | 0.56 | NA | 44 | 0.51 |
| **Age Group** | | | | | | | | |
| | | | 15-24 | 4643 | 14.44 | 15-24 | 1092 | 12.54 |
| | | | 25-34 | 6579 | 20.46 | 25-34 | 1584 | 18.18 |
| | | | 35-44 | 6292 | 19.56 | 35-44 | 1569 | 18.01 |
| 45-54 | 10923 | 27.13 | 45-54 | 5602 | 17.42 | 45-54 | 1452 | 16.67 |
| 55-64 | 13186 | 32.75 | 55-64 | 5190 | 16.14 | 55-64 | 1575 | 18.08 |
| 65-74 | 9461 | 23.5 | 65-74 | 2853 | 8.87 | 65-74 | 1030 | 11.82 |
| 75-85 | 6698 | 16.63 | 75-84 | 684 | 2.13 | 75-84 | 338 | 3.88 |
| | | | 85-99 | 84 | 0.26 | 85-99 | 30 | 0.34 |
| | | | NA | 235 | 0.73 | NA | 41 | 0.47 |
| **Income** | | | | | | | | |
| $150k+ | 6214 | 15.43 | | | | | | |
| $100-149k | 7439 | 18.47 | Top Third | 8468 | 26.33 | Top Third | 2178 | 25 |
| $50-99k | 13928 | 34.59 | Middle Third | 16127 | 50.14 | Middle Third | 4215 | 48.39 |
| $20-49k | 8663 | 21.51 | Bottom Third | 3931 | 12.22 | Bottom Third | 1225 | 14.06 |
| <$20k | 1669 | 4.14 | No Answer | 3307 | 10.28 | No Answer | 860 | 9.87 |
| NA | 2355 | 5.85 | NA | 329 | 1.02 | NA | 233 | 2.67 |

When comparing the network structure of health behaviours between male and female respondents, several small but statistically significant edge differences were detected through network comparison tests controlling for multiple comparisons with Bonferroni corrections. Specifically, sex differences were observed between walking and sitting activity frequency ($\beta_{male}$ = .00, $\beta_{female}$ = -.03, $p < .001$), light physical activity and fruit/vegetable intake ($\beta_{male}$ = .03, $\beta_{female}$ = .09, $p < .001$), exercise and smoking ($\beta_{male}$ = -.09, $\beta_{female}$ = -.04, $p < .001$), walking and alcohol ($\beta_{male}$ = .03, $\beta_{female}$ = .06, $p = .04$), and between alcohol consumption and fruit/vegetable intake ($\beta_{male}$ = .03, $\beta_{female}$ = .08, $p < .001$). When the clique percolation method for network community detection was applied to the male and female networks, no discernable communities were identified.

A comparison of between networks split by annual incomes below and above $50k again revealed small but statistically significant differences. Differences in edge weights were detected between smoking and light physical activity ($\beta_{above}$ = .00, $\beta_{below}$ = -.04, p < .001), smoking and fruit/vegetable consumption ($\beta_{above}$ = -.10, $\beta_{below}$ = -.16, p < .001), and smoking and exercise ($\beta_{above}$ = -.07, $\beta_{below}$ = -.03, p = .04). No communities were detected in either network.

Comparing networks based on the splits identified by model-based partitioning, differences between four edge weights were observed between those aged 45-64 and 65-85. These differences include the associations between exercise and smoking ($\beta_{younger}$ = -.08, $\beta_{older}$ = -.05, p = .02), such that the relationship between exercise and smoking was small and negative (β = -.08) for those aged 45-65 and small and negative (β = -.05) for those aged 65-85. Additional differences were observed between exercise and fruit/vegetable consumption ($\beta_{younger}$ = .16, $\beta_{older}$ = .10, p <.001), smoking and alcohol consumption ($\beta_{younger}$ = .06, $\beta_{older}$ = .10, p <.001), and walking and light physical activity ($\beta_{younger}$ = .06, $\beta_{older}$ = .00, p <.001). Community detection identified one community in the sample ages 65-86 and no communities for those 34-64. For older participants, a total of twelve combinations of k=4 with values of i ranging from .01 to .065 had entropy values which exceeded the upper bounds of the confidence interval for k=4. As all combinations identified the same number of communities the highest value of i was selected. This resulted in the identification of walking, exercise, fruit/vegetable consumption, and smoking as a clique.

#### 4.3.4 iCARE Participants

Across the first four surveys of the international iCARE study a total of n=23,168 respondents were included in analysis after removing cases with incomplete data on health behaviour variables. The sample was majority Female (71%) with an average age of 43 years old (SD =

16). The distribution of 10-year age groups is presented in Table 1. When asked how their annual income compared to others in their nation, the distribution of responses was: top third (26%), middle third (50%) bottom third (12%) and no answer (10%).

For surveys 5-10 of the iCARE study a total of n= 8,711 respondents were included in analysis following listwise deletion of non-responses on health behaviour items. The sample was majority Female (74%) with an average age of 46 years old (SD = 17). Distributions of age groups and annual incomes were comparable to the sample across surveys 1-4 (see Table 1).

### 4.3.5 iCARE Correlations

Polychoric correlations for health behaviour variables from surveys 1-4 and 5-10 are presented in Table 2. Correlations between health behaviours ranged between $\rho$ = -.18 to $\rho$ = .50 with the strongest positive associated observed between physical activity and healthy diet ($\rho$ = .50) during surveys 1-4 and the strongest negative relationships between indoor mask use and alcohol consumption ($\rho$ = -.18) for surveys 1-4.

In both samples, smoking and vaping showed strong associations (surveys 1-4, $\rho$ = .49; surveys 5-10, $\rho$ = .48) as did social distancing and hand washing (surveys 1-4, $\rho$ =.39, surveys 5-10, $\rho$ = .27) and social distancing indoor mask use in surveys 5-10 ($\rho$ = .40) but not in surveys 1-4 ($\rho$ = -.01).

### 4.3.6 iCARE Networks

Network models of iCARE health behaviours were estimated with edge weights from the resulting network similar in magnitude to partial correlations in Table 3.

**Table 3.** CLSA Health Behaviours: Partial Polychloric Correlations and Summary Statistics

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. Walking | - | | | | | | |
| 2. Sitting | -.03*** | - | | | | | |
| 3. Light Physical Activity | .05*** | -.03*** | - | | | | |
| 4. Exercise | .07*** | -.03*** | .06*** | - | | | |
| 5. Fruit & Vegetable | .12*** | 0.01 | .07*** | .14*** | - | | |
| 6. Smoking | -.03*** | -.01* | -0.01 | -.06*** | -.13*** | - | |
| 7. Alcohol | .07*** | .06*** | .05*** | .07*** | 0.01 | .12*** | - |
| Mean | 3.06 | 3.9 | 1.3 | 1.61 | 4.05 | 0.85 | 4.29 |
| SD | 1.12 | 0.37 | 0.52 | 0.79 | 1.79 | 0.74 | 1.99 |
| Min | 1 | 1 | 1 | 1 | 1 | 0 | 1 |
| Max | 4 | 4 | 4 | 4 | 7 | 3 | 7 |

Note: *** p<=.001, ** p<=.01, *p<=.05

**Table 4.** iCARE Health and Pandemic Behaviours: Partial Polychloric Correlations and Summary Statistics

| | iCARE Surveys 1-4 | | | | | | | | | iCARE Surveys 5-10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| 1. Physical Activity | - | | | | | | | | | - | | | | | | | | |
| 2. Healthy Diet | 0.50*** | - | | | | | | | | 0.48*** | - | | | | | | | |
| 3. Alcohol | 0.11*** | -0.01* | - | | | | | | | 0.11*** | -0.12*** | - | | | | | | |
| 4. Smoking | -0.08*** | -0.01 | 0.19*** | - | | | | | | -0.09*** | 0 | 0.06*** | - | | | | | |
| 5. Vaping | 0 | -0.05*** | 0.04*** | 0.49*** | - | | | | | 0.07*** | 0.04*** | -0.01 | 0.48*** | - | | | | |
| 6. Drugs | - | - | - | - | - | - | | | | -0.02 | -0.03*** | 0.25*** | 0.24*** | 0.36*** | - | | | |
| 7. Wash Hands | -0.02*** | 0.09*** | 0 | 0.04*** | -0.03*** | - | - | | | 0.02 | 0.04*** | 0.09*** | 0.05*** | 0.02 | -0.14*** | - | | |
| 8. Indoor Mask | -0.03*** | 0 | -0.18*** | 0.01* | -0.01 | - | -0.08*** | - | | -0.02* | -0.03*** | 0.02 | 0.02 | -0.08*** | -0.01 | 0.18*** | - | |
| 9. Social Distance | 0 | 0.06*** | 0.02*** | 0.11*** | -0.11*** | - | 0.39*** | -0.01 | - | 0 | 0.03*** | 0.02 | -0.06*** | -0.04*** | -0.03*** | 0.27*** | 0.40*** | - |
| Mean | 3.09 | 3.53 | 2.19 | 1.57 | 1.05 | | 3.86 | 2.79 | 3.82 | 3.54 | 3.99 | 2.96 | 1.44 | 1.16 | 1.3 | 3.85 | 3.92 | 3.74 |
| SD | 1.09 | 0.89 | 1.03 | 0.91 | 0.28 | | 0.4 | 1.27 | 0.46 | 1.29 | 0.98 | 1.58 | 1.16 | 0.73 | 0.98 | 0.41 | 0.39 | 0.54 |
| Min | 1 | 1 | 1 | 1 | 1 | | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Max | 5 | 5 | 5 | 4 | 3 | | 4 | 4 | 4 | 6 | 6 | 6 | 6 | 6 | 6 | 4 | 4 | 4 |

Note: *** p<=.001, ** p<=.01, *p<=.05. Health behaviours were assessed with different measures in surveys 1-4 compared to surveys 5-10 and are not directly comparable

**Figure 1.** CLSA Health Behaviours

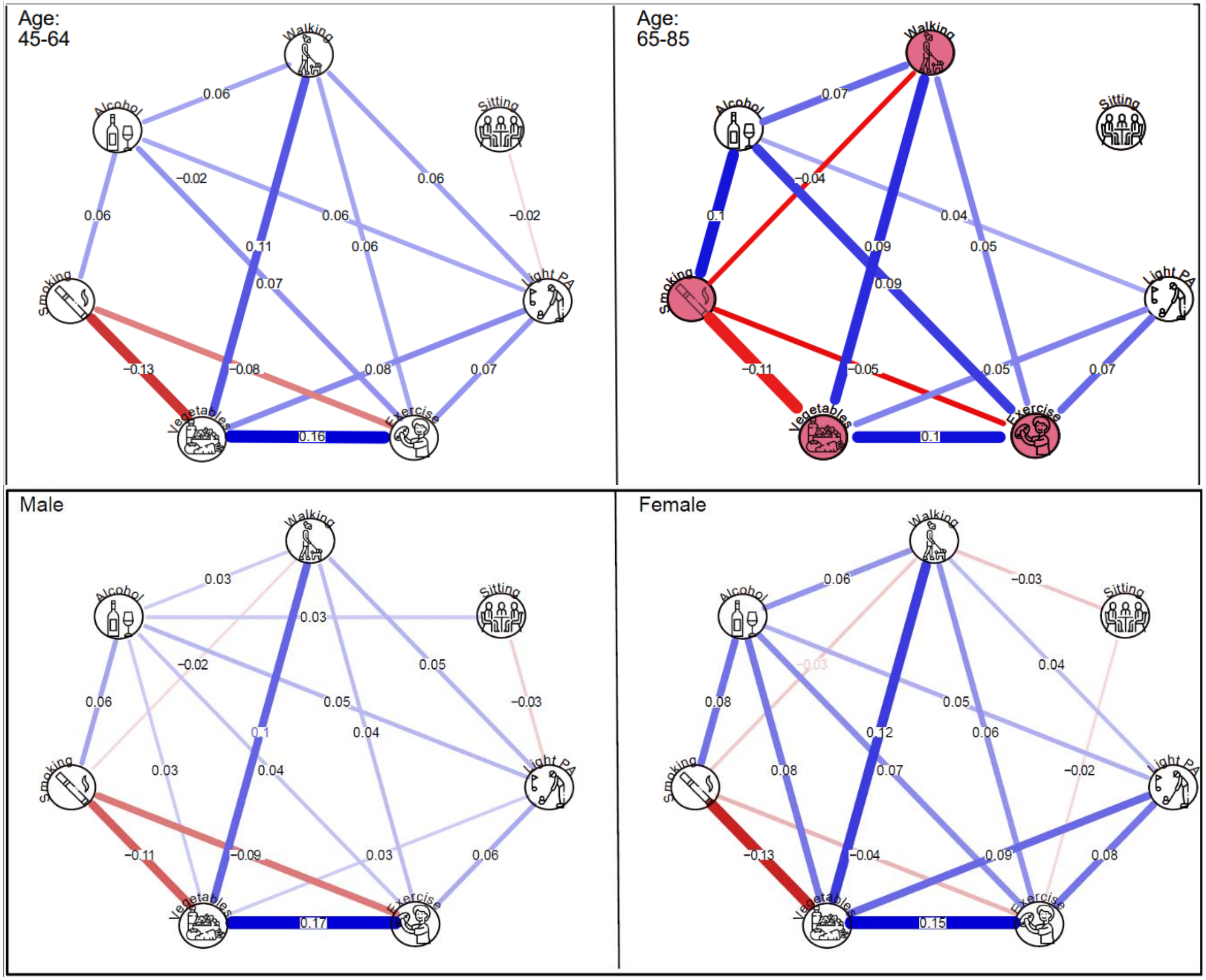
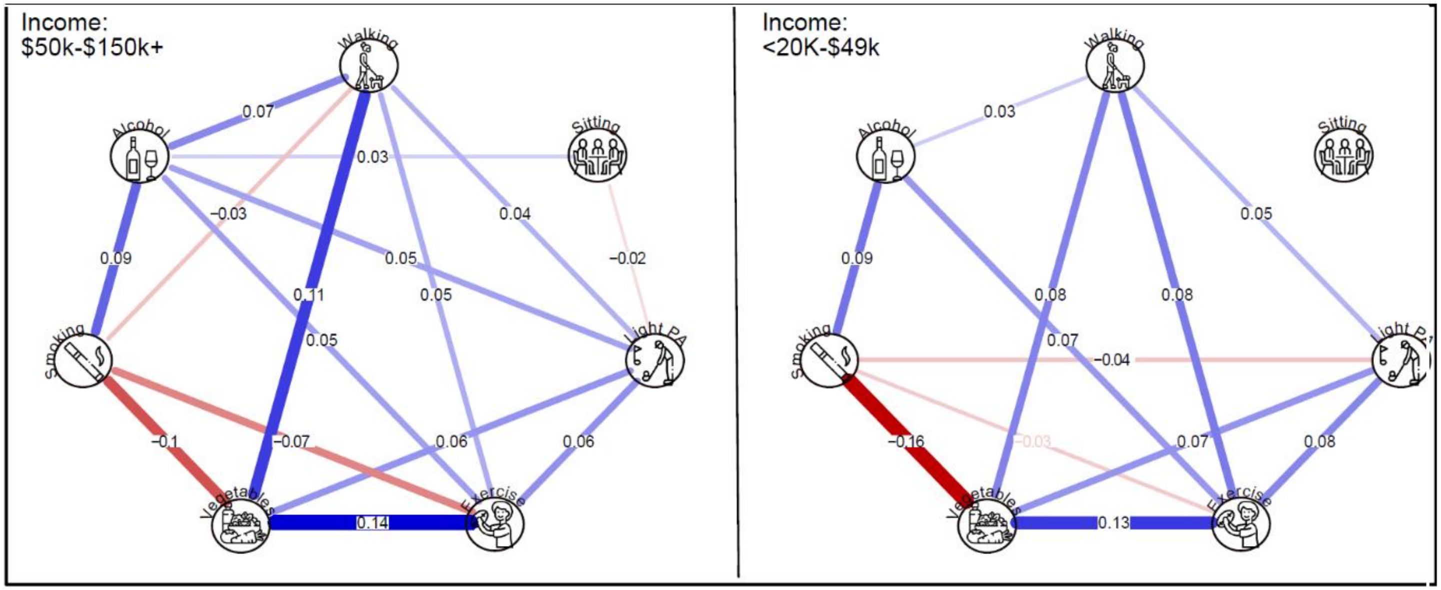


**Figure 1.** CLSA Health Behaviours (Continued)



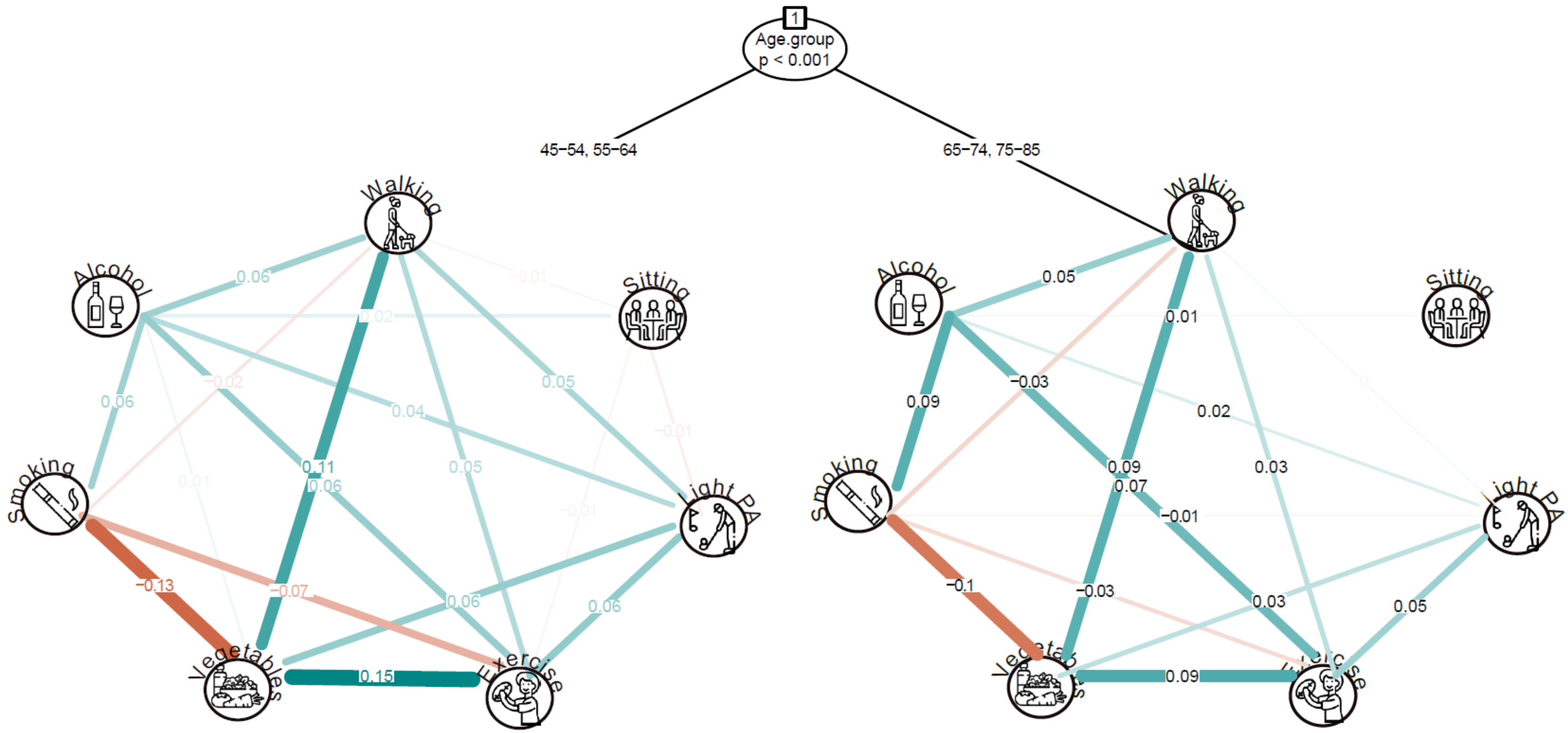

Notes: Networks are Gaussian Graphical Models (GGMs). Community detection uses clique percolation method. Colorized nodes represent cliques.

**Table 5.** CLSA Health Behaviour Network Comparison Tests

| | Walking | Sitting | Light PA | Exercise | Smoking | Alcohol | Vegetables |
|---|---|---|---|---|---|---|---|
| Walking | - | | | | | | |
| Sitting | S | - | | | | | |
| Light PA | A | | - | | | | |
| Exercise | | | | - | | | |
| Smoking | | | I | A,S,I | - | | |
| Alcohol | S | | | | A | - | |
| Vegetables | | | S | A | I | S | - |

Notes: A= age difference, S = sex difference, I = income difference; Range of edge weight differences .03-.07; Differences in edge weights assessed through network comparison tests controlling for family-wise error rate with Bonferroni corrections

**Figure 2.** Network tree partitioning CLSA health behaviours by age group.



For iCARE data, the sociodemographic variables of sex, annual income, and age groups have multiple levels. For sex, the number of participants who selected 'other' for sex ($n_{wave1-4} = 98$, $n_{wave5-10} = 26$) were not large enough to form stable network estimations and instead networks between males and females were compared. Recursive partitioning was conducted with age group and income entered as covariates in separate analysis. The age group of 85-95 did not contain sufficiently large sample size for stable network estimation and were excluded from analyses. Of the remaining age groups the largest split ($p < .001$) was identified to be between those aged 15-44 and 45-74. The dataset was then split into two groups based on these age groupings and networks were then estimated and compared. For income, a split ($p < .001$) was identified between those with an income in the bottom third and those with an income in the middle or top third.

Network comparisons tests revealed several differences in edge weights between younger (15-44) and older (45-74) participants in surveys 1-4. Differences were observed between physical activity and healthy diet ($\beta_{younger} = .47$, $\beta_{older} = .41$, $p < .001$) with the positive associations between behaviours slightly higher for younger participants than older participants. Additionally, differences were detected between healthy diet and cigarettes ($\beta_{younger} = .00$, $\beta_{older} = -.06$, $p < .001$), alcohol and cigarettes ($\beta_{younger} = .20$, $\beta_{older} = .11$, $p < .001$), alcohol and vaping ($\beta_{younger} = .04$, $\beta_{older} = .00$, $p < .001$), physical activity and indoor masks ($\beta_{younger} = -.05$, $\beta_{older} = .00$, $p = .03$), hand washing and indoor masks ($\beta_{younger} = -.07$, $\beta_{older} = .00$, $p < .001$), and indoor masks and social distancing ($\beta_{younger} = .00$, $\beta_{older} = -.04$, $p < .001$). Community detection analysis identified two overlapping cliques in older participants but no communities in the younger sample. In the older sample five possible combinations of k=3 were identified with intensities ranging from .05-.07 and each identifying two communities. The combination with the highest intensity was selected (i=.07) which identified social distancing, hand washing, and healthy diet formed one community while physical activity, healthy eating, alcohol consumption, and cigarettes formed a second community.

A similar pattern emerged when comparing age-based networks in surveys 5-10 with statistically significant differences observed between alcohol and cigarettes ($\beta_{younger}$ = .13, $\beta_{older}$ = .00, p <.001), cigarettes and vaping ($\beta_{younger}$ = .32, $\beta_{older}$ = .20, p <.001), alcohol and drugs ($\beta_{younger}$ = .17, $\beta_{older}$ = .11, p = .04), cigarettes and drugs ($\beta_{younger}$ = .26, $\beta_{older}$ = .11, p <.001), and indoor masks and hand washing ($\beta_{younger}$ = .13, $\beta_{older}$ = .00, p <.001). Community detection analysis identified two non-overlapping communities in the networks of both older and younger participants. For older participants, thirty combinations of k=3 with two communities and intensity ranges from .01-.155 had entropy valued exceeding the 95% confidence interval. As all options were identical except for intensity, the combination with the highest intensity was selected which identified one clique containing cigarettes, vaping, and drug use, and a second clique containing physical activity, healthy eating, and alcohol consumption. For younger participants, ten possible combinations of k=3 with two communities (i range =.14-.185) and 26 combinations of k=3 with three communities (i range = .01-.125) had entropy values which exceeded the upper bounds of the 95% confidence interval for k=3. The combination with the highest intensity identified one clique comprised of hand washing, indoor mask use, and social distancing while a second clique contained cigarette consumption, vaping, and recreational drug use.

Comparisons of sex differences revealed four differences in edge weights for surveys 1-4 and one difference for surveys 5-10. For surveys 1-4 differences were evident between healthy diet and hand washing ($\beta_{male}$ = .09, $\beta_{female}$ = .05, p = .03), cigarettes and indoor masks ($\beta_{male}$ = .04, $\beta_{female}$ = .00, p <.001), hand washing and indoor masks ($\beta_{male}$ = .00, $\beta_{female}$ = -.06, p <.001), and alcohol and social distancing ($\beta_{male}$ = .05, $\beta_{female}$ = .00, p <.001). Conversely, for surveys 5-10 only the relationship between indoor mask use and social distancing differed by sex ($\beta_{male}$ = .36, $\beta_{female}$ = .16, p <.001). While no communities were detected for either sex in surveys 1-4, two non-equivalent and non-overlapping communities were detected for males and females in surveys 5-10. For males, 43 combinations of k=3 with intensities ranging from .01-.22 were identified with the highest intensity combination revealing one community containing hand washing, social distancing, and indoor mask use and a second community containing cigarettes, vaping, and drug use. For females, 13 combinations of k=3 with intensity ranging from .10-.16 had entropy scores exceed the upper bound of the 95% confidence interval. The combination with the highest intensity identified one community with cigarettes, vaping, and drug use, and a second community containing physical activity, healthy eating, and alcohol consumption.

A network comparison test between networks comprised of lower income (those in 'bottom third') and higher income ('middle' and 'top third') revealed no statistically significant differences between edges while controlling for multiple comparisons. A single community for those with higher income included drugs, vaping, cigarettes, and alcohol. Two cliques were identified for those with lower incomes with one clique containing drugs, vaping, and cigarettes and a second community containing physical activity, healthy eating, and alcohol consumption.

**Figure 3.** iCARE Surveys 1-4 Health and Pandemic Behaviours

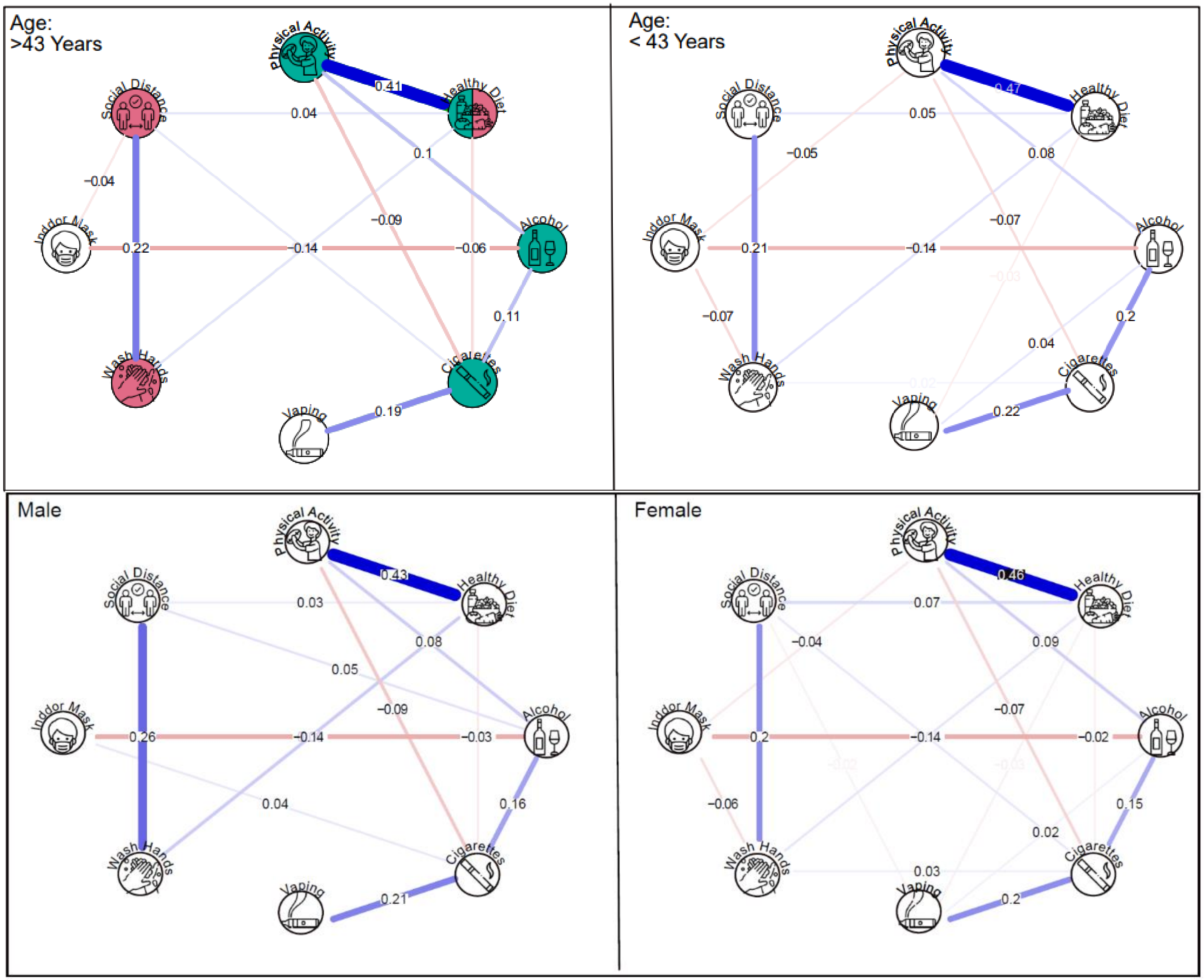
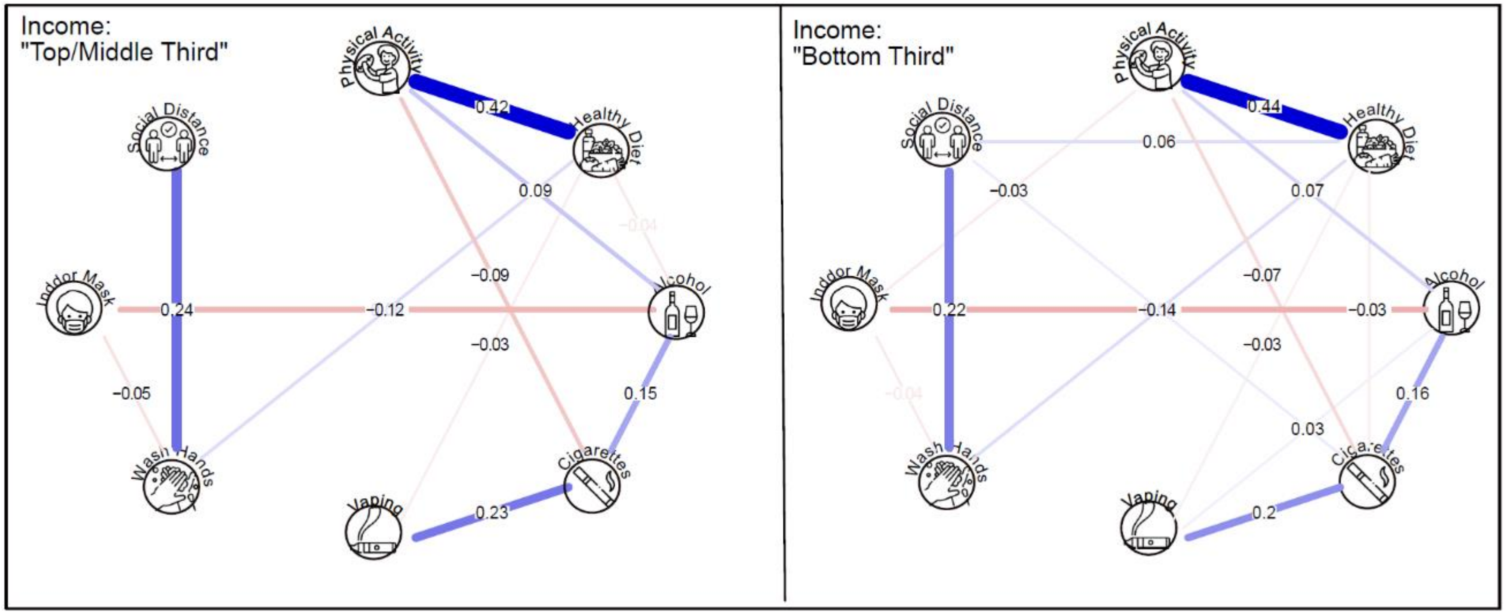


**Figure 3.** iCARE Surveys 1-4 Health and Pandemic Behaviours (Continued)




Notes: Networks are Gaussian Graphical Models (GGMs). Community detection uses clique percolation method.

**Table 6.** iCARE Surveys 1-4 Health Behaviour Network Comparison Tests

| | Physical Activity | Healthy Diet | Alcohol | Cigarettes | Vaping | Wash Hands | Indoor Mask | Social Distance |
|---|---|---|---|---|---|---|---|---|
| Physical Activity | - | | | | | | | |
| Healthy Diet | A | - | | | | | | |
| Alcohol | | | - | | | | | |
| Cigarettes | A | | A | - | | | | |
| Vaping | | | A | | - | | | |
| Wash Hands | | S | | | | - | | |
| Indoor Mask | A | | | S | | A,S | - | |
| Social Distance | | | S | | | | A | - |

Notes: A= age difference, S = sex difference, I = income difference; Range of edge weight differences .04-.09; Differences in edge weights assessed through network comparison tests controlling for family-wise error rate with Bonferroni corrections.

**Figure 4.** iCARE Surveys 5-10 Health and Pandemic Behaviours

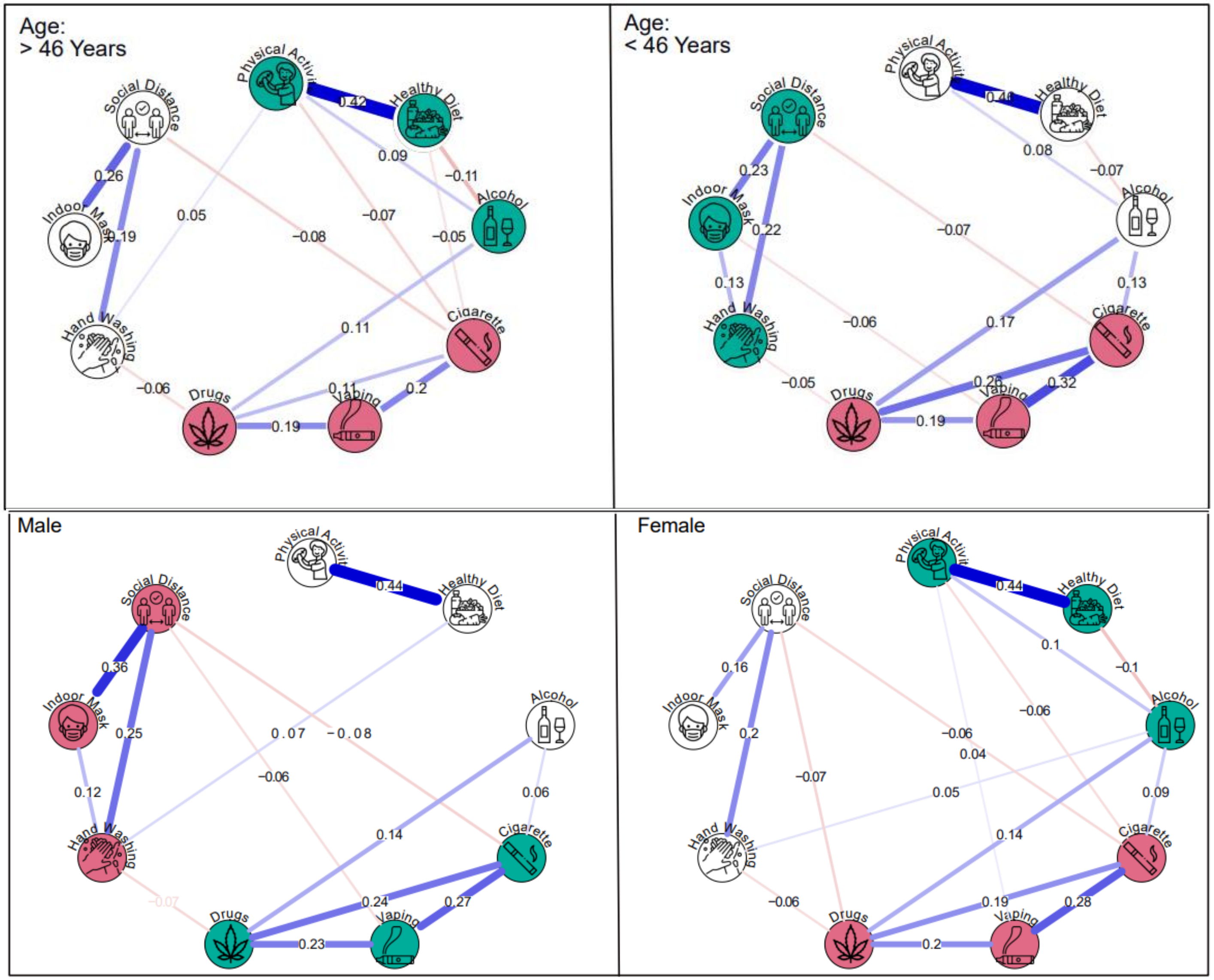
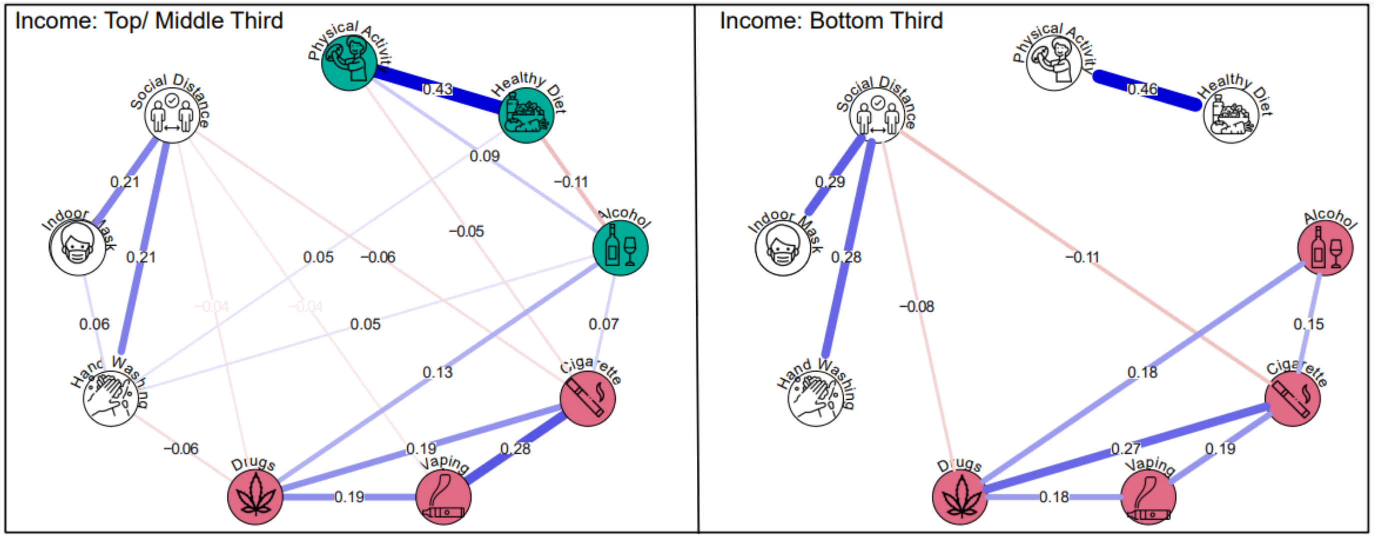


**Figure 4.** iCARE Surveys 5-10 Health and Pandemic Behaviours (Continued)



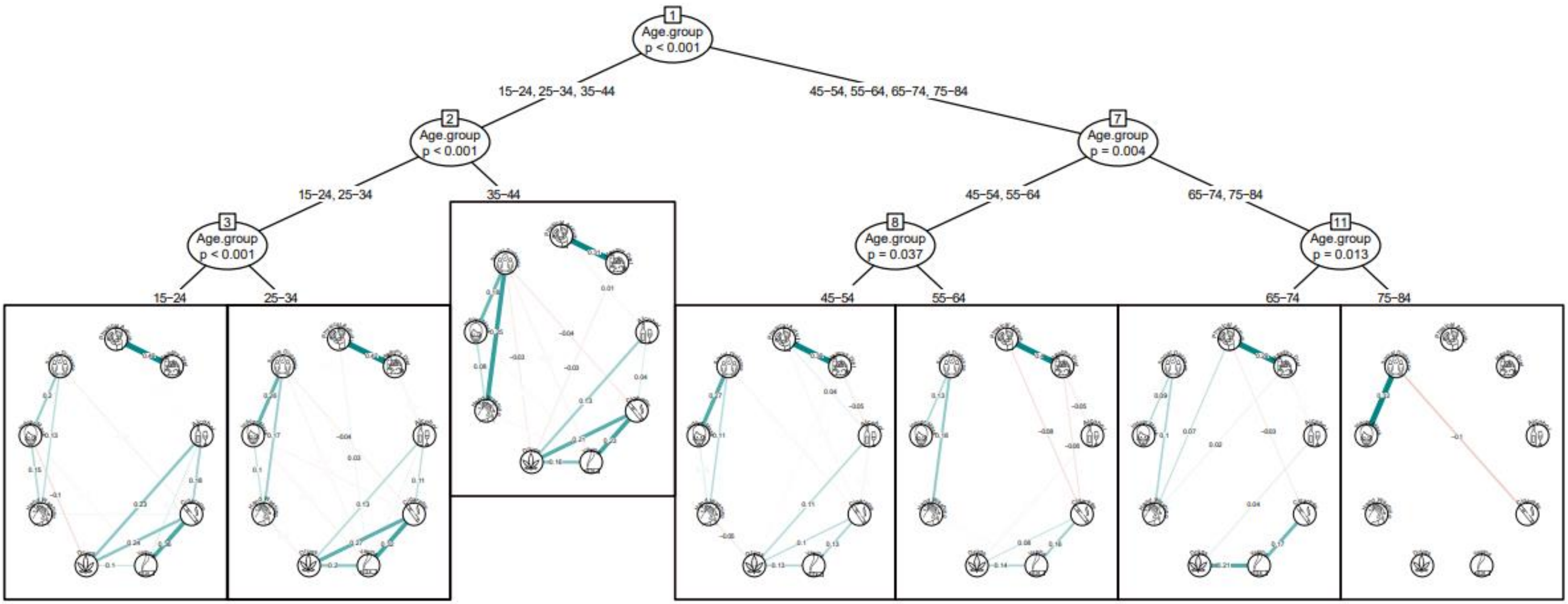

Notes: Networks are Gaussian Graphical Models (GGMs). Community detection uses clique percolation method.

**Table 7**. iCARE Surveys 5-10 Health Behaviour Network Comparison Tests

| | Physical Activity | Healthy Diet | Alcohol | Cigarettes | Vaping | Drugs | Wash Hands | Indoor Mask | Social Distance |
|---|---|---|---|---|---|---|---|---|---|
| Physical Activity | - | | | | | | | | |
| Healthy Diet | | - | | | | | | | |
| Alcohol | | | - | | | | | | |
| Cigarettes | | | A | - | | | | | |
| Vaping | | | | A | - | | | | |
| Drugs | | | A | A | | - | | | |
| Wash Hands | | | | | | | - | | |
| Indoor Mask | | | | | | | A | - | |
| Social Distance | | | | | | | | S | - |

Notes: A= age difference, S = sex difference, I = income difference; Range of edge weight differences .07-.20; Differences in edge weights assessed through network comparison tests controlling for family-wise error rate with Bonferroni corrections

**Figure 5.** Network tree partitioned by age groups.



## 4.4 Discussion

This chapter aimed to model the multivariate relationships between reported health behaviours with network analysis, characterize patterns of sociodemographic variability with recursive network partitioning and comparisons tests, and to identify any clusters or communities between health behaviours through community detection. Analysis of national (CLSA) and international (iCARE) datasets revealed known associations between some behaviours (e.g., physical activity and healthy eating; e.g., Woolcott, Dishman, Motl, MatthI, & Nigg, 2013), while identifying other mostly small relationships between health behaviours. Sociodemographic heterogeneity was evident in terms of statistically significant across age groups, sex, and income levels; however, effect sizes were small. Finally, communities of health behaviours were identified via community detection but the associations connecting communities were often small.

The tendency for higher levels of physical activity to be associated with healthy eating is well known (e.g., Arı & Çakır, 2021; Johnson et al., 1998). In the CLSA we observed sex differences in the strength of the positive association between fruit/vegetable consumption and light physical activity, with this association stronger in females than males while the positive linear relationship between strenuous exercise and fruit/vegetable consumption was stronger in those aged 45-64 compared to those aged 65-85. Although multivariate health behaviour associations have rarely been compared by sex, studies have shown that on average women eat more fruits and vegetables than men (Kvaavik, Meyer, & Tverdal, 2004; Prättälä, Paalanen, Grinberga, Helasoja, Kasmel, & Petkeviciene, 2007; Baker & Wardole, 2003), women engage in less light physical activity than men (Lee, 2005), and both strenuous exercise and fruit and vegetable consumption decrease with age (Tsunoda et al., 2013). The benefit of the network approach over traditional approaches is that the interdependence between these health behaviours are modelled to account for the influence of other health behaviours.

A similar pattern was observed in the first four surveys of the iCARE study where healthy diet was more strongly associated with physical activity in younger (15-44) people compared to their older counterparts (45-74), however, no effects of age were observed in the final six surveys of data collection. Regarding sex differences, the stronger association between diet and physical activity for women is consistent with evidence that men generally engage in more risky health behaviours (Courtenay, McCreary, & Merighi, 2002). Unfortunately, however, associations between diet and physical activity are infrequently presented by sociodemographic sub-group, making comparisons to other findings difficult.

Regarding the interconnectivity of COVID-19 specific health behaviours in the iCARE study, a positive association between hand washing and social distancing was observed across surveys 1-4 ($\rho$ =.39) and surveys 5-10 ($\rho$ =.27). Although several studies have investigated hand washing and social distancing as outcome behaviours or as predictors of a Covid-19 diagnosis (Duan et al., 2022; Luszczynska et al., 2022; Lima-Costa et al., 2020) there is little, if any, analysis of the bivariate or multivariate associations between these behaviours. Interestingly, the association between social distancing and indoor mask use was negligible ($\rho$ =.01) during survey surveys 1-4 (March – Sept 2020) but became much stronger ($\rho$ =.40) during surveys 5-10 (Sept 2020 – June 2021). This is consistent with changing behavioural norms across the duration of the pandemic response in Canada where mask use increased during this time period (Binka et al, 2023). Additionally, hand washing was negatively related to indoor mask use during surveys 1-4 ($\rho$ =-.08) and this effect was stronger in younger participants aged 15-44 than older participants ages 45-74. In contrast, hand washing and mask use were positively associated during surveys 5-10 ($\rho$ =.18) and this effect was stronger in males than in females.

Finally, the majority of differences across sociodemographic factors in the iCARE study were attributable to age which accounted for 7/11 (65%) of statistically significant differences in surveys 1-4 and 5/6 (83%) differences in surveys 5-10. As illustrated in Figure 5, the connectivity between health behaviours tends to diminish as the age of the group increases with connectivity higher for those 15-24 and sparse for those 75-84. Interestingly, the apparent decreases in network connectivity over age are consistent with the ‘connectivity hypothesis’ (Cramer et al., 2016). According to the connectivity hypothesis, highly connected networks are more susceptible to phase transitions (e.g., from a ‘healthy’ to ‘unhealthy’ state) as strong connections between nodes enables spreading activation. In the mental health literature, in which networks are typically comprised of associations between symptoms, the hypothesis is that highly connected networks are more likely susceptible to the risk of transitioning to an unhealthy mental state (Cramer et al., 2016). A recent systematic review of the network approach within the psychopathology literature found ‘qualified support’ for the connectivity hypothesis in studies using both cross-sectional and time-series data (Robinaugh et al., 2020). Although the connectivity hypothesis has yet to be applied to behaviour change, the connectivity hypothesis aligns with the observed trend of decreased connectivity of health behaviours across age groups. This hypothesis warrants further consideration in future research.

#### 4.4.1 Comparing Findings Across Datasets

Partial polychoric correlations between seven of health behaviours measures assessed in the CLSA were small (range = -.13, .14; M = .06) and a similar pattern was observed with iCARE data (range = -.08, .19; M = .10) except for a larger relationship between changes in physical activity and healthy diet since the beginning of the covid-19 pandemic ($\rho$ = .48). An exploration of sociodemographic heterogeneity between networks of CLSA health behaviours revealed statistically significant associations across age groups but not sex or income. A similar pattern was observed for health behaviour variables in the iCARE convenience sample.

Differences in edge weights between groups distinguished by age, sex, and income in the CLSA were present but small (range = .03-.07). Edge weight differences in the iCARE study were in a similar range with the largest observed difference reflecting a stronger association between indoor mask use and social distancing in males ($\beta$ = .36) compared to females ($\beta$ = .16). Differences in network communities were present in iCARE sample but not in the CLSA. While some communities reflected potentially interesting exploratory findings, other differences in community detections were often the result of very small differences in edge weights between groups and call into question which differences, in any, are clinically meaningful.

### 4.4.2 Sources of Variability

The sources of variability in the strength of some relationships observed between health behaviour across the CLSA and iCARE (e.g., food consumption and healthy eating) is unknown but several possible factors could provide partial explanations. One possible explanation is that the observed correlations are merely statistical noise. If one were to view the patterns of correlations between health behaviours only in the CLSA sample, with an average correlation of $\rho$ = .07, one might reasonably ask if interconnectivity between behaviours amounts to nothing more than the ‘crud factor’. The crud factor refers to idea that in the behavioral research everything correlates with everything else (e.g., Orben & Lakens, 2020). For example, in some fields within psychology a correlation less than $\rho$ = .10 is not considered hypothesis supporting as the observed relationships between theoretically relevant and irrelevant constructs can reach this level of effect size (Fergunson & Heene, 2021). Although I am not aware of a ‘crud-factor’ cut-off in the field of healthy psychology, it seems unlikely that the correlations observed in the CLSA sample are clinically meaningful.  However, it is possible that this threshold of evidence may be suitable for more mature literatures (c.f., multiple health behaviour science) and investigating smaller effects may lead to exploratory hypothesis development in the future.

Where items are comparable (physical activity, healthy eating/fruit and vegetable consumption, smoking, alcohol use), iCARE correlations were similar in size to CLSA (range $\rho$ = -.11, .11) except for the relationship between physical activity and healthy diet ($\rho$ = .48). Possible reasons for this discrepancy include the framing of the question (iCARE asked for change in behaviour since pandemic, CLSA items ask for weekly frequencies), variation in response options ranging from four to seven item scales, and diverging characteristics of the samples (the CLSA used representative sampling[5] of Canadians while the iCARE study relied on an international convenience sample). It is also possible that age differences between samples contributed to variability in the relationship between health behaviours.

### 4.4.3 Strengths and Limitations

This chapter extended the network analysis with CLSA presented in Chapter 2 by exploring sociodemographic variability in the interconnectedness of health behaviours with techniques from network psychometrics. Additionally, analyses were also performed on an international sample which contained measures of health behaviours specific to the COVID-19 pandemic. The large sample sizes of the CLSA and iCARE studies provide confidence in the stability of the observed effects while results from the CLSA in particular allows for generalizations to the Canadian population. However, several limitations should be noted including the exploratory nature of the analysis, researcher degrees of freedom, and issues with the data and data models.

Exploratory phenomena detection is critical within the basic-to-applied science pipeline. The ability to describe, model, and predict behaviour is essential for informing the creation of

[5] Sampling weights are available for the CLSA dataset but methods for incorporating weights into network analysis have not yet been published.

(multiple) health behaviour interventions. Nonetheless, exploratory phenomena detection such as the analysis performed here is subject to many researcher degrees of freedom (e.g., treating data as ordinal or continuous, model selection, frequentist or Bayesian approaches, selecting the levels of intensity and number of cliques in CPA, and selecting the variable set for testing heterogeneity). One approach for addressing these myriad decisions is to conduct a multiverse analysis in which analysis is conducted to include all possible analytical decisions. However, given the small partial correlations between health behaviour the likelihood of a full multiverse analysis revealing clinically meaningful results seems low.

Finally, although recent simulation studies have found that graphical gaussian network models perform surprisingly well with skewed ordinal data (Epskamp & Isvoranu, 2022), it is possible that the limited response options in the CLSA and iCARE study could have created ceiling and floor effects. For example, the mean score for engaging in sitting activities in the CLSA sample was 3.9/4 while in the iCARE sample the mean response for social distancing and hand washing were 3.86/4 and 3.82/4, respectively.

#### 4.4.4. Conclusions

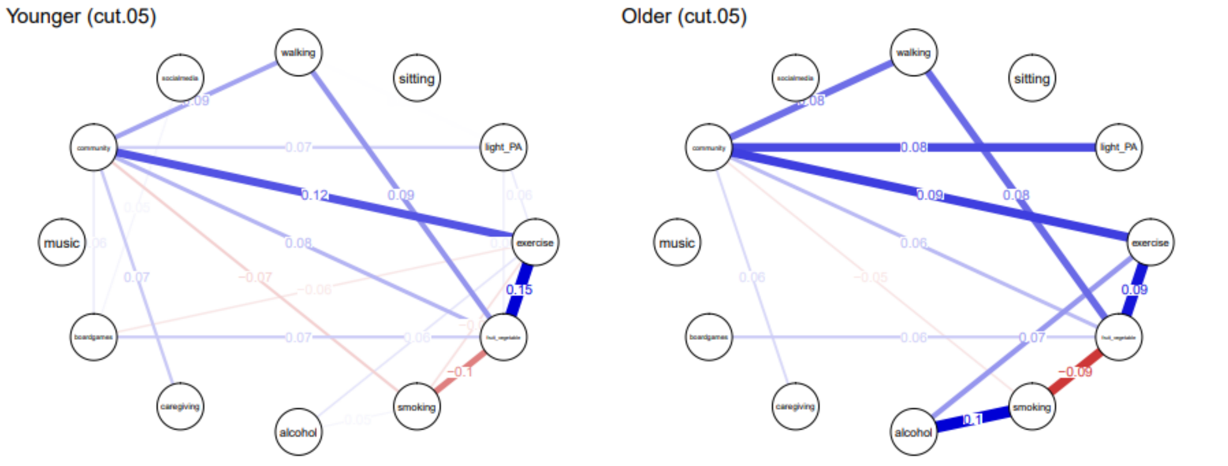
This chapter sought to identify patterns of co-variation between health behaviours in two large sample through techniques derived from the network psychometrics literature. Although limited by the cross-sectional nature of the data, network analysis were well-suited to the task of modelling the interconnectedness between health behaviours while recursive partitioning and network comparison tests provided simple and flexible tools for identifying sociodemographic variability. Unfortunately, the network community detection algorithm was less insightful than expected—in the present context with a low number of behaviours, and weak associations in the CLSA, a simple visual inspection would have yielded identical insights with less effort. Yet, network psychometrics proved a useful tool for assessing the interconnectedness of multiple health behaviours and their sociodemographic variability.

## **4.6 Appendix I:** Health and Non-Health Behaviour Correlations and Networks

**Table 8**. Partial polychoric correlations between health and non-health behaviours in CLSA data

| | Health and Non-Health Behaviours | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Walking | - | | | | | | | | | | | |
| 2. Sitting | -0.02 | - | | | | | | | | | | |
| 3. Light Physical Activity | 0.04 | -0.03 | - | | | | | | | | | |
| 4. Exercise | 0.05 | -0.03 | 0.05 | - | | | | | | | | |
| 5. Fruit & Vegetable | 0.11 | -0.01 | 0.05 | 0.14 | - | | | | | | | |
| 6. Smoking | -0.02 | -0.01 | 0 | -0.05 | -0.11 | - | | | | | | |
| 7. Alcohol | 0.07 | 0.06 | 0.05 | 0.07 | 0.01 | 0.13 | - | | | | | |
| 8. Caregiving | -0.04 | 0.04 | -0.01 | 0.01 | -0.05 | -0.01 | 0.03 | - | | | | |
| 9. Boardgames | -0.02 | 0.09 | 0.03 | -0.07 | 0.08 | 0.05 | 0 | -0.03 | - | | | |
| 10, Music | 0.03 | 0 | 0.02 | 0.03 | 0.02 | -0.06 | 0 | -0.03 | 0.03 | - | | |
| 11. Community | 0.11 | 0 | 0.09 | 0.12 | 0.08 | -0.08 | 0.03 | -0.06 | 0.08 | 0.08 | - | |
| 12. Social Media | -0.01 | -0.02 | -0.01 | -0.02 | -0.02 | -0.06 | 0.08 | 0.04 | -0.01 | -0.05 | 0 | - |
| Mean | 3.06 | 3.9 | 1.3 | 1.61 | 4.05 | 0.85 | 4.29 | 1.54 | 3.33 | 1.53 | 3.01 | 1.45 |
| SD | 1.12 | 0.37 | 0.52 | 0.79 | 1.79 | 0.74 | 1.99 | 0.5 | 1.54 | 1.13 | 0.6 | 0.5 |
| Min | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 1 |
| Max | 4 | 4 | 4 | 4 | 7 | 3 | 7 | 2 | 5 | 5 | 4 | 2 |

**Figure 6** CLSA Health and Non-Health Behaviours.

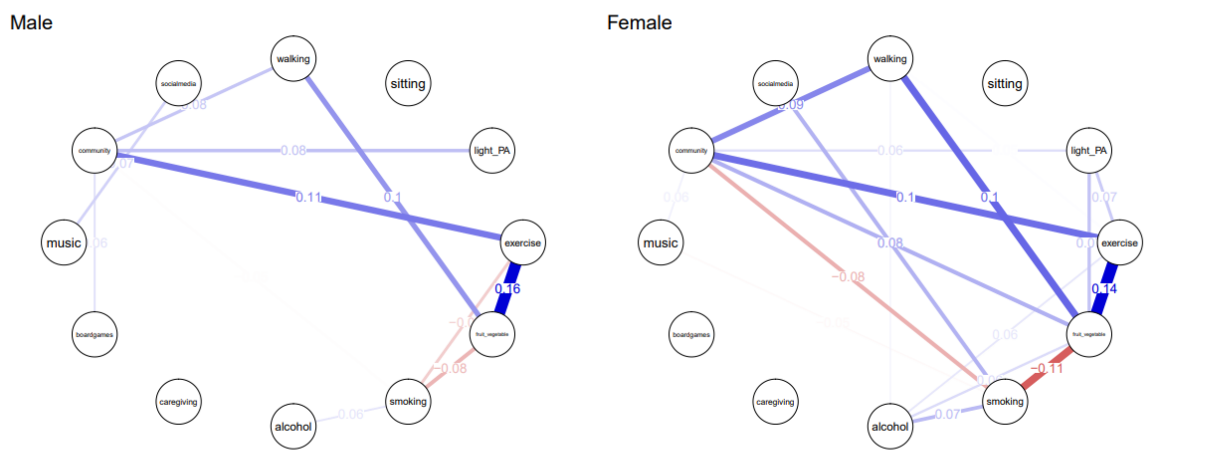



**<u>Differences in edge weight (Δ in β)</u>**

walking/light PA (.03)
exercise/fruit vegetable(.06)
smoking/alcohol (.04)

**<u>Communities:</u>**

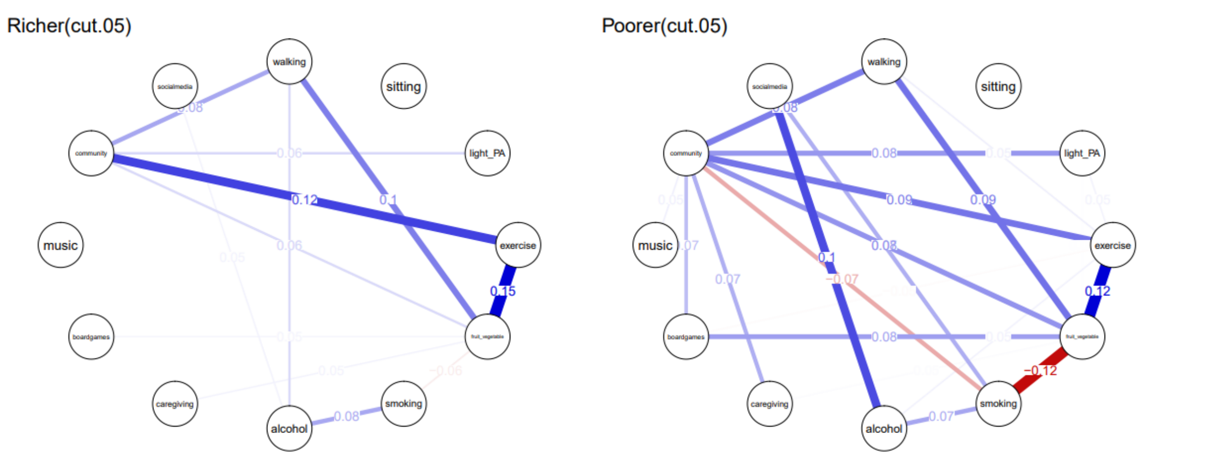
None




**<u>Differences in edge weight (Δ in β)</u>**

light PA/fruit vegetable(.05)
exercise/smoking(.04)
walking/boardgames(.03)
smoking/music(.05)
fruit veg/community(.04)
smoking/socialmedia(.08)
music/socialmedia(.07)

**Communities:**
None




**<u>Differences in edge weight (Δ in β)</u>**

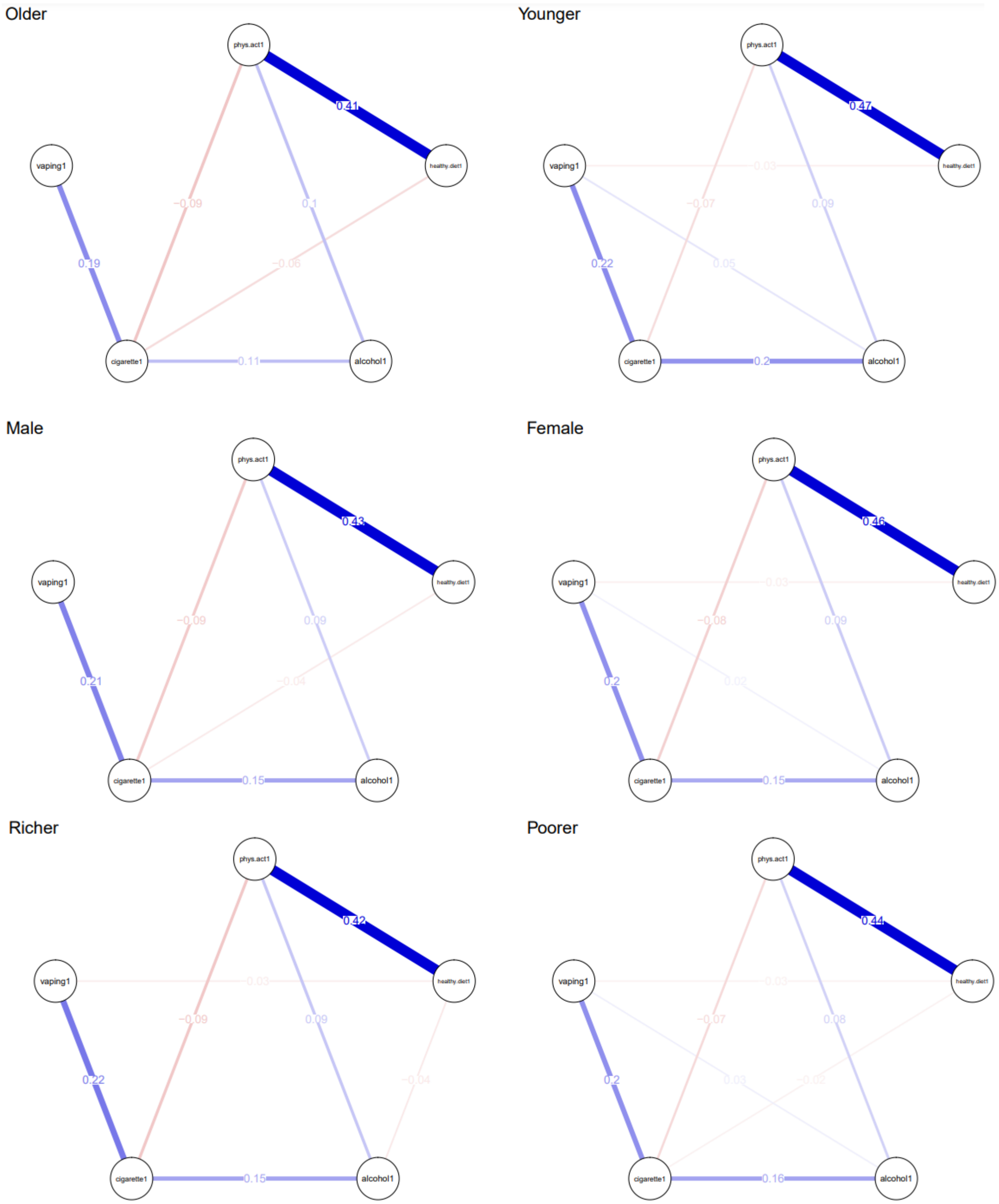
fruit veg/smoking(.06)
smoking/social media(.07)

**<u>Communities:</u>**

None

Notes: Networks are Mixed Graphical Models (MGMs). Differences in edge weights assessed through network comparison tests controlling for family-wise error rate with Bonferroni corrections. Community detection uses clique percolation method.

**Figure 7.** iCARE Surveys 1-4 Health Behaviours




**Differences in edge weight (Δ in β)**

phys act/healthy diet (.05)
healthy diet/cigarette (.06)
alcohol/cigarette (.09)
alcohol/vaping (.05)

**Communities:**

None

**Differences in edge weight (Δ in β)**

phys act/healthy diet (.03)

Communities:

one clique in male sample, not really useful

**Differences in edge weight (Δ in β)**

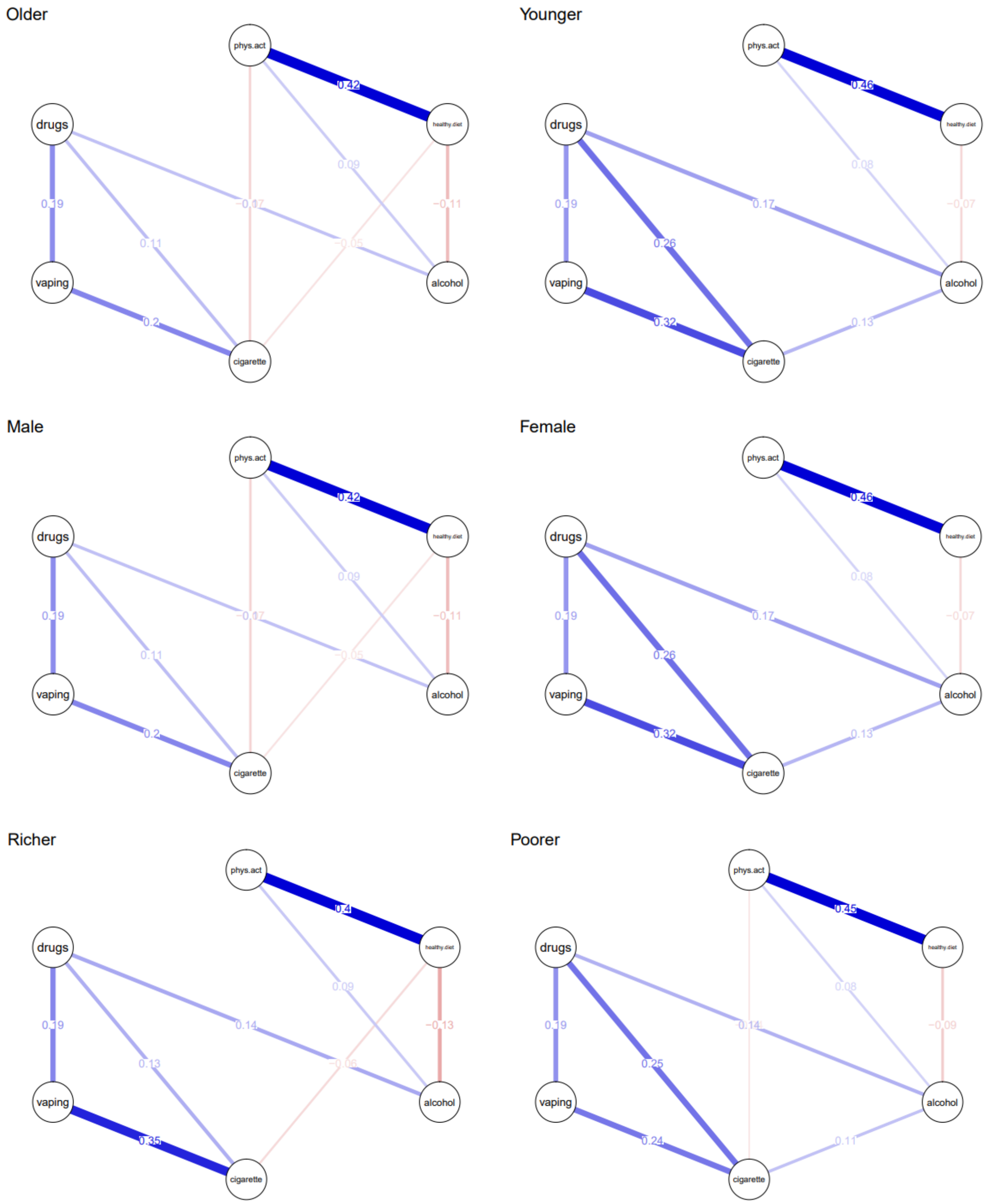
None

**Communities**:

None

Notes: Networks are Gaussian Graphical Models (GGMs). Differences in edge weights assessed through network comparison tests controlling for family-wise error rate with Bonferroni corrections. Community detection uses clique percolation method.

**Figure 8.** iCARE Surveys 5-10 Health Behaviours




**Differences in edge weight (Δ in β)**

Alcohol/cigarette (.13)
cigarette/vaping (.12)
alcohol/drugs(.07)
cigarette/drugs(.15)

**Communities:**

None

**Differences in edge weight (Δ in β)**

None

**Communities:**

One community in Male but not helpful

**Differences in edge weight (Δ in β)**

alcohol/cigarette (.11)
cigarette/drugs (.12)

**Communities:**

None

Notes: Networks are Gaussian Graphical Models (GGMs). Differences in edge weights assessed through network comparison tests controlling for family-wise error rate with Bonferroni corrections. Community detection uses clique percolation method

CHAPTER 5

# A MULTIPLE BEHAVIOUR ANALYSIS FOR HEALTH BEHAVIOURS DURING COVID-19


## Abstract

**Background:** The aim of this study is to examine the temporal dynamics of health behaviours (e.g., physical activity, alcohol consumption) and pandemic related health behaviours (e.g., hand washing, physical distancing) using network psychometrics.

**Methods:** This hypothesis generating analysis uses temporal network models to fit temporal networks, contemporaneous networks, and between-subject networks from items within the International COVID-19 Awareness and Responses Evaluation (iCARE) survey. The iCARE study is an international multi-wave cross-sectional observational cohort study of public awareness, attitudes, and responses to public health policies implemented to reduce the spread of COVID-19 on people around the world.

**Results:** Temporal network models fit the data poorly due to violations of statistical assumptions and results should be interpreted with caution. Descriptive statistics revealed that over six months, adherence to mask wearing, social distancing, hand washing, physical activity, and alcohol consumption remained generally stable. People reported a decrease in healthy diet before this behaviour returned to pre-pandemic levels. Between February and May 2020 respondents to the iCARE survey also reported smoking cigarettes, using recreational drugs, and vaping ‘a lot more’ since the start of the pandemic; however, this pattern reversed abruptly from May to July 2020 with most participants reporting they engage in these behaviours ‘a lot less’ than before the pandemic or ‘not at all’.

**Conclusions:** The analysis presented in this chapter sought to model the temporal dynamics of health behaviours and pandemic specific behaviours across a period of six months during the onset of the COVID-19 pandemic. Abrupt mean level changes in several health behaviours (smoking, recreational drug use, and vaping) lead to violation of statistical assumptions and a poor fit between model and data. However, the application of temporal network analysis to the study of multiple health behaviours is well suited to address key research questions in the field such as ‘how do multiple health behaviours co-vary with one another over time’. Future research employing intensive time series data and measuring affective and cognitive mediators of behaviour, in addition to health behaviours, has the potential to contribute valuable hypothesis generating insights to the basic science of multiple health behaviour research.

## 5.1 Introduction

Behaviours such as alcohol consumption, healthy eating, and physical activity are among the most commonly studied health behaviours due to their relationship with preventable chronic diseases (e.g., Fisher et al., 2011; Reeves & Rafferty, 2005; Colley et al., 2018; Brassard et al., 2018; Zhao et al., 2015). However, the COVID-19 pandemic has led to the uptake of several of new health behaviours being adopted to protect against transmission and infection such as physical distancing, mask wearing, and hand washing. Human behaviour is influenced by complex biopsychosocial processes which, for many, have been impacted by the global pandemic. Understanding how newly adopted behaviours such as mask wearing and social distancing influence health behaviours is important for supporting behaviour change in situ. Longitudinal data collected over the duration of the COVID-19 pandemic provides an opportunity to model the interrelationships between health behaviours and identify potential behavioural patterns (e.g., bi-directional feedback loops) which can be used to generate causal hypotheses for future testing and to identify promising targets for interventions.

In Chapter 4 patterns of covariation between pandemic related behaviours and traditionally studied health behaviours were explored at the cross-sectional level. This analysis revealed negative associations between alcohol consumption and indoor mask use and positive associations between smoking cigarettes and engaging in social distancing. In addition to this analysis, several studies have demonstrated evidence of relationships between traditionally studied health behaviours and pandemic specific health behaviours using cross-sectional designs. For example, across two samples from the Netherlands (n = 520) and the United Kingdom (n = 502), Chambon et al (2022) modelled a mixed graphic network models comprised of attitudes, emotions, and behaviours related to the pandemic. Constructs included in the network were derived from theories such as the health belief model (Rosenstock, 1966), the theory of planned behaviour (Ajzen, 1991), and cognitive and affective measures which have been identified to be influential in pandemic contexts (Bish & Michie, 2010). In this analysis preventative health behaviours (e.g., social distancing, hand washing, face touching) were measured with a single item while only smoking was measured as a health behaviour. Results showed that preventative behaviours shows mutual dependence relationships with support for public health measures ($\beta$ = .21), perceptions that measures are effective ($\beta$ = .20), and the behavioral norms of family and friends ($\beta$ = .27).

Another cross-sectional study by Peixoto et al (2020) used data from data a nationally representative Brazilian sample (n = 5,827) at the beginning of the pandemic to investigate the relationships between protective pandemic behaviours (hand washing, mask wearing, and staying home) and health risk behaviours (smoking, fruit and vegetable consumption, physical activity, and alcohol consumption). Analysis using logistic models revealed several relationships between behaviours. Specifically, people who consumed low-risk levels of alcohol were more likely to wash their hands, people who were formally smokers had a higher chance of wearing a mask, and that people who engaged in frequent physical activity were less likely to wear a mask (Peixoto et al., 2020).

Much of the research on pandemic related behaviour has thus far been cross-section in nature with longitudinal studies being less common (McMillan, van Allen, & Presseau, 2022). Research has shown that temporal effects are influential in health-related behaviours during a pandemic given the demonstrable changes in behaviours and underlying cognitive and affective constructs exhibited during a pandemic (e.g., Chambon, Dalege, Elberse, & van Harreveld, 2022; Qin, Sanders, Prasetyo, Syukron & Pretice, 2021). For example, Qin et al (2021) examined the dynamic relationships between behavioural responses to COVID-19 and perceptions of risk in a three wave survey design (n = 1240) in the United States during the onset of the pandemic. This study observed dynamic interactions between perceived harmfulness, a facet of risk perception, and preventative behaviours (a composite of ten pandemic specific behaviours) over time such that risk perceptions at one time point influences behaviours at the following time point and vice versa (Qin, Sanders, Prasetyo, Syukron & Pretice, 2021).

Another study used temporal network analysis was used to model behavioural, affective, and attitudinal responses to the COVID-19 over five waves of data collection in a Dutch sample (N = 2399) during the onset of the pandemic (Chambon, Dalege, Elberse, & van Harreveld, 2022). The variables entered into the network were those identified by Bish and Michie (2010) to be involved in behavioural compliance during pandemics and included many constructs contained within protection motivation theory (Rogers, 1975), the theory of planned behaviour (Ajzen, 1991) and the health belief model (Rosenstock, 1974). Behavioural measures included ‘healthy lifestyle’ (increases or decreases in healthy activity, eating, sleeping prior to the pandemic) and compliance with public health measures such as social distancing and hand washing. Analysis revealed that over time, healthy lifestyle predicted increases in ‘healthy physical changes’ while compliance with public health measures demonstrates several bidirectional effects and feedback loops to create positive reinforcement structures between support for health measures, involvement in the pandemic, vaccination intention, and behavioural compliance (Chambon, Dalege, Elberse, & van Harreveld, 2022).

The ability to identify feedback loops which can create reinforcing patterns over time is an important feature of temporal network analysis. These bidirectional relationships can form the basis of causal hypothesis testing with the use of interventions. While Chambon et al (2022) focused on a broad range of factors hypothesized to impact behavioural compliance, the present study aims to identify any temporal relationships between pandemic specific behaviours (e.g., mask wearing, social distancing) and traditionally studies health behaviours (e.g., alcohol consumption, smoking).

### 5.1.1 Temporal network analysis

Gaussian Graphical Models (GGMs) are the simplest form of network model which performs node-wise regression with regularization on a selection of variables to reduce the likelihood of spurious associations (Borsboom et al., 2021). Although GGMs are most commonly applied to cross-sectional data, recent methodological advances have enabled network estimated for panel and intensive time series data (Epskamp, 2020). These networks apply multilevel vector autoregressive modelling approaches to repeated measures data and allow for within and between person modelling (Jordan, Winer, & Salem, 2020). Importantly, within person effects can be further differentiated to compute temporal networks and contemporaneous networks. Temporal networks use vector autoregression to compute a directed network by modelling the lagged associations between a given variable over time to provide insights into 'Granger causality' wherein a variable at a given time point is predictive other variables in later time points (Jordan, Winer, & Salem, 2020; Granger 1969). The ability to model autocorrelations is another feature of network analysis (c.f., ordinary least squares regression). In temporal network analysis an autocorrelation reflects how strongly a given node is related to previous measures of the same node (Jordan et al., 2020).

A contemporaneous network models within-person regression residuals from estimating temporal effects and contain within-person associations that are not explained by temporal relationships (i.e., autoregressive or cross-lagged effects). Because contemporaneous effects contain the within-person effects that are not explained by temporal effects, they are often thought to provide information on associations which occur outside of the measurement window (i.e., when the repeated measurements are assessed). Finally, a between person network is also estimated in which the participant data is aggregated across time points and models as Pairwise Markov Random Field (PMRF; Epskamp, 2020).

### 5.1.2 Study Aims

Using longitudinal data from the iCARE study (Bacon et al., 2021) the aims of this project are to: 1) model the within-person temporal associations between health and pandemic-specific behaviours; and 2) identify contemporaneous within-person associations between health and pandemic-specific behaviours.

## 5.2 Methods

### 5.2.1 The iCARE Study

The International COVID-19 Awareness and Responses Evaluation (iCARE) Study is an international multi-wave cross-sectional observational cohort study of public awareness, attitudes, and responses to public health policies implemented to reduce the spread of COVID-19 on people around the world (www.mbmc-cmcm.ca/covid19). Survey data began in March 2020 using convenience snowball sampling (globally) and parallel representative sampling in targeted countries. Survey data can be linked at the country/province-level with Oxford Government Policy Tracker data, Google Mobility data, and Johns Hopkins case/death/recovery data.

The study is led by the Montreal Behavioural Medicine Centre (MBMC: www.mbmc-cmcm.ca) in collaboration with a team of 200 international collaborators from 42 countries. It has received REB approval from the Comité d’éthique de recherche du CIUSSS-NIM (Centre intégré universitaire de santé et de services sociaux du Nord-de-l’île-de-Montréal), approval # : 2020-

2099 / 25-03-2020. Recruitment began on March 27th, 2020 and the survey is available in 34 languages.[6]

A subset of participants who were recruited as part of a convenience sample volunteered to complete multiple successive surveys to support longitudinal data collection. Recruitment for longitudinal data began with the seventh wave of iCARE data collection (December 2020-January 2021) and all participants were a convenience sample of Canadians. Participants involved in longitudinal data collection complete the same surveys as administered to all iCARE participants but were provided with a unique identifier to link their survey responses. Participants were able to opt into the longitudinal data collection after completing any of the cross-sectional iCARE surveys.

Analysis conducted by the iCARE team suggests that relative to the representative sample, and the 2016 census results, the iCARE convenience sample is not representative on a number of dimensions and those who participated were more likely than the general population to adhere to pandemic related health preventative health measures (Joyal-Desmarais et al., 2021). Mirroring this work, a comparison between the demographic characteristics of the longitudinal sample used in the present analysis and the 2016 census results are presented in Table 1.

### 5.2.2 Sociodemographic Indicators

Data assessing several sociodemographic indicators were collected from the longitudinal iCARE survey. Variables included in analysis included age (grouped by 10-year age brackets), sex (male/female/other), education (college or university degree, graduate/postgraduate degree,

[6] The preceding two paragraphs were written by the iCARE team; inclusion of this text is required for authors publishing studies with iCARE data.

secondary/high school), geographical location (Canadian provinces and territories), and estimated household income relative to Canadian context (bottom third, middle third, top third).

### 5.2.3 Health Behaviours

Across waves 7-11, all health behaviours were assessed with a common question stem and set of response options. Specifically, participants were asked “In general, how have the following behaviours changed since the start of COVID-19?” and responded on a 1 (I do think a lot more) to 6 (I don’t do this) scale which was reverse coded in analysis such that higher responses indicate greater frequencies. Each of the five health behaviours assessed in waves 1-4 were also assessed during waves 5-10 (i.e., *physical activity, healthy diet, alcohol consumption, cigarette consumption, vaping consumption*). In addition, during waves 5-10 participants also reported the frequencies of their recreational drug use (marijuana, cocaine, opioids, hallucinogens, etc.). Several pandemic specific questions were also selected from the iCARE survey. Across waves 7-11 participants were asked to “indicate the frequency with which you have adopted each action/behaviour in response to the COVID-19 pandemic” on a 1 (most of the time) to 4 (never) scale with an option to identify that a given behaviour was not applicable to one’s situation. The behavioural items included in analysis were: *hand washing with soap and water, wearing a face mask outdoors,* and *staying at least 1-2 metres / 3-6 feet away from other people.* An item assessing weather participants *wear a face mask in indoor spaces (shops, restaurants, public transit, at work)* was excluded from analysis as there was no variability in the responses. All items were reverse coded for analysis so that higher scores indicate a greater behavioural frequency.

### 5.2.4 Analysis

The analysis presented here relies on the *psychonetrics* R package (Epskamp, 2021) which allows for temporal network estimation from panel data involving three or more measurement waves. A lag-1 dynamic latent variable model for panel data (dlvml) was fitted to data from the iCARE longitudinal sample. The ‘model search’ algorithm (Isvoranu & Epskamp, 2021) was used in analysis to compare a full model, a pruned model, and a pruned stepup model in four steps. First, a ‘full or saturated’ model was fitted to the data in which all edges were included for temporal, contemporaneous, and between-subjects networks. Second, a stepwise ‘pruned’ model search was performed to identify a model with the optimal BIC. Third, in the ‘step up model’ edges are re-added into the model with iterations of until at $\alpha$=0.05 until the BIC can no longer be improved. Forth and finally, these three models can then be compared based on model fit statistics with the best fitting model being selected for interpretation. Assumptions for temporal network models include stationarity (mean and variance are consistent across time points) and equidistant measurement points (measurement taken at equally distant time points; Jordan et al., 2020).

## 5.3 Results

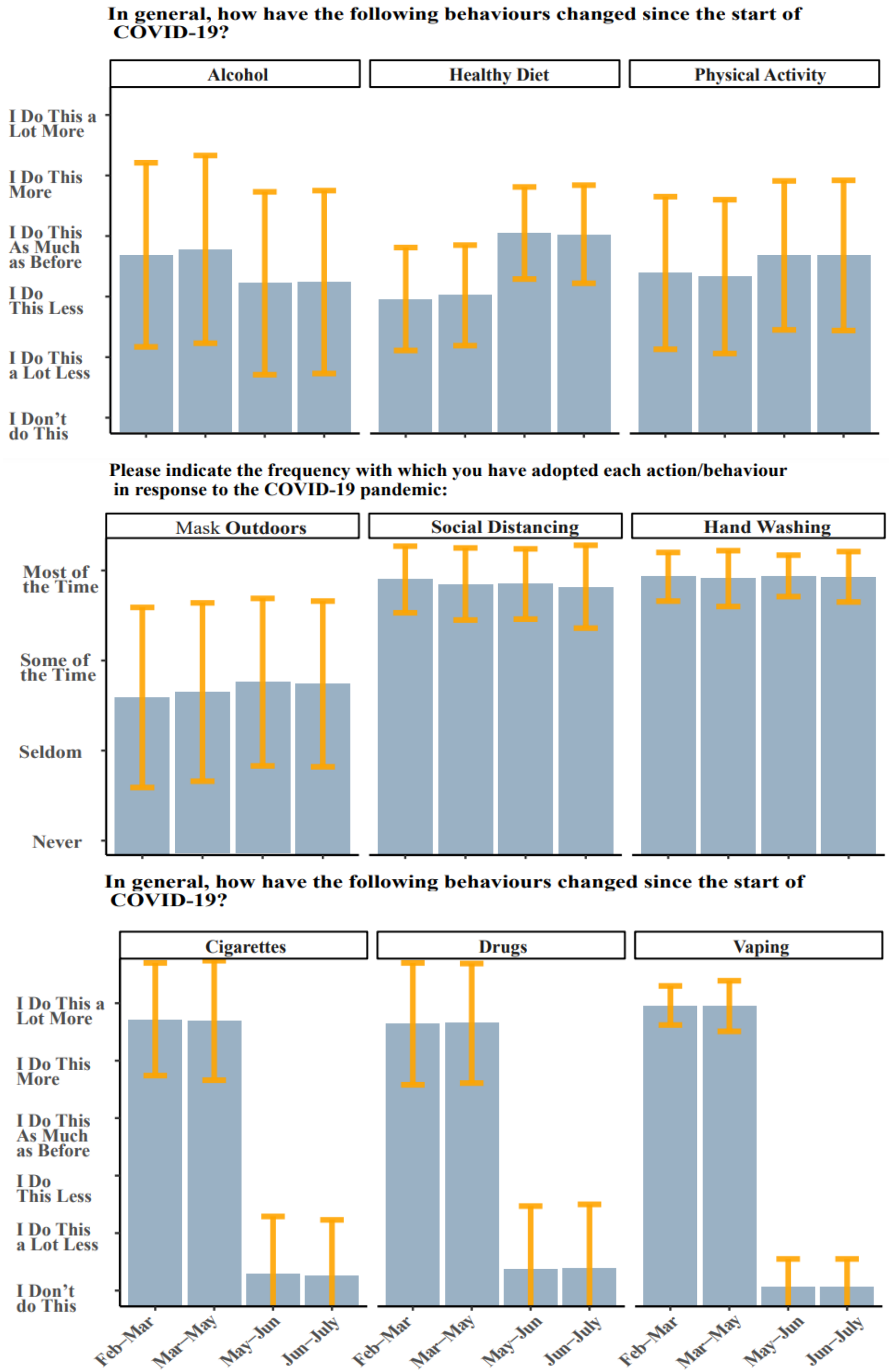
### 5.3.1 Participants

A total of 1,476 participants completed at least one longitudinal survey. One hundred and forty-nine participants began a given survey more than once and their most complete survey was retained in analysis. Data from Wave 7 was omitted due to a low response rate and listwise deletion was applied to variables used in analysis across Waves 8-11 resulting in a final sample of n=254 participants representing 1,016 observations. The convenience sample was comprised mainly of women (76.4%) with at least a college or university degree (77.9%) who resided in the province of Quebec (77.6%) and estimated their reported annual incomes to be in the top third (28.3%) or middle third (50.4%) nationally. Participants ranged in age from 19 to 80 years old (M = 54.9, SD = 16.5) with 57.5% of respondents were between the ages of 55-74.

### 5.3.2 Health Behaviour Descriptive Statistics

Mean level responses for each health behaviour are presented in Figure 2. On average, across waves eight through eleven, self-reports of changes in physical activity levels since the beginning of the COVID-19 pandemic were between ‘I do this less’ and ‘I do this as much as before’ ($M_{wave8}$ = 3.39, $SD_{wave8}$ = 1.26; $M_{wave9}$ = 3.33, $SD_{wave9}$ = 1.27; $M_{wave10}$ = 3.69, $SD_{wave10}$ = 1.23; $M_{wave11}$ = 3.68, $SD_{wave11}$ = 1.24). For healthy diet, the average response for waves eight and nine were closer to ‘I do this less’ ($M_{wave8}$ = 2.96, $SD_{wave8}$ = .85; $M_{wave9}$ = 3.02, $SD_{wave9}$ = .83) while the average response for waves ten and eleven were closer to ‘I do this as much as before’ ($M_{wave10}$ = 4.05, $SD_{wave10}$ = .76; $M_{wave11}$ = 4.03, $SD_{wave11}$ = .81). Mean level changes in alcohol consumption remained stable across measurement waves with respondents between ‘I do this less’ and ‘I do this as much as before’ ($M_{wave8}$ = 3.69, $SD_{wave8}$ = 1.52; $M_{wave9}$ = 3.78, $SD_{wave9}$ = 1.55; $M_{wave10}$ = 3.22, $SD_{wave10}$ = 1.51; $M_{wave11}$ = 3.24, $SD_{wave11}$ = 1.51). Large differences in mean level responses were evident between waves eight/nine and ten/eleven for cigarette smoking ($M_{wave8}$ = 5.72, $SD_{wave8}$ = .98; $M_{wave9}$ = 5.70, $SD_{wave9}$ = 1.04; $M_{wave10}$ = 1.29, $SD_{wave10}$ = 1.00; $M_{wave11}$ = 1.26, $SD_{wave11}$ = .97), vaping ($M_{wave8}$ = 5.96, $SD_{wave8}$ = .34; $M_{wave9}$ = 5.95, $SD_{wave9}$ = .44; $M_{wave10}$ = 1.07, $SD_{wave10}$ = .48; $M_{wave11}$ = 1.07, $SD_{wave11}$ = .48), and recreational drug use ($M_{wave8}$ = 5.64, $SD_{wave8}$ = 1.06; $M_{wave9}$ =5.65 , $SD_{wave9}$ = 1.04; $M_{wave10}$ = 1.38, $SD_{wave10}$ = 1.09; $M_{wave11}$ = 1.39, $SD_{wave11}$ = 1.11).

**Figure 1.** Means and Standard Deviations for Health Behaviours



For each of these behaviours, mean scores were between ‘I do this a lot more’ and ‘I do this more’ since the beginning of the pandemic across waves eight/nine and between ‘I don’t do this’ and ‘I do this a lot less’ across waves ten/eleven. Finally, mean level scores remained generally consistent across waves for hand washing use ($M_{wave8}$ = 3.93, $SD_{wave8}$ = .27; $M_{wave9}$ = 3.91, $SD_{wave9}$ = .31; $M_{wave10}$ = 3.94, $SD_{wave10}$ = .23; $M_{wave11}$ = 3.93, $SD_{wave11}$ = .28), wearing a mask outdoors use ($M_{wave8}$ = 2.59, $SD_{wave8}$ = 1.00; $M_{wave9}$ = 2.65, $SD_{wave9}$ = .99; $M_{wave10}$ = 2.76, $SD_{wave10}$ = .93; $M_{wave11}$ = 2.74, $SD_{wave11}$ = .92), and social distancing use ($M_{wave8}$ = 3.90, $SD_{wave8}$ = .37; $M_{wave9}$ = 3.85, $SD_{wave9}$ = .40; $M_{wave10}$ = 3.85, $SD_{wave10}$ = .39; $M_{wave11}$ = 3.82, $SD_{wave11}$ = .46). Hand washing and social distancing scored indicate that people adopted the behaviours closer to ‘most of the time’ than ‘some of the time’ while people reported wearing masks outside closer to ‘some of the time’ than ‘seldom’.

### 5.3.3 Network Analysis

Three network models were estimated and compared using the model search algorithm in the psychonetrics package (Table 2). When compared to the full/unsaturated model, the ‘pruned stepup’ model presented the best fit to the data with the lowest AIC and BIC and a $X^2$ statistic indicating that the hypothesis of perfect fit cannot be rejected ($\Delta X^2$ = 75.57, p = 1.0). However, RMSEA values were each above the generally accepted range (.05-.08; Fabrigar et al., 1999) and indicate poor data fit. This is likely due to violations of the assumption of stationarity (i.e., substantial mean level changes in cigarettes, vaping, and recreational drug use).

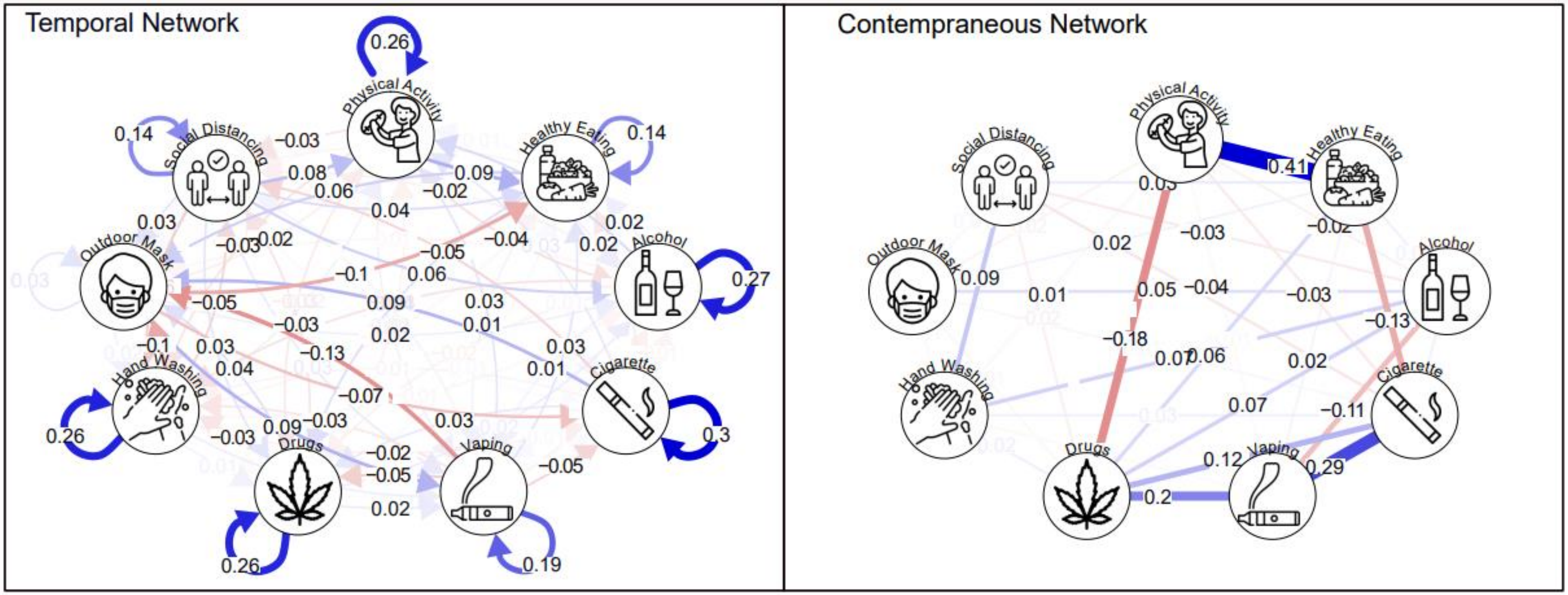
Within person associations between traditionally studied health behaviours and newly adopted health behaviours in response to the COVID-19 pandemic were modelled within a network analysis framework. The best fitting model revealed a bidirectional temporal relationship between outdoor mask use and vaping suggesting that those who wear a mask outdoors were more likely to vape (β = -.09) and those who vape were less likely to report wearing a face mask outdoors (β = .11) across the survey waves. Additionally, associations between traditional and novel health behaviours were observed between outdoor mask wearing and healthy eating (β = -.10). Within-person associations were also present when the effect of time was removed (contemporaneous networks). These associations included an expected relationship between positive affect and healthy eating (β = .41), vaping and cigarettes (β = -.16), vaping and cigarettes (β = .28), vaping and drug use (β = .20), drug use and cigarettes (β = .08) and physical distancing and hand washing (β = .12).

**Table 1.** Demographic Information for Waves 8 - 11

| | Longitudinal Data (N = 254) | | 2016 Census | Difference |
|---|---|---|---|---|
| | N | % | % | Δ % |
| **Sex** | | | | |
| Female | 194 | 76.4% | 50.89% | 25.51% |
| Male | 57 | 22.4% | 49.11% | -26.71% |
| Other | 3 | 1.2% | NA | NA |
| **Education** | | | | |
| College or University Degree | 106 | 41.7% | 47.52% | -5.82% |
| Graduate/Postgraduate Degree | 92 | 36.2% | 7.74% | 28.46% |
| Secondary/High School | 55 | 21.7% | 26.42% | -4.72% |
| Primary/Elementary School or Less | 0 | 0.0% | 18.29% | -18.29% |
| I Don’t Know/I Prefer Not to Answer | 1 | 0.4% | NA | NA |
| **Canadian Province** | | | | |
| Québec | 197 | 77.6% | 23.22% | 54.38% |
| Ontario | 20 | 7.9% | 38.25% | -30.35% |
| British Columbia | 15 | 5.9% | 13.22% | -7.32% |
| Alberta | 9 | 3.5% | 11.57% | -8.07% |
| Nova Scotia | 8 | 3.1% | 2.63% | 0.47% |
| Manitoba | 2 | 0.8% | 3.63% | -2.83% |
| New Brunswick | 1 | 0.4% | 2.13% | -1.73% |
| Newfoundland | 1 | 0.4% | 1.48% | -1.08% |
| Saskatchewan | 1 | 0.4% | 3.12% | -2.72% |
| Prince Edward Island | 0 | NA | .41% | NA |
| Yukon | 0 | NA | .10% | NA |
| Northwest Territories | 0 | NA | .12% | NA |
| Nunavut | 0 | NA | .10% | NA |
| **Age*** | | | | |
| 0-14 | NA | 0% | 16.61% | NA |
| 15-24 | 17 | 6.69% | 12.14% | -5.45% |
| 25-34 | 25 | 9.84% | 13.13% | -3.29% |
| 35-44 | 27 | 10.6% | 12.93% | -2.33% |
| 45-54 | 24 | 9.45% | 14.33% | -4.88% |
| 55-64 | 69 | 27.2% | 13.97% | 13.23% |
| 65-74 | 77 | 30.3% | 9.65% | 20.65% |
| 75-84 | 15 | 5.91% | 5.04% | 0.87% |
| 85+ | NA | 0% | 2.19% | NA |

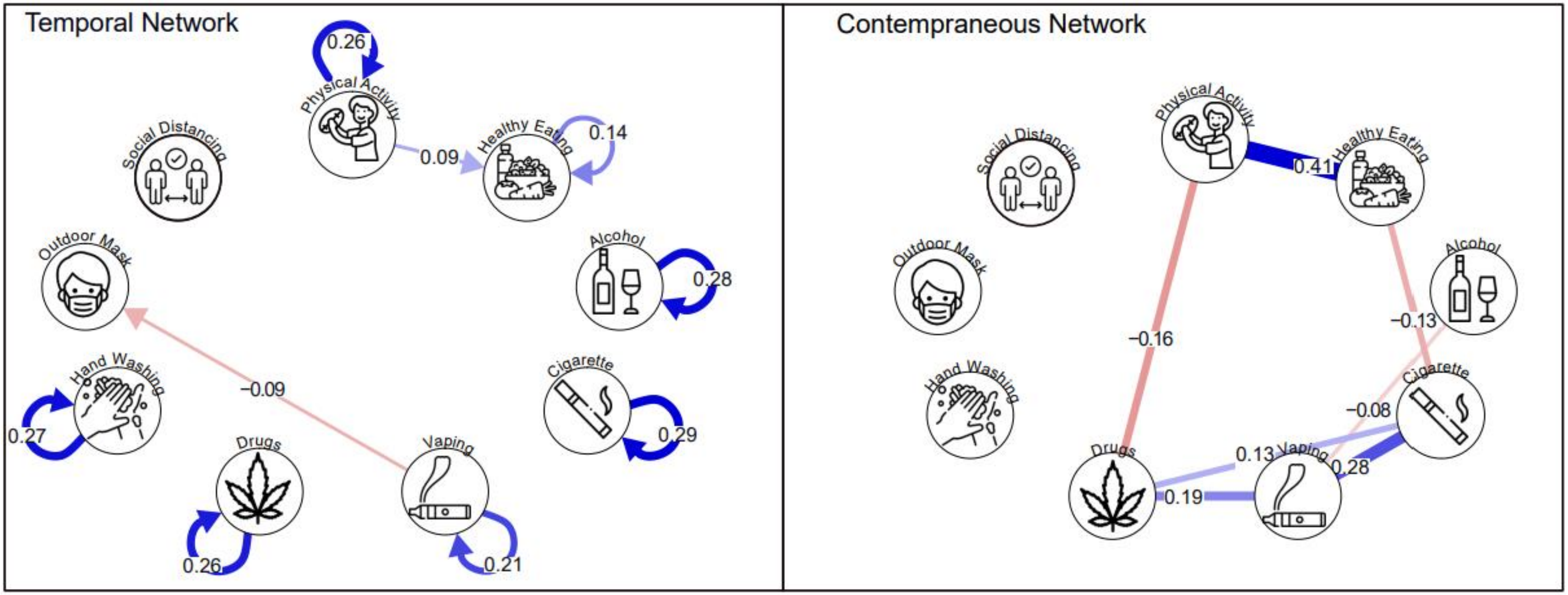
**Note:** *Demographic statistics were derived from Wave 8 data, any changes in ages across surveys eight through eleven are not accounted for.

**Figure 2.** Temporal and Contemporaneous Network Analysis (Model = Full)



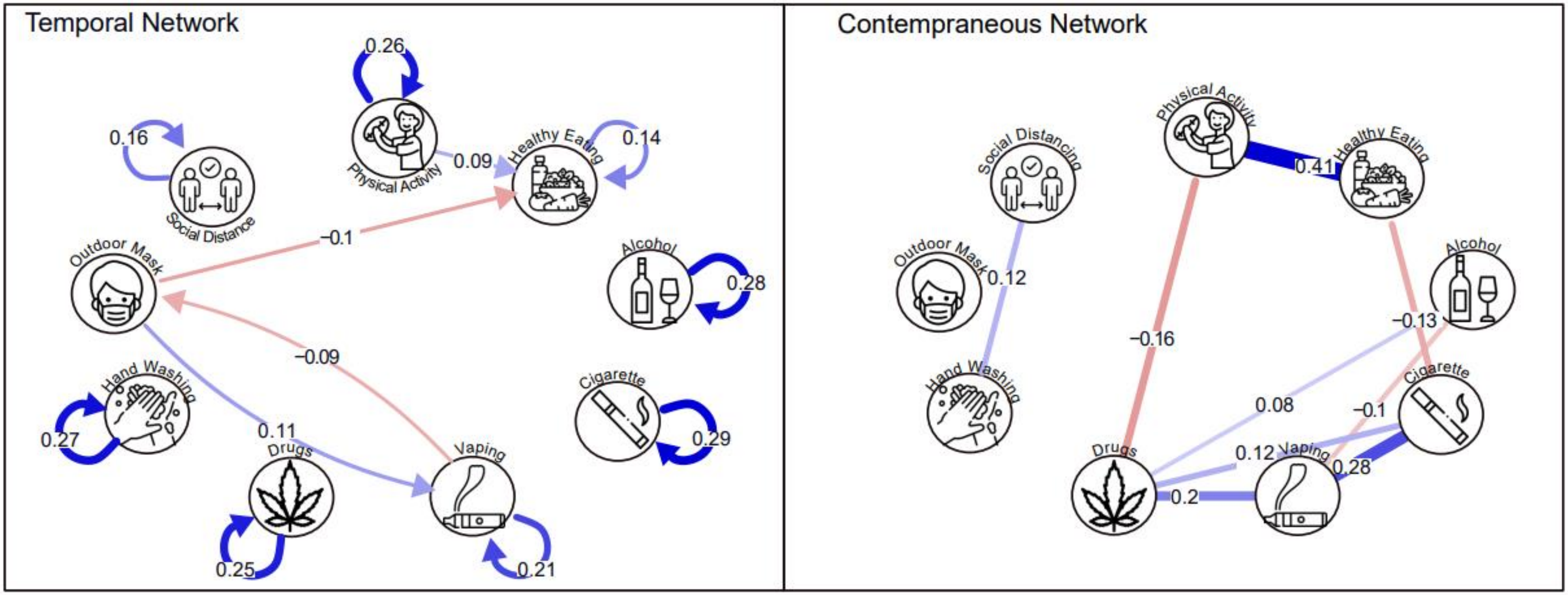

Notes: Figure depicts temporal and contemporaneous networks for n = 254 participants across waves 8-11. Directed edges in temporal networks represent 'Granger causality' or the lag-1 autoregressive relationships between variables over time. The undirected edges in the contemporaneous network represent within-person associations which remain when temporal effects are removed.

**Figure 3.** Temporal and Contemporaneous Network Analysis (Model = Pruned)




Notes: Figure depicts temporal and contemporaneous networks for n = 254 participants across waves 8-11. Directed edges in temporal networks represent 'Granger causality' or the lag-1 autoregressive relationships between variables over time. The undirected edges in the contemporaneous network represent within-person associations which remain when temporal effects are removed.

**Figure 4.** Temporal and Contemporaneous Network Analysis (Model = Pruned Stepup)




Notes: Figure depicts temporal and contemporaneous networks for n = 254 participants across waves 8-11. Directed edges in temporal networks represent 'Granger causality' or the lag-1 autoregressive relationships between variables over time. The undirected edges in the contemporaneous network represent within-person associations which remain when temporal effects are removed.

**Table 2.** Network Model Fit Statistic Comparisons

| Model | DF | AIC | BIC | RMSEA | $X^2$ | $X^2$ Diff | DF Diff | p |
|---|---|---|---|---|---|---|---|---|
| Full | 522 | 23530.04 | 24166.76 | 0.22 | 6951.22 | | | |
| Pruned Stepup | 652 | 23345.61 | 23522.48 | 0.20 | 7026.79 | 75.57 | 130 | 1.0 |
| Pruned | 659 | 23424.88 | 23576.98 | 0.20 | 7120.06 | 93.27 | 7 | < 0.0001 |

## 5.4 Discussion

Across a period of six months during the initial onset of the COVID-19 pandemic adherence to mask wearing, social distancing, hand washing, physical activity, and alcohol consumption remained generally stable. People reported a decrease in healthy eating between February and May before this behaviour returned to pre-pandemic levels. Between February and May respondents to the iCARE survey also reported smoking cigarettes, using recreational drugs, and vaping 'a lot more' since the start of the pandemic; however, this pattern reversed abruptly from May to July with most participants reporting they engage in these behaviours 'a lot less' than before the pandemic or 'not at all'.

Temporal network analysis was employed to model within person associations between health behaviours over time. Temporal networks revealed that physical activity was positively associated with increased levels of future healthy eating, while wearing a mask outdoors was associated with decreased levels of healthy eating over time. A bidirectional relationship was observed between wearing a mask outdoors and vaping behaviour such that wearing a mask outdoors predicted more future vaping behaviour and vaping predicted lower mask use over time. Within-person associations that were not attributable to temporal effects i.e., contemporaneous effects, showed strong positive associations between physical activity and healthy eating, between smoking cigarettes and vaping, and between recreational drug use and vaping. Negative associations were observed between physical activity and drug use and between healthy eating and smoking. However, the nature of the data and the underlying assumptions of the statistical models were a poor fit and results should be interpreted with caution.

This analysis included nine health impacting behaviours in the network model. There are several factors which influence feature selection including statistical power, theory-driven factors, characteristics of the dataset, and research questions. The present research was focused on health behaviours as the primary outcomes of interest and included only health impacting and pandemic specific behaviours. However, given the demonstrable within-person associations between health behaviours and pandemic specific behaviours, future research could include mechanisms of behavioural activation (e.g., HAPA constructs) to capture the features and dynamics of behavioural systems more fully as they relate to multiple health impacting behaviours. A temporal network of health behaviours and underlying affective and cognitive mediators has the potential to generate theories of multiple behaviour change by illuminating patterns of connectivity in the psychosocial systems involved in behaviour.

In addition to the number of features included in the model, the duration of time between measurements can influence what processes are modelled as temporal effects. In the case of the iCARE study data was collected with month long intervals between measures whereas the measures behaviours typically occur on hourly and/or daily time frames (e.g., physical activity may be performed daily while vaping may be an hourly occurrence). Therefore, another challenge in the modelling of temporal effects of health behaviours is measure the behaviors in accordance with the timeframes of which the behaviours occur (Jordan et al., 2020).

Future research could use intensive time series data derived from experience sampling to measure health behaviour systems and their dynamic interactions on time frames which reflect the typical behavioural activation. Fortunately, studies assessing multiple health behaviours—some during the pandemic—have been conducted (e.g., Villinger et al., 2022; Do, Wang, Courtney, & Dunton, 2021); however, few have conducted analysis from a multiple behaviour perspective or have used network analysis (c.f., Fried, Papanikolaou, & Epskamp, 2022). For example, in one 14-day experience sample study conducted in Germany during the first week of national lockdowns, participants (n = 49) reported their daily health behaviours (physical activity, sedentary activity, healthy eating, alcohol consumption, sleep) as well as pandemic specific behaviours (leaving home, having in person contacts) and risk perceptions for contracting COVID (Villinger et al., 2022). Multilevel modelling analysis revealed average levels of health behaviours remained stable over time despite large individual heterogeneity and that people reported higher risk perceptions on days when they left their home and had in-person contacts that day. However, relationships between health behaviours and pandemic specific behaviours were not assessed. Employing network methodology with such data have the potential to identify patterns of temporal covariation between behaviours and cognitive mediators which techniques such as multilevel modelling does not capture.

### 5.4.1 Limitations

The application of temporal network analysis for longitudinal data analysis contains inherent strengths and limitations. In contrast to cross-sectional analysis, longitudinal data enables the modelling of within and between person effects to be disambiguated which can provide a more comprehensive analysis of the relationships between measured and/or latent constructs. Additionally, when compared to other applicable methods for analyzing longitudinal data, autocorrelations become a feature and not a restraint of temporal network analysis (Jordan et al., 2020). However, the underlying assumptions of temporal network analysis must also be met. For example, violations of the assumption of stationarity can be consequential. In the iCARE sample mean level changes in smoking, vaping, and recreational drug use were evident with sharp declines in smoking, vaping, and drug use after wave 9 (wave 8 Feb-March; wave 9 March-May 2021; wave 10 May-June; wave 11 June-July). This is likely due to the vaccine rollout, seasonality, and the protective measures being lifted in Canada (mostly Quebec). Violating the assumption of non-stationarity likely contributed to poor model fit statistics and unexpectedly strong autocorrelations for smoking, drug use, and vaping. Given the clear change in reported responses between May and June, future research could explore the effect of the pandemic on changes in smoking, vaping, and/or recreational drug using interrupted time series analysis to examine changes in behaviour and associated environmental and intra-individual factors.

Finally, the iCARE sample used in analysis was non-representative across several important dimensions including sex, education, geographical location, and income levels. Additionally, the sample was more likely than the national average to have already adopted recommended health practices (Bacon et al, 2021). This is evident in the use of indoor mask use, which was not included in the analysis due to the complete absence of response variability.

### 5.4.2 Conclusions

The analysis presented in this chapter sought to model the temporal dynamics of health behaviours and pandemic specific behaviours across a period of six months during the onset of the COVID-19 pandemic. Abrupt mean level changes in several health behaviours (smoking, recreational drug use, and vaping) lead to violation of statistical assumptions and a poor fit between model and data. However, the application of temporal network analysis to the study of multiple health behaviours is well suited to address key research questions in the field such as ‘how do multiple health behaviours co-vary with one another over time’. Future research employing intensive time series data and measuring affective and cognitive mediators of behaviour, in addition to health behaviours, has the potential to contribute valuable hypothesis generating insights to the basic science of multiple health behaviour research.

CHAPTER 6

# GENERAL DISCUSSION

## 6.1 Overview

This dissertation aimed to advance the basic science of multiple health behaviours by examining the co-occurrence and co-variation of health impacting behaviours. Using cross-sectional and longitudinal data from the Canadian Longitudinal Study of Aging (Raina et al., 2009) and the International Covid-19 Awareness, Responses, and Evaluation Study (Bacon et al., 2021), I identified seven clusters of commonly co-occurring health behaviours and their sociodemographic characteristics (Chapter 2), compared these clusters against individual behaviours for classifying and predicting health outcomes using machine learning (Chapter 3), explored the interconnectedness of traditionally studied health behaviours and pandemic specific behaviours (Chapter 4), and modelled the temporal relationships between health behaviours over time during the Covid-19 pandemic (Chapter 5).

The main contributions of this dissertation to the literature include: the identification of commonly co-occurring health behaviours in a large nationally representative sample of older Canadians and the first known empirical comparison of co-occurrence versus co-variation based approaches for understanding the interconnectedness between health behaviours (van Allen et al., 2023), the first known comparison of machine learning techniques for predicting and classifying health outcomes from both clusters and individual health behaviour, a thorough examination of the interconnected relationships between behaviours and how these relationships vary by sociodemographic factors using novel network recursive partitioning analysis, and a relatively novel application of dynamic temporal network analysis to the study of multiple health and pandemic-specific behaviours during the Covid-19 pandemic.

In this general discussion chapter I reflect and discuss themes prevalent across Chapters 1-5. These themes include *machine learning* (co-occurrence and prediction/classification), *network psychometrics* (co-variation and complexity), and *multiple behaviour theory*. This dissertation primarily contained data-driven studies to identify the co-occurrence and co-variation between health behaviours, the results of which are described in self-contained chapters. The general discussion focuses on methodological issues and approaches for extending this work in future projects.

## 6.2 Machine learning: co-occurrence, clustering, prediction, and classification

Unsupervised machine learning was used to group people into clusters based on similarity of health behaviour co-occurrence (Chapter 2). Subsequently, supervised machine learning was used to predict and classify health outcomes based on the previously identified clusters (Chapter 3). The purpose of these analysis was to identify the prevalence of behavioural combinations (Chapter 2) and to test whether these combinations were stronger predictors of health outcomes than individual health behaviours (Chapter 3). In the following subsections I reflect upon the use of cluster analysis for modelling co-occurrence (6.2.1) and the use of supervised machine learning for comparing clusters and individual behaviours (6.2.2).

### 6.2.1 Co-occurrence and clustering

Cluster analysis is a class of unsupervised machine learning techniques frequently used to partition people into groups based on similarities of a feature set; for this thesis, I applied this technique to health behaviours. As discussed in Chapter 2 integrating the research findings from cluster analysis studies is difficult due to substantial heterogeneity in measurement, risk factors included in analysis, analytical approaches, and researcher degrees of freedom. This issue has been noted previously in systematic reviews of health behaviour clustering studies (e.g., Whitaker et al., 2021; Noble, Paul, Turon, & Oldmeadow, 2015). In addition to this issue, there are broader limitations with the use of cluster analysis in health behaviours research. These include the questionable pragmatic utility of these studies and methodological limitations of the analysis itself. These limitations are expanded upon below and followed by opportunities for future research.

Research employing cluster analysis in the multiple behaviour literature commonly cite the utility of cluster analysis for informing population level intervention targeting and prioritization. For example, one systematic review of clustering studies involving smoking, nutrition, alcohol, and physical activity concluded that the existence of behavioural combinations supports the need for behavioural interventions to target and prioritize multiple behaviours such as co-occurring smoking and alcohol consumption. (Noble, Paul, Turon, & Oldmeadow, 2015). However, the extent to which those developing such interventions in public health or health psychology actually draw from findings from such cluster analyses as part of informing the development and/or evaluation of health behaviour change interventions on the results from cluster analysis is unclear. There may be an under-recognised opportunity to assess this issue, and a focused scoping review of the intervention literature is warranted in future research to assess the pragmatic utility of health behaviour clustering studies.

A perhaps underappreciated aspect of cluster analysis is that by their nature, clustering algorithms will always identify clustering patterns, irrespective of underlying behavioural co-occurrence. Said another way, hierarchical cluster analysis will always produce clusters even when no underlying cluster exists, in a similar way that linear regression will always identify a linear relationship between variables, even if the linear relationship is negligible. Some clustering techniques, such as agglomerative hierarchical clustering and k-means clustering, do not provide estimates of goodness-of-fit while techniques such as latent class analysis are evaluated with fit metrics such as Bayesian Information Criterion (Sinha, Calfee, & Delucchi, 2021). Additionally, the number of research degrees of freedom in cluster analysis are numerous. For example, in Chapter 3, the selection of clustering algorithm was essentially arbitrary, and the selection of the linkage methods (e.g., Ward, complete), health behaviour selection and data pre-processing, and the optimal number of clusters both contained researcher degrees of freedom. Only exploring a full set analytical decisions via a multiverse analysis (Steegan, Tuerlinckx, Gelman, & Vanpaemel, 2016; Harder, 2020) would reveal the variance in analytical outputs due to researcher degrees of freedom. Without such analysis, it is difficult to give high confidence to the outputs of Chapter 3 given that the results will almost certainly differ if performed by multiple researchers. However, when the stated purpose of an analysis is to identify the prevalence of co-occurring behaviours in a population for the purpose intervention development and tailoring at the population level, It is possible that cluster analysis may not be the ideal method.

Imagine the following study design: a nationally representative survey of health behaviours, sociodemographic factors, and health outcomes where health behaviours are measured in accordance with Canadian guidelines (e.g., MVPA for physical activity, drinks per week for alcohol). Health behaviours are dichotomized into ‘adhere to guidelines' and 'not adhering to guidelines' and simple descriptive statistics are used for analysis to answer the question 'how many Canadians are adhering to multiple health behaviour guidelines' – a fundamental question which is not answered in the literature. To answer the question "who needs to do what differently', simple cross-tabulations are used to assess the frequency of all behavioural combinations. Associations between these combinations, sociodemographic factors, and health outcomes are used to describe the individuals in each grouping of multiple behaviour adherence. With longitudinal data, the temporal associations between multiple health behaviour adherence and health outcomes can be modelled.

This behavioural profile approach (e.g., Shaw & Agahi, 2012) has two main advantages over cluster analysis. First, national guidelines are informed by multidisciplinary expert panels (e.g., Butt et al., 2020) that consider a variety of factors including the relationship between behaviours and health outcomes. The dichotomous split of (non)adherence is informed by the literature and expert opinion while in the case of cluster analysis the dividing line between groups is data driven and can be influenced by measurement characteristics and algorithmic idiosyncrasies. Essentially, guideline-based profiles incorporate scientific knowledge when grouping people based on their co-occurring behaviours while cluster analysis omits this knowledge (however, guidelines are subject to change when new evidence or standards arise). Second, when compared to cluster analysis, the construction of behavioural profiles requires far fewer researcher degrees of freedom. For example, in Chapter 2 the clustering algorithm, the number of clusters, and the linkage methods used in the analysis were each selected from a range of possible options through researcher consensus. The results of the analysis could have differed substantially depending on researcher decisions which are in some cases entirely arbitrary (such as which clustering method to use). In contrast, there are fewer researcher degrees of freedom in the behavioural profile approach when dichotomizing adherence based on established guidelines. Importantly, these advantages rely on behavioural measurements align with national guidelines. For an example of behavioural profiles using baseline CLSA data which do not align with guidelines see Appendix I. Briefly, this analysis explored associations between behavioural combinations and sociodemographic/health indicators and revealed patterns with behaviour combinations that were not evident with behaviours in isolation.

Ultimately, only an empirical comparison of co-occurrence based methods can determine which methods are most suitable for multiple behaviour research. Using the hypothetical research design previously discussed, this can be achieved by creating behavioural profiles and clusters derived from multiple techniques (e.g., agglomerative hierarchical, k-means, latent class) and compare the descriptive, predictive, and classification ability relative to the benchmark of individual behaviours. Combinations of co-occurring behaviours more strongly associated with health outcomes than individual behaviours will signify synergistic or compounding effects between behaviours. If clusters outperform behavioural profiles for predicting/classifying health outcomes, this would suggest that data-driven algorithms have identified behavioural combination frequencies that are more strongly related to health outcomes than those prescribed in guidelines. Such a result could inform new guidelines that incorporate multiple behaviour interactions.

### 6.2.2. Prediction and classification

This dissertation used unsupervised machine learning to group individuals into clusters based on similarities in their co-occurring health behaviours (Chapter 2) and then used supervised machine learning to predict and classify health outcomes from clusters and individual behaviours (Chapter 3). The purpose of this analysis was to compare the utility of two predictor sets (clusters and individual behaviours) which contain the same information in different units. This analysis was designed to test an understudied feature of health behaviour clusters, namely, whether combinations of multiple health behaviours are stronger predictors of health outcomes than individual behaviours. The results of this analysis indicated that health behaviours in isolation were weak predictors of general health and were not able to classify people living without chronic conditions or living with type II diabetes specifically (Chapter 3). Although health behaviours were stronger classifiers of chronic condition status by some metrics (e.g., AUC, accuracy), the results are not informative as they could be as no models were able to identify positive cases of people living without conditions. This may be due to several factors, including class imbalance in the outcome variables for classification analysis, the short temporal distance between baseline and follow-up time points, and the intentionally small predictor sets for testing a focused hypothesis. However, the effect sizes ($R^2$ = .10) for continuous health outcomes were comparable to the effect sizes of impactful but non-modifiable contributors to health outcomes such as personality ($R^2$ = .12; Wasylkiw & Fekken, 2002) which reaffirms the potential for behaviour change to impact subjective measures of health. Future research interested in addressing the clusters vs behaviour question could include a more comprehensive set of predictor variables to include all factors relevant to health outcomes to investigate which approach can correctly predict and classify positive cases of chronic condition status.

### 6.3 Networks and behavioural science theory: reductionism or complexity?

This dissertation employed cross-sectional (Chapters 2 & 3) and dynamic network (Chapter 4) analysis to identify associations between behaviours across sociodemographic factors and to estimate temporal relationships between behaviours. Networks in Chapters 2 and 3 were used to model the partial correlations between health behaviours across different sociodemographic characteristics and between datasets. These outputs fill a gap in the literature by documenting the conditional independence relationships between health impacting behaviours in Canadian and (mostly Canadian) international samples. The results of these studies largely confirmed the strength and directions of bivariate relationships between behaviours when accounting for the shared covariance with other behaviours, while highlighting the impact that measurement variability can have on analytical outputs. The dynamic networks modelled in Chapter 4 were unfortunately uninformative due to a mismatch between data characteristics and modelling assumptions; however, the use of temporal networks for identifying potentially novel patterns of temporal interconnectivity between behaviours remains a promising avenue of research. Ultimately, this work used existing and novel methodologies that can be further extended in future work through the integration of theories and methods from the complex systems literature.

Importantly, only behaviours were included in these networks. However, as the behavioural science of multiple behavioural pursuits has shown, behaviours are situated within an interconnected and dynamic network of behaviours, incentives, emotional reactions, motivations, and cognitive appraisals (e.g., Vancouver, Weinhardt, & Schmidt, 2010; Schmidt & DeShon, 2007; Louro, Pieters, & Zeelenberg, 2007; Schwarzer & Luszczynska, 2008). Environmental context and variations in intra-individual personality can also impact behaviour (e.g., van Allen et al., 2021; Allen, Vella, & Laborde, 2015). This dissertation was limited to the cross-sectional and temporal relationships between behaviours without consideration of cognitive, affective, and environmental factors. This was primarily due to the trade-offs of working with secondary data analysis, namely the trade-off between data access and control of survey design. However, I will argue that the behavioural science of multiple behaviour pursuit could benefit from incorporating complex systems theory and methods beyond simple network psychometrics. For example, concepts such as phase transitions (Trefois, Antony, Goncalves, Skupin, & Balling, 2015), attractor landscapes (Barrett, 2014), resilience to change (Kalisch et al., 2019), and spreading activation with densely connected networks (Borsboom, 2017) could provide a complimentary theoretical lens to understand multiple behaviour enactment and prioritization.

Interconnected systems at the biological, psychological, social, and environmental levels—all of which can vary between individuals—influence the uptake, maintenance, and cessation of these behaviours. Further complicating matters, the vast array of biopsychosocial factors influencing health behaviours change over time, may operate at different time scales, and can interact in nonlinear ways to produce unpredictable behaviour. Traditionally, behavioural science research has adopted a methodological reductionist approach to isolate subsets of interacting components in a larger system or phenomenon. However, given that humans meet the general criteria for complex systems it is worth considering whether behavioural science is ignoring natural features of complex systems in our understanding of how behaviours change over time.

### 6.3.1 Stable states

An important consequence of the nonlinear properties of complex systems is that the state of a system can suddenly change in response to external perturbations. A system that can transition between two stable states is termed a bi-state system. Although systems can have more than two stable states, bi-state systems representing healthy and unhealthy states are particularly important for understanding, predicting, and intervening upon maladaptive health behaviours. In the context of health behaviours, the initiation and termination of health behaviours represent phase transitions, as do relapses into unhealthy behavioural patterns. The stable states of equilibrium to which a system tend to gravitate towards are often conceptualized as 'attractor landscapes'. The attractor landscape framework is applied in a variety of fields including neuroscience (Rolls & Deco, 2011), epidemiology (Keeling et al., 2001), and political science (Coleman et al., 2007) to describe the tendency for complex systems to become 'stuck' in either a healthy or unhealthy state (see Figure 1). Attractors can be thought of as the habits, or preferred states, of a system (Barrett, 2014). The ability to predict a change from one attractor state to another would represent a scientific advancement in the behavioural science of multiple behaviours. Fortunately, examples of this predictive ability have been demonstrated in the field of mental health research by identifying tipping points and early warning signs (e.g., Wichers et al., 2016; Olthof et al., 2019).

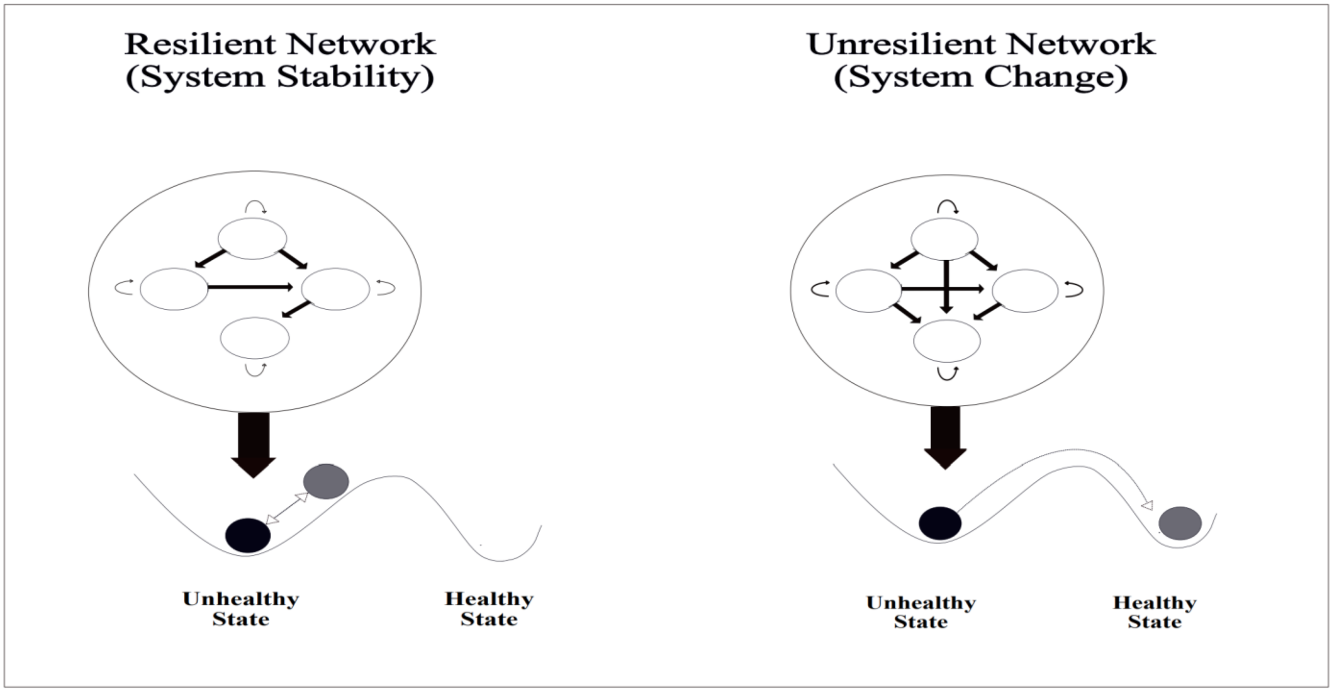



Figure 1. Attractor landscapes for a resilient network (no system change from unhealthy to healthy state) and an resilient network (system change from unhealthy to healthy state).

### 6.3.2 Phase transitions and tipping points

Prior to a phase transition between attractor states a behavioural system, represented by a network, can reach a tipping point where it transitions from one state of equilibrium to another. Such transitions are referred to as ‘phase transitions’ (see Figure 2). These tipping points are often preceded by early warning signs which can be used to predict phase transitions (Borsboom 2017; Fried & Cramer, 2017; Olthof et al., 2019). The temporal changes in networks prior to phase transition allow for greater reliability in predicting the network state in the future. These early warning signs are evident in the transition from healthy to depressed states (van de Leemput et al., 2014; Wichers et al., 2016), chronic episodic diseases (Rikkert et al., 2016), and mood disorders (Olthof et al., 2019). Accurately detecting the tipping points in these phase transitions provides an opportunity to intervene and prevent a network from transitioning from a healthy to unhealthy state. To my knowledge, no studies have explored the concept of critical slowing down in the context of behaviour change. However, examples of potential applications are plentiful. Does, for example, the behavioural systems involved in smoking behaviour for an ex-smoker slow down prior to relapse, and becomes less resilient to perturbations (i.e., internal temptations or external triggers). If so, then identifying this tipping point could inform behaviour change interventions through more accurately identifying cue recognition and subsequent self-regulatory efforts. Additionally, if tipping points for target behaviours can be measured in real time (e.g., via autocorrelations on self-report data obtained through experience sampling), there is the possibility of informing 'just in time adaptive interventions' (e.g., Nahum-Shani, Hekler, & Spruijt-Metz, 2015). In the context of multiple behaviour pursuit, tipping points and early warning signs can be studied through simulations using the formal computational model of multiple goal pursuit (Schmidt & DeShon, 2007; Vancouver et al., 2010). Identifying tipping points and early warning signs in this context could extend our ability to predict when people will be successful in pursuing multiple health goal pursuits.

### 6.3.3 Spreading activation

Another way in which complex systems, modelled as networks, can assist in understanding and predicting behavioural engagement or change by understanding how the spreading activation of networks can lead to systems change. Spreading activation can occur between nodes in a network to influence the state of the system has given rise to the 'connectivity hypothesis'. According to the connectivity hypothesis, highly connected networks are more susceptible to phase transitions (i.e., are less resilient to change) as strong connections between nodes enables spreading activation. A recent systematic review of the network approach within the psychopathology literature found 'qualified support' for the connectivity hypothesis in studies using both cross-sectional and time-series data (Robinaugh et al., 2020). In contrast to networks of mental health symptoms where activated symptoms are undesirable, networks involved in promoting health behaviours are likely to benefit from increased connectivity, depending on the components of the network. In Chapter 4 I observed that connectivity between health behaviours tended to decrease in strength across (cross-sectional) age groups. From the perspective of the network connectivity hypothesis it is possible that a network connectivity effect is evident in health behaviours and moderated by age. However, the cross-sectional nature of this analysis does not allow for a rigorous test of this idea and alternative explanations such as the selection, optimization, and compensation theory (Freund & Baltes, 1998) which provides an alternative explanation for the observed patterns in the data.

When considering the spreading activation of networks, it is important to understand the thresholds that's each node must reach before having a meaningful impact on other connected nodes. In the context of multiple health behaviour pursuit, an acurate identification of the node thresholds (at the group an individual levels) for health behaviours and their underlying cognitive and affective systems, could also inform health behaviour change intervention design. For example, the Health Action Process Approach (HAPA; Schwarzer, Lippke, & Luszczynska, 2011) is a contemporary model that specifies the processes involved in health behaviour change. The model mirrors a directed network wherein psychological constructs are activated by other constructs (e.g., intention to perform a behaviour is influenced by task self-efficacy, outcome expectancies, and risk perception, and intention in turn influences action and coping planning). Gaining insights into the thresholds required for one node to activate another, and how these thresholds may vary within individuals, may enable a better understand the mechanistic processes involved in health behaviour initiation, change, and maintenance. For example, we could explore the thresholds required for an intention to perform a behaviour to initiate spreading activation and translate into the formation of an action plan in different contexts between and within individuals.

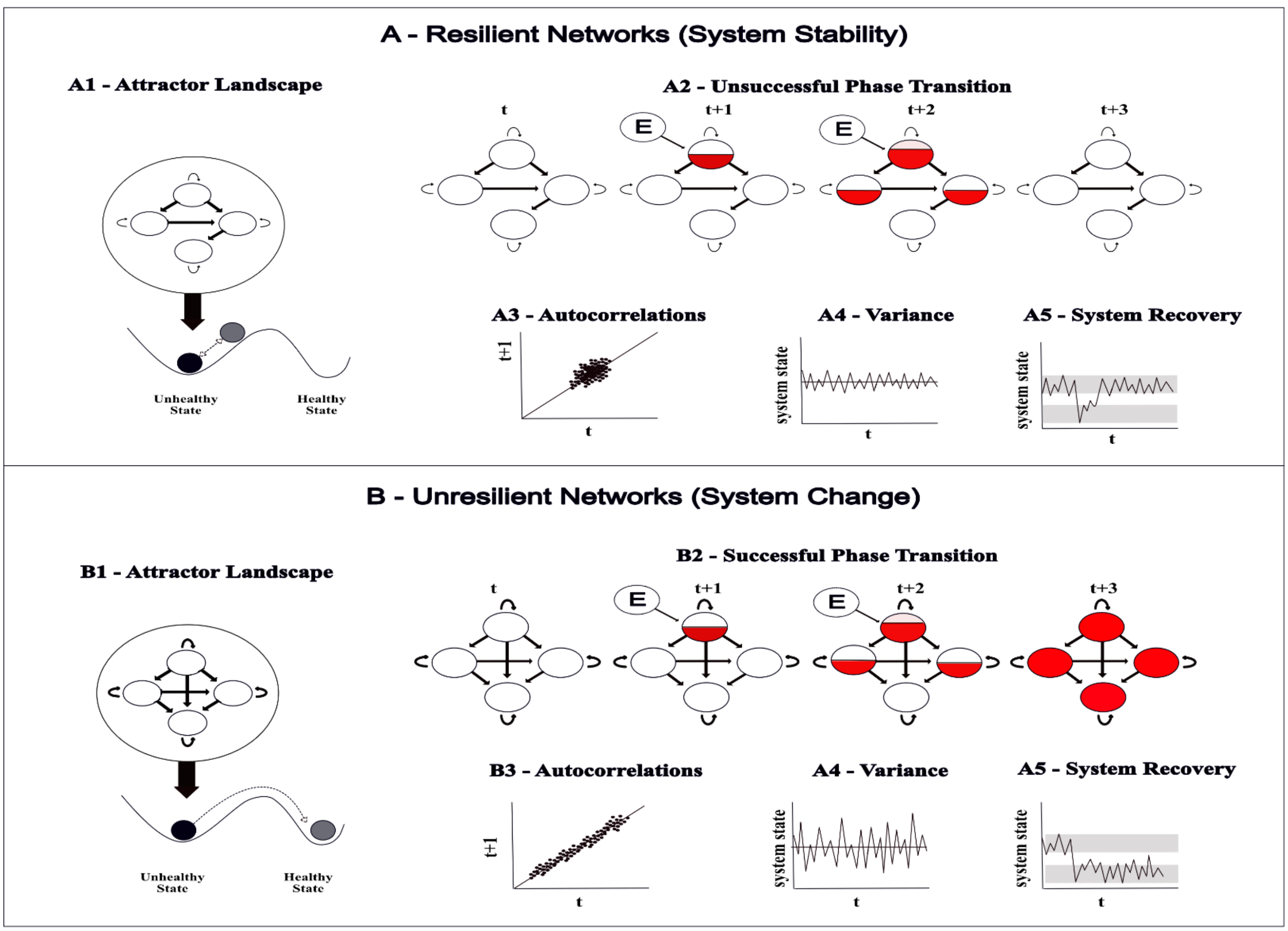


**Figure 2** Network dynamics in resilient (top) and non-resilient (bottom) networks. The attractor landscape in a resilient network (1A) has a higher tipping point than a non-resilient network (2A) which must be reached before the network will fall into the basin of attraction for an unhealthy state. Panels 1B and 2B illustrate the four-phase process of a changing from a healthy to an unhealthy state in response to an external stimulus (denoted by node E). In 1B, the network has low connectivity (sparse and weak connections between nodes) which limited the spreading activation effect and the network returns to a healthy state equilibrium. However, the densely connected and strong connections in the non-resilient network (2B) are conducive to spreading activation and the network shifts from a healthy to unhealthy state over time. Note that the thickness of the connections between nodes, and the self-loops.

### 6.3.4 Network connectivity and resilience/susceptibility to change

The spreading activation effect, and the network connectivity hypothesis, both illustrate how network typology (i.e., structure) can influence the behaviour of a system. Although to my knowledge no tests of this hypothesis have been performed for health behaviours, the idea that network topology (i.e., structure) may be involved in susceptibility/resilience to change highlights the potential for novel theories that are made possible by adopting a network approach to the study of behavioural enactment and change. Building on the idea that network topology plays a role in phase transitions, recent work in the mental health domain has sought to reconcile traditional view of resilience with the connectivity hypothesis (Kalisch et al., 2019). Resilience, or the ability to maintain or recover from adverse events, is generally conceptualized as a fixed trait where some individuals are more resilient that others. Kalisch and colleagues (2019) proposed a ‘hybrid symptoms-and-resilience factor’ model in which network connectivity drives resilience to phase transition, but time-varying moderating resilience factors exert a dampening effect on connections between nodes. For example, in a symptom network containing strongly connected nodes representing social dysfunction and anxiety, cognitive reappraisal may serve as resilience factor that dampens the connection between social connection and anxiety (Kalisch et al., 2019).

In the context of health behaviour pursuits, resistance or readiness to change is often assessed through stages-of-change theories (e.g., Prochaska & Norcross, 2001). When viewed through the lens of the network connectivity hypothesis, behaviour change arises when an external or internal perturbation causes a spreading activation among connected system components and results in a phase transition. For example, in Figure 1b, the state of the system representing smoking behaviour transitions from a stable state of engagement in smoking to a stable state of abstinence. Conceptually, the process involved in a bi-state phase transition can be represented in four simplified stages (see Figure 1a). Here, I am adapting Borsboom's (2017) explanation of phase transitions to the context of health behaviour change for tobacco use. First, a system consisting of determinants of tobacco use are in a stable state of equilibrium representing consisting smoking behaviour. Second, an external stimulus activates a targeted component of the system (e.g., a behavioural intervention increases self-efficacy). Third, a spreading activation effect propagates through the system (e.g., increased self efficacy leads to more positive attitude towards cessation which in turn increases one's intention to change behaviour). Fourth, the activated system has transitioned from an unhealthy to a healthy state. That a system can remain in an altered state after the initial stimuli is no longer present is another feature of complex systems. Specifically, 'hysteresis' occurs when a system state depends upon both the inputs to the system and the history of the system (Trefois et al., 2015). In the context of a complex systems perspective then, behavioural interventions are perturbations or shocks to the system designed to change the system to a healthier state. Behavioural maintenance, or the continuation of behaviour change, is an example of hysteresis.

Taken together, complex systems theory represents an underused perspective for understanding health behaviour initiation (phase transition and spreading activation), maintenance (hysteresis), and habits (attractor states). Leveraging the methods of complexity science often requires the use of computational models (Robinaugh et al., 2019; Roninaugh et al., 2021) which rely on accurate estimates of relationships between constructs and node thresholds. This dissertation aimed to estimate some of these relationships, but more basic science is required to support these efforts. The following two sections describe these efforts in more detail.

**6.3.5 Co-variation: the importance of basic science for formal theory development.** The relationship between health behaviours and the development of chronic conditions has been known for decades (Ockene, Sorensen, Kabat-Zinn, Ockene, & Donnelly, 1988). Additionally, evidence for compounding or synergistic effects of multiple health behaviours have been established for behaviours such as alcohol and tobacco (La Torre et al., 2013). Despite these known associations, robust population level associations between health behaviours are not established. Analysis of simple partial correlations between health behaviours and pandemic-specific behaviours with network analysis and large datasets (Chapters 4-6) provide useful estimates of these associations. However, as the discrepancies in the strength of associations between datasets have illustrated, measurement heterogeneity between assessments can result in unstable associations in some instances. Additionally, the utility of nomothetic statistics for individual behaviour change is also questionable (Pirccirillo & Rodebaugh, 2019). As the behavioural science of multiple behavioural pursuits has shown, behavioural priorities are situated within an interconnected and dynamic network of behaviours, incentives, emotional reactions, motivations, and cognitive appraisals (e.g., Vancouver, Weinhardt, & Schmidt, 2010; Schmidt & DeShon, 2007; Louro, Pieters, & Zeelenberg, 2007; Schwarzer & Luszczynska, 2008). Therefore, any behaviour *change* initiative would benefit from an understanding of the strength and direction of associations between behaviours and relevant cognitive and situational variables in order to anticipate knock-on effects and dynamic interplay between measured constructs. These basic associations are not yet well-established and a systematic review and network meta-analysis is warranted to better understand the association. Robust estimates between relevant factors can then serve as the basis for the development of formal models of multiple health behaviour change. The need for basic behavioural science to produce accurate estimates for the relationships between constructs is essential for the development of formal computational models which is discussed further in section 6.4.

## 6.4 Behavioural Science Theory and Health Behaviours: Towards Formal Idiographic Models

Psychology often prefers narrative theory to formal/computational theory (Fried, 2020) and formalized models are comparatively rare. However, outside of fields of health psychology and public health, researchers have been developing formal computational models of multiple goal pursuits that incorporate concepts from complexity science (Neal et al., 2017). Building on the multiple-goal pursuit model (MGPM; Vancouver et al., 2010) the MGPM* extends this computational model through integrating a sequential sampling model from decision field theory (Busemeyer &Townsend, 1993) to describe how preferences for actions arise when many actions are possible. Presently, as far as we know, this model is the most advanced attempt to create a unified theory of self-regulation and goal pursuit. Although much of this work has been done in the field of organizational psychology (Neal et al., 2017), this model of multiple goal pursuits could be adapted to the health behaviour context. In pursuit of this objective, network psychometric models using constructs specific to the health behaviour context could be used to provide initial range estimates of the associations between constructs to test simulation models prior to field testing.

Formalizing theories with mathematical equations and modelling them with computation methods arguably represents an advancement for psychological theory in general (Fried, 2020; Robinaugh et al., 2020). Through modelling a well-specified theory with ordinary differential equations to describe how each mechanism changes over time in responses to changes from external fields and fluctuations in accompanying nodes in the network, simulation-based models can allow researchers to 1) test for tipping points and node thresholds within the network, 2) explore hypothesis relating to individual differences in resilience to phase transitions, 3), model the effect of interventions on the network, and 4) iterate on computational models when new evidence becomes available (Robinaugh et al 2019). The ability to map reasonable parameter estimates to a computational model is essential for the development of models that predict real world outcomes (Robinaugh et al., 2019; Robinaugh, Haslbeck, Ryan, Fried, & Waldorp, 2021). Additionally, for such models to have practical utility socio-cognitive constructs will need to be incorporated. More basic science work is needed understand the patterns of co-variation between health behaviours and underlying constructs to support these efforts in the multiple health behaviour space. Temporal network analysis (e.g., Chapter 5) will be particularly useful for informing the strength, direction, and range of associations between constructs over time. These initial formal models can be derived from data using nomothetic approaches and subsequently adapted to idiographic contexts to support individuals in their pursuits of multiple health behaviour change.

### 6.5 Conclusions

This dissertation examined the co-occurrence and co-variation of multiple health impacting behaviours while testing the utility of under-employed statistical methods in the health behaviour space. I identified patterns of co-occurring health behaviours (Chapter 2) and found that these clusters were not better predictors of health outcomes relative to individual behaviours (Chapter 3). Furthermore, I analyzed the conditional dependence relationships between health behaviours (Chapter 4) which can be used to inform simulation studies and formal models of multiple behaviour enactment in the future. Lastly, I modelled the temporal dynamics of multiple health behaviours (Chapter 5) and identified temporal relationships between pandemic specific behaviour and traditional risk behaviours. Future research attempting to explain the processes involved in multiple health behaviour pursuits should incorporate the cognitive, affective, and contextual factors involved in behavioural activation, maintenance, and change. Network psychometrics are a useful tool for modelling these interconnected systems, and theory and methods from the complex systems literature offer a complimentary perspective to the traditional reductionist approach to behavioural science. Future research interesting in the co-occurrence of health behaviours at the population level should determine whether cluster analysis is used for its stated purpose of informing interventions at the national level and to empirically compare the utility of clustering approaches and other approaches such as health behaviour profiles with measures tied to national guidelines.

# APPENDIX: BEHAVIOUR PROFILE ANALYSIS

## 7.1 Introduction

Categorizing people into groups based on similar behaviours, preferences, or attitudes is a common task in the behavioural sciences. In health psychology and public health researchers and practitioners are often interested in segmenting a population into groups based on the frequencies of which they engage in health behaviours which contribute to health outcomes. To address this, researchers often use person-centered analysis such as cluster analysis or behavioural profiles to group people into categories (e.g., Clatworthy et al., 2005; Platat et al., 2006; van Allen et al., 2021). The results from these population-based segmentation analyses can then be used to identify 'who needs to do what differently' in intervention studies to decrease the prevalence of preventable diseases.

Methodologically, cluster analysis has advantages and disadvantages for characterizing health behaviours. The central advantage of clustering people into categories is that the algorithm assigns each person to a cluster based on between person similarity on a given set of features (e.g., health behaviours). Categorizing people in this way can uncover behavioural variability that variable-centered analysis can overlook. For example, previous cluster analysis on multiple health behaviours (van Allen et al., 2021) using data from the Canadian Longitudinal Study of Aging (Raina et al., 2009) revealed associations that would have been overlooked with simple analyses such as correlations. Specifically, three clusters were defined by varying combinations of walking frequency and alcohol consumption while correlations between the two variables were negligible (~r=.07).

However, clinically meaningful co-occurring behaviours that are known in the literature and present in the CLSA data were not present in the observed clusters. The combination of high physical activity and frequent sedentary behaviour, for example, is common in individuals who participate in sports (Weiler et al., 2015); data supporting this behavioural combination was present in the CLSA data but was not recovered with the cluster analysis reported in Chapter 2. Such distinctions, were not captured in the cluster analysis which illustrates the trade-offs between parsimony and nuance using hierarchical cluster analysis to describe co-occurring health behaviours.

In the multiple health behaviour change literature, cluster analysis is often performed on cross-sectional data as a descriptive exercise. Cluster analysis relies on simple algorithms to group people into clusters based on similar scores on a given set of features (e.g., health behaviours) and is a useful tool for tailoring population level behavioural interventions. However, in some instances, intervention designers may wish to target a specific combination of health behaviours not specified in our (or others') cluster analysis, or to target a subset of the population based on age groups, income, or other sociodemographic factors. In these cases, *health behaviour profiles* may be more helpful for researchers and behaviour change practitioners. Health behaviour profiles are person-centered configurations of multiple behaviours which represent all possible combinations of a given set of health behaviours (Shaw & Agahi, 2012). In the CLSA dataset, we have identified eight health behaviours of interest based on what has been measured (smoking, alcohol consumption, sleep, light physical activity, strenuous exercise, walking, fruit and vegetable consumption, and sedentary behaviour). If each variable is dichotomized, this would result in $2^8 = 256$ distinct behavioural profiles, each representing a unique combination of health behaviours. The number of profiles would also increase rapidly if researchers were interesting in examining non-dichotomized variables with more than two levels. Although health behaviour profiles provide more nuance and specificity than a traditional cluster analysis, the volume of outputs is cumbersome using traditional research dissemination methods (e.g. static tables).

## 7.2 Methods

Variables are identical to those used in previous chapters. A description of how items were filtered for the behavioural profiles are presented in Table 1. Visualized cross-tabs are presented and briefly interpreted.

**Table 1. Study Measures and Behavioural Profile Filters**

| Measure | Response Options | Label | Filter |
|---|---|---|---|
| Physical Activity Scale for the Elderly (PASE; Washburn et al., 1993). Reported physical activity levels over previous 7 days.<br>Subscales:<br>• Walking<br>• Light/moderate physical activity (PA)<br>• Exercise/strenuous physical activity (Exercise)<br>• Sitting | 1 = never,<br>2 = seldom (1-2 days),<br>3 = sometimes (3-4 days),<br>4 = often (5-7 days) | Active | Walking >=2 & PA >=2 & Exercise >=2 |
| | | Inactive | Walking <=2 & PA <=2 & Exercise <=2 |
| | | Sedentary | Sitting >=3 |
| | | Non-Sedentary | Sitting <=2 |
| Merge of two items:<br>"Have you ever smoked a whole cigarette?"<br>"At the present time, do you smoke cigarettes daily, occasionally or not at all?" | 0 = have never smoked<br>1 = do not currently smoke at all<br>2 = occasionally smoke<br>3 = smoke daily | Smoker | Smoking == "Smoke Occasionally" \| Smoking == "Smoke Daily" |
| | | Non-Smoker | Smoking == "Never Smoked" \| Smoking == "Don't Smoke" |
| Single item:<br>"About how often during the past 12 months did you drink alcohol?" | 1 (less than once a month) to 7 (almost every day) | Low Alcohol | Alcohol == 1 \| Alcohol == 2 |
| | | Medium Alcohol | Alcohol == 3 \| Alcohol == 4\| Alcohol == 5 |
| | | High Alcohol | Alcohol == 6 \| Alcohol == 7 |
| Single item:<br>During the past month, on average, how many hours of actual sleep did you get at night | Continuous 0-24 hours | Low Sleep | Sleep <=5 |
| | | Medium Sleep | Sleep == 6 \| Sleep == 7 \| Sleep == 8 |
| | | High Sleep | Sleep >=9 |
| Single item from:<br>AB SCREEN II (Abbreviated Seniors in the Community Risk | 1= less than two<br>2= two<br>3= three<br>4= four<br>5= five<br>6= six | Low Fruit/Vegetable | Fruit_Vegetable <=2 |
| | | Medium Fruit/Vegetable | Fruit_Vegetable == 3 \| Fruit_Vegetable == 4\| |

| | | | |
|---|---|---|---|
| Evaluation for Eating and Nutrition II)<br><br>In general, how many servings of fruits and vegetables do you eat in a day? | 7= seven or more | | Fruit_Vegetable == 5 |
| | | High Fruit/Vegetable | Fruit_Vegetable >= 6 |

## 7.3 Results

Associations between the frequencies of health behaviours with sociodemographic factors and health indicators are presented in Table 2. When considering the frequencies of single health behaviours, deviations from the mean-centered overall sample for self-reported general health ranged from M = -.44 (daily smokers) to M = .45 (those who exercise 5-7 days per week). Self-reported mental health ranged from M = -.29 (daily smokers) to M = .28 (those who exercise 5-7 days per week). A similar pattern is observed for self-reported healthy aging with those who exercise often reporting the highest levels of healthy aging (M = .43) and those who smoke daily reporting the lowest (M = -.43). The lowest body mass index score was reported by people who engaged in physical activity often (M = -.32) with the highest scores reported by those who never walk (M = .22) and those who consume low amounts of alcohol (M = .22). In the overall sample, a total of 8.06% of respondents live without any chronic conditions with a range of 14.41% (physical activity 5-7 days per week) to 5.72% (those who do not take walks). Sex differences were pronounced across health behaviour frequencies but most apparent in fruit and vegetable consumption with 19.04% more males than females eating less than two servings per week, when compared to the overall sample, and 14.81% more females eating more than six servings per week. Variability across income brackets were also evident for different health behaviours with people with higher annual incomes engaging in exercise 3-5 days per week more than the overall sample. The opposite pattern of results was observed for daily smoking where frequencies were higher for those in lower income brackets. Finally, variability across age brackets revealed expected relationships with younger participants engage in fewer sitting activities, exercise 3-4 days per week, smoke occasionally, and drink a ‘medium’ amount of alcohol.

Associations between behavioural combinations and sociodemographic/health indicators are presented in Table 3 while the top and bottom five combinations are presented in separate tables for counts (Table 4), health indicators (Table 5), chronic condition prevalence (Table 6), and annual income brackets (Table 7). Overall, the variability in health indicators and sociodemographics were greater when considering behavioural combinations, which revealed insights not evident when considering single behaviours in isolation.

Each of the top five behavioural combinations with the strongest associations with self-report health indicators (general health, mental health, healthy aging, life satisfaction, and BMI) included high levels of physical activity. Compared to the overall sample, the top five behavioural combinations also showed patterns of associations with being male, earning a higher annual income, and being in a younger age bracket. Conversely, the behavioural combinations with the strongest negative deviations from the sample mean each included either smoking or low sleep and were associated with being female, earning a lower annual income, and being in a younger age bracket.

**Table 2**. Health indicators associated with health behaviour frequencies (item level)

| | | General Health | | Mental Health | | Healthy Aging | | BMI | | No Chronic Conditions | Sex | Annual Income | | | | | Age Group | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | count | M | SD | M | SD | M | SD | M | SD | CC | male | <20k | 20K | 50k | 100k | 150k | 45 | 55 | 65 | 75 |
| Walking: Never | 7847 | −0.22 | 1.07 | −0.08 | 1.02 | −0.18 | 1.07 | 0.22 | 1.14 | −2.34 | −2.22 | 0.94 | 3.59 | 0.05 | −2.28 | −3.48 | −3.92 | −2.65 | 1.02 | 5.46 |
| Walking: Seldom(1-2 days) | 7257 | −0.07 | 0.99 | −0.05 | 1.01 | −0.09 | 0.99 | 0.09 | 1.05 | −0.33 | −0.80 | −0.50 | −0.80 | 0.32 | 0.83 | 0.38 | 2.99 | 0.38 | −1.89 | −1.58 |
| Walking: Sometimes (3-4 days) | 8557 | 0.01 | 0.96 | 0.01 | 0.98 | −0.00 | 0.97 | 0.04 | 1.00 | 0.16 | −2.83 | −1.00 | −1.81 | 1.03 | 1.20 | 0.71 | 1.22 | 0.29 | 0.24 | −1.85 |
| Walking: Often (5-7 days) | 24111 | 0.14 | 0.95 | 0.07 | 0.98 | 0.12 | 0.96 | −0.11 | 0.91 | 0.87 | 1.78 | −0.66 | −1.51 | 0.10 | 0.78 | 1.67 | −0.41 | 1.13 | 0.66 | −1.48 |
| Sitting: Never | 183 | 0.01 | 1.12 | 0.04 | 1.03 | 0.05 | 1.11 | −0.18 | 0.98 | 0.68 | 6.09 | 3.62 | 2.98 | −4.44 | −0.61 | −2.22 | 1.67 | −6.32 | 0.64 | 3.90 |
| Sitting: Seldom(1-2 days) | 864 | 0.13 | 1.00 | 0.01 | 0.98 | 0.10 | 0.99 | −0.20 | 0.93 | 5.37 | 0.21 | 0.00 | −0.54 | −2.15 | 1.63 | 2.27 | 14.31 | 0.18 | −8.35 | −6.23 |
| Sitting: Sometimes (3-4 days) | 2616 | 0.09 | 0.95 | −0.00 | 0.97 | 0.08 | 0.94 | −0.10 | 0.94 | 2.41 | −1.97 | −0.20 | −1.55 | 0.20 | 0.24 | 1.55 | 9.50 | −1.19 | −3.98 | −4.43 |
| Sitting: Often (5-7 days) | 44131 | 0.02 | 0.99 | 0.01 | 0.99 | 0.01 | 0.99 | 0.01 | 1.00 | −0.22 | −0.01 | −0.47 | −0.58 | 0.37 | 0.34 | 0.36 | −1.06 | 0.36 | 0.68 | −0.08 |
| PA: Never | 33198 | −0.04 | 1.00 | −0.02 | 1.01 | −0.05 | 1.01 | 0.05 | 1.02 | −0.30 | 0.32 | 0.28 | 0.64 | −0.17 | −0.38 | −0.53 | −0.20 | −0.30 | −0.09 | 0.49 |
| PA: Seldom(1-2 days) | 3698 | 0.22 | 0.92 | 0.12 | 0.95 | 0.20 | 0.93 | −0.13 | 0.90 | 0.81 | 0.41 | −2.45 | −4.65 | 1.65 | 3.52 | 2.93 | −0.56 | 1.80 | 1.64 | −2.98 |
| PA: Sometimes (3-4 days) | 438 | 0.23 | 0.93 | 0.23 | 0.91 | 0.25 | 0.92 | −0.21 | 0.91 | 1.76 | −1.61 | −2.25 | 0.40 | 1.07 | −0.33 | 2.28 | −1.77 | 7.73 | −2.17 | −3.89 |
| PA: Often (5-7 days) | 111 | 0.25 | 0.94 | 0.02 | 1.02 | 0.11 | 0.95 | −0.32 | 0.85 | 6.35 | −2.25 | −0.26 | −4.88 | −0.97 | −0.78 | 6.12 | 0.83 | −1.37 | 8.13 | −7.69 |
| Exercise: Never | 26547 | −0.13 | 1.00 | −0.07 | 1.01 | −0.12 | 1.00 | 0.12 | 1.05 | −1.23 | −1.54 | 1.07 | 2.78 | 0.81 | −1.69 | −3.39 | −3.44 | −0.13 | 1.30 | 2.18 |
| Exercise: Seldom(1-2 days) | 5890 | 0.21 | 0.93 | 0.11 | 0.95 | 0.18 | 0.93 | −0.14 | 0.89 | 1.43 | −1.09 | −2.44 | −5.84 | −0.12 | 2.75 | 5.98 | 4.56 | 0.22 | −0.51 | −4.37 |
| Exercise: Sometimes (3-4 days) | 2422 | 0.41 | 0.86 | 0.22 | 0.91 | 0.37 | 0.89 | −0.25 | 0.82 | 3.25 | 6.10 | −3.81 | −9.93 | −0.99 | 7.81 | 9.13 | 7.62 | 2.68 | −2.96 | −7.43 |
| Exercise: Often (5-7 days) | 1000 | 0.45 | 0.92 | 0.28 | 0.93 | 0.43 | 0.89 | −0.25 | 0.81 | 3.54 | 10.60 | −3.07 | −8.00 | −1.30 | 4.80 | 8.90 | 3.70 | 2.10 | −1.00 | −4.90 |
| Never Smoked | 15684 | 0.11 | 0.97 | 0.08 | 0.97 | 0.12 | 0.96 | −0.06 | 1.00 | 1.36 | −7.22 | −0.62 | −1.99 | −1.07 | 0.77 | 2.27 | 3.51 | −1.62 | −2.06 | 0.07 |
| Don't Smoke | 30558 | 0.01 | 0.99 | 0.00 | 0.99 | 0.00 | 0.99 | 0.05 | 0.98 | −0.83 | 3.71 | −0.92 | 0.12 | 0.97 | 0.33 | −0.13 | −3.33 | −0.17 | 1.93 | 1.47 |
| Smoke Occassionally | 862 | −0.14 | 1.01 | −0.14 | 1.04 | −0.16 | 0.99 | −0.00 | 1.01 | 1.92 | −0.49 | 1.99 | 0.91 | −2.77 | −0.06 | 0.22 | 11.04 | 8.14 | −8.32 | −10.96 |
| Smoke Daily | 3983 | −0.44 | 1.07 | −0.29 | 1.13 | −0.43 | 1.08 | −0.15 | 1.07 | 0.65 | −0.79 | 9.04 | 6.53 | −3.32 | −5.20 | −7.47 | 9.33 | 6.06 | −5.55 | −9.94 |
| Alcohol: Low | 10649 | −0.20 | 1.04 | −0.12 | 1.03 | −0.17 | 1.04 | 0.22 | 1.16 | −1.96 | −12.05 | 3.61 | 7.55 | −1.71 | −4.22 | −5.93 | 0.12 | −1.05 | −0.06 | 0.89 |
| Alcohol: Medium | 20685 | 0.09 | 0.94 | 0.05 | 0.96 | 0.06 | 0.95 | −0.02 | 0.94 | 1.68 | 1.50 | −2.35 | −4.09 | 1.33 | 2.51 | 3.24 | 5.55 | 1.64 | −2.63 | −4.67 |
| Alcohol: High | 12331 | 0.18 | 0.94 | 0.11 | 0.97 | 0.16 | 0.95 | −0.20 | 0.81 | 0.14 | 10.84 | −3.10 | −5.61 | 2.51 | 3.38 | 3.90 | −6.30 | −0.44 | 3.93 | 2.71 |
| Fruit/Veg: <=2 week | 11613 | −0.19 | 1.02 | −0.13 | 1.05 | −0.17 | 1.04 | 0.10 | 0.99 | 0.17 | 19.04 | 2.05 | 2.65 | 0.34 | −2.19 | −2.76 | −0.19 | −0.66 | 0.29 | 0.45 |
| Fruit/Veg: 3-5 week | 25209 | 0.04 | 0.97 | 0.03 | 0.97 | 0.02 | 0.97 | 0.01 | 1.00 | −0.01 | −2.95 | −1.00 | −0.91 | 0.25 | 0.94 | 0.94 | −0.12 | 0.23 | 0.06 | −0.28 |
| Fruit/Veg: >=6 week | 10525 | 0.23 | 0.94 | 0.15 | 0.95 | 0.22 | 0.94 | −0.13 | 0.98 | 0.18 | −14.81 | −2.15 | −3.93 | 0.65 | 2.08 | 3.25 | 0.27 | 1.71 | 0.60 | −2.68 |

**Note:** Heatmap coloring highlights positive deviations from group mean (green) and negative deviations from group mean (red). Color intensity corresponds to strength of deviation (lighter color = smaller deviation, darker color = larger deviation).

**Table 3**. Eighty-four behavioural combinations and associations with health indicators.

84 Behaviour Profiles

Health Outcomes & Sociodemographics Indicators

| | | Health Indicators | | | | | | Sociodemographics | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Profile | N | Gen.H[1] | Men.H[1] | H.Age[1] | LifeSat[1] | BMI[1] | No CC[2] | Male[2] | <$20k[2] | $20-$49k[2] | $50-$99k[2] | $100-$149k[2] | $150k+[2] | 45-54[2] | 55-64[2] | 65-74[2] | 75-85[2] |
| Sedentary Non-Smokers | 42400 | 0.06 | 0.04 | 0.05 | 0.05 | 0.02 | −0.14 | −0.03 | −1.15 | −1.15 | 0.62 | 0.71 | 1.05 | −1.32 | −0.35 | 1.00 | 0.57 |
| Sedentary & Med Fruit | 24676 | 0.04 | 0.03 | 0.02 | 0.05 | 0.01 | −0.14 | −2.99 | −1.03 | −0.96 | 0.37 | 0.92 | 0.93 | −0.40 | 0.32 | 0.22 | −0.24 |
| Non-Smoker & Med Fruit | 23155 | 0.06 | 0.04 | 0.05 | 0.07 | 0.02 | −0.13 | −2.51 | −1.50 | −1.28 | 0.56 | 1.19 | 1.36 | −0.88 | −0.18 | 0.43 | 0.53 |
| Sedentary Med Sleep | 22981 | 0.13 | 0.06 | 0.09 | 0.05 | 0.01 | 0.06 | 1.48 | −1.68 | −4.35 | 0.30 | 2.36 | 3.69 | −0.85 | 1.01 | 1.34 | −1.60 |
| Non-Smoker & Med Sleep | 22372 | 0.15 | 0.08 | 0.11 | 0.06 | 0.02 | −0.06 | 1.35 | −1.94 | −4.66 | 0.16 | 2.53 | 4.15 | −1.17 | 0.16 | 1.53 | −0.62 |
| Sedentary & Med Alcohol | 18999 | 0.10 | 0.06 | 0.06 | 0.08 | −0.02 | 1.55 | 1.25 | −2.68 | −4.43 | 1.53 | 2.60 | 3.59 | 4.97 | 1.86 | −2.17 | −4.77 |
| Non-Smoker & Med Alcohol | 18881 | 0.12 | 0.08 | 0.09 | 0.10 | −0.01 | 1.49 | 1.31 | −2.91 | −4.66 | 1.31 | 3.00 | 3.92 | 4.81 | 1.17 | −2.06 | −4.03 |
| Sedentary & High Alcohol | 11503 | 0.20 | 0.11 | 0.17 | 0.15 | −0.20 | 0.05 | 10.85 | −3.29 | −6.13 | 2.55 | 3.75 | 4.29 | −6.47 | −0.23 | 4.33 | 2.27 |
| Inactive & Sedentary | 11421 | −0.22 | −0.10 | −0.22 | −0.14 | 0.23 | −1.76 | −3.20 | 0.82 | 2.92 | 0.33 | −1.72 | −3.04 | −1.04 | −1.32 | −0.18 | 2.44 |
| Sedentary & Low Fruit | 11321 | −0.19 | −0.13 | −0.17 | −0.16 | 0.10 | 0.11 | 19.00 | 2.02 | 2.69 | 0.33 | −2.20 | −2.76 | −0.41 | −0.70 | 0.41 | 0.59 |
| Non-Smoker & High Alcohol | 11129 | 0.22 | 0.13 | 0.20 | 0.17 | −0.18 | −0.04 | 11.13 | −3.70 | −6.30 | 2.80 | 3.64 | 4.68 | −7.47 | −1.15 | 4.69 | 3.84 |
| Med Alcohol & Med Fruit | 10505 | 0.11 | 0.07 | 0.05 | 0.10 | −0.02 | 1.49 | −1.12 | −2.93 | −4.75 | 1.31 | 3.12 | 4.06 | 5.68 | 1.96 | −2.96 | −4.78 |
| Med Alcohol & Med Sleep | 10324 | 0.18 | 0.10 | 0.12 | 0.08 | 0.01 | 1.47 | 1.97 | −3.04 | −7.19 | 0.21 | 4.23 | 6.61 | 4.79 | 1.88 | −1.45 | −5.32 |
| Inactive Non-Smokers | 10309 | −0.18 | −0.07 | −0.17 | −0.10 | 0.26 | −1.79 | −2.97 | 0.26 | 2.35 | 0.25 | −1.24 | −2.41 | −1.72 | −2.18 | 0.13 | 3.67 |
| Sedentary & High Fruit | 10292 | 0.23 | 0.15 | 0.22 | 0.14 | −0.12 | 0.09 | −14.69 | −2.14 | −3.93 | 0.68 | 2.07 | 3.16 | −0.04 | 1.68 | 0.78 | −2.52 |
| Non-Smoker & High Fruit | 9980 | 0.24 | 0.16 | 0.23 | 0.16 | −0.12 | 0.23 | −14.69 | −2.33 | −4.23 | 0.62 | 2.18 | 3.69 | −0.18 | 1.40 | 1.01 | −2.33 |
| Non-Smoker & Low Fruit | 9789 | −0.13 | −0.08 | −0.11 | −0.10 | 0.14 | 0.04 | 20.41 | 0.67 | 1.89 | 0.80 | −1.47 | −1.83 | −1.73 | −2.18 | 1.50 | 2.32 |
| Sedentary & Low Alcohol | 9524 | −0.17 | −0.10 | −0.15 | −0.13 | 0.22 | −2.01 | −12.22 | 3.13 | 7.03 | −0.97 | −3.97 | −5.80 | −0.39 | −0.77 | 0.45 | 0.62 |
| Non-Smoker & Low Alcohol | 9436 | −0.16 | −0.09 | −0.13 | −0.11 | 0.23 | −2.08 | −12.11 | 2.58 | 7.23 | −1.09 | −3.90 | −5.58 | −1.27 | −1.74 | 0.70 | 2.22 |
| High Alcohol & Med Sleep | 6578 | 0.24 | 0.14 | 0.19 | 0.15 | −0.17 | −0.00 | 10.93 | −3.71 | −8.96 | 1.88 | 4.80 | 7.07 | −6.76 | 0.72 | 4.82 | 1.13 |
| High Alcohol & Med Fruit | 6217 | 0.22 | 0.13 | 0.18 | 0.19 | −0.20 | 0.18 | 8.87 | −3.61 | −7.31 | 2.61 | 4.54 | 5.01 | −6.19 | 0.44 | 4.04 | 1.61 |
| Inactive & Med Fruit | 5982 | −0.17 | −0.05 | −0.19 | −0.09 | 0.23 | −1.99 | −8.29 | 0.18 | 2.66 | 0.30 | −1.02 | −2.52 | −1.04 | −1.44 | −0.31 | 2.70 |
| Low Alcohol & Med Fruit | 5181 | −0.16 | −0.09 | −0.14 | −0.11 | 0.24 | −2.13 | −16.25 | 2.42 | 8.03 | −1.48 | −3.93 | −5.36 | −1.28 | −0.79 | 1.04 | 0.94 |
| Inactive & Med Sleep | 5146 | −0.10 | −0.04 | −0.14 | −0.10 | 0.25 | −1.36 | −0.71 | −0.71 | −0.34 | 0.22 | 0.43 | −0.72 | −1.27 | −0.64 | 0.99 | 0.82 |
| Med Alcohol & High Fruit | 4499 | 0.30 | 0.18 | 0.27 | 0.18 | −0.14 | 1.65 | −15.29 | −3.71 | −7.02 | 0.54 | 4.09 | 6.66 | 5.61 | 3.25 | −2.44 | −6.52 |
| Inactive & Med Alcohol | 4445 | −0.09 | −0.03 | −0.14 | −0.05 | 0.17 | −0.23 | 0.03 | −2.30 | −1.42 | 2.17 | 1.27 | 0.29 | 5.12 | 0.04 | −2.61 | −2.64 |
| Low Alcohol & Med Sleep | 4362 | −0.08 | −0.08 | −0.10 | −0.12 | 0.23 | −1.94 | −10.26 | 2.67 | 4.51 | −0.85 | −2.53 | −3.96 | −0.87 | 0.07 | 0.65 | 0.05 |
| Med Alcohol & Low Fruit | 4309 | −0.09 | −0.05 | −0.11 | −0.07 | 0.09 | 2.29 | 23.93 | −1.17 | −1.24 | 2.90 | 0.24 | −0.19 | 4.76 | 0.21 | −1.12 | −3.95 |
| Sedentary Smokers | 4120 | −0.35 | −0.24 | −0.36 | −0.33 | −0.12 | 0.73 | −1.24 | 6.64 | 4.65 | −2.53 | −3.38 | −5.71 | 8.85 | 6.91 | −5.78 | −10.08 |
| Inactive & Low Fruit | 3771 | −0.39 | −0.23 | −0.36 | −0.28 | 0.25 | −0.85 | 13.22 | 2.05 | 5.10 | 0.07 | −2.84 | −4.68 | 0.74 | −1.16 | −1.12 | 1.44 |
| Sedentary Low Sleep | 3661 | −0.28 | −0.28 | −0.28 | −0.40 | 0.22 | −2.79 | −5.48 | 2.66 | 1.30 | −2.21 | −1.40 | −1.63 | −0.11 | 1.19 | 0.28 | −1.46 |
| Non-Smoker & Low Sleep | 3494 | −0.26 | −0.25 | −0.24 | −0.36 | 0.23 | −2.88 | −5.71 | 1.89 | 0.73 | −1.83 | −0.77 | −1.45 | −1.59 | 0.74 | 0.78 | −0.04 |
| High Alcohol & Low Fruit | 2799 | −0.02 | −0.03 | −0.02 | −0.02 | −0.10 | 0.34 | 30.18 | −1.70 | −2.33 | 3.22 | 0.58 | 1.31 | −6.26 | −2.10 | 3.32 | 4.94 |
| Inactive & Low Alcohol | 2782 | −0.41 | −0.19 | −0.39 | −0.27 | 0.46 | −3.32 | −14.95 | 4.36 | 8.12 | −1.44 | −4.63 | −7.19 | −0.50 | −2.02 | 0.40 | 2.02 |
| Active & Sedentary | 2767 | 0.33 | 0.19 | 0.31 | 0.19 | −0.31 | 1.99 | 0.67 | −2.89 | −6.71 | −0.19 | 4.79 | 6.57 | 2.46 | 3.53 | −0.60 | −5.49 |
| Active Non-Smokers | 2665 | 0.36 | 0.21 | 0.33 | 0.22 | −0.31 | 2.03 | 1.07 | −3.27 | −7.21 | −0.15 | 4.99 | 7.20 | 2.81 | 2.82 | −0.62 | −5.10 |
| High Alcohol & High Fruit | 2601 | 0.39 | 0.24 | 0.34 | 0.25 | −0.32 | 0.09 | −5.73 | −3.86 | −7.88 | 1.24 | 5.45 | 6.33 | −6.25 | 0.60 | 5.93 | −0.39 |
| Low Alcohol & Low Fruit | 2494 | −0.34 | −0.22 | −0.31 | −0.29 | 0.27 | −1.44 | 4.51 | 6.36 | 8.08 | −2.21 | −4.93 | −7.61 | 2.11 | −1.65 | −0.30 | −0.26 |
| Inactive & High Alcohol | 2475 | −0.05 | −0.01 | −0.05 | 0.02 | −0.02 | −1.03 | 9.77 | −2.64 | −2.18 | 3.61 | 1.14 | −0.25 | −6.64 | −1.49 | 3.23 | 4.81 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Low Alcohol & High Fruit | 1972 | 0.01 | 0.04 | 0.03 | 0.01 | 0.08 | −1.72 | −23.09 | 0.16 | 3.18 | 2.10 | −2.29 | −4.17 | 1.03 | 0.81 | −0.73 | −1.21 |
| Smoker & Med Sleep | 1933 | −0.23 | −0.18 | −0.30 | −0.29 | −0.11 | 1.56 | 1.49 | 4.73 | 3.52 | −2.26 | −1.32 | −4.03 | 7.84 | 7.83 | −5.14 | −10.64 |
| Smoker & Med Fruit | 1916 | −0.27 | −0.18 | −0.32 | −0.25 | −0.11 | 1.39 | −8.81 | 4.77 | 3.71 | −3.44 | −2.02 | −3.94 | 9.81 | 5.53 | −5.03 | −10.41 |
| Smoker & Low Fruit | 1782 | −0.50 | −0.36 | −0.49 | −0.48 | −0.12 | 0.92 | 11.67 | 9.59 | 6.90 | −2.48 | −6.00 | −7.70 | 8.59 | 7.96 | −6.34 | −10.31 |
| Inactive & High Fruit | 1766 | −0.02 | 0.01 | 0.01 | 0.00 | 0.15 | −2.06 | −20.56 | −0.46 | −0.70 | 0.24 | −0.30 | −0.73 | −1.45 | −1.08 | 1.40 | 1.04 |
| Smoker & Med Alcohol | 1703 | −0.24 | −0.17 | −0.28 | −0.28 | −0.12 | 3.80 | 2.81 | 3.78 | 2.04 | 1.19 | −2.73 | −3.89 | 14.55 | 7.34 | −9.72 | −12.28 |
| Active & Med Sleep | 1571 | 0.41 | 0.24 | 0.36 | 0.21 | −0.29 | 1.81 | 2.01 | −3.57 | −8.27 | −3.10 | 5.60 | 11.06 | 2.00 | 4.22 | 0.41 | −6.72 |
| Sedentary High Sleep | 1511 | −0.09 | −0.16 | −0.06 | −0.01 | 0.12 | −4.55 | −7.87 | 3.33 | 5.72 | −1.43 | −3.70 | −4.50 | −11.11 | 1.09 | 4.07 | 5.85 |
| Med Alcohol & Low Sleep | 1504 | −0.15 | −0.21 | −0.18 | −0.30 | 0.14 | −1.54 | −3.29 | −0.42 | −1.86 | −1.22 | 1.15 | 1.59 | 4.39 | 3.17 | −2.32 | −5.34 |
| Active & Med Fruit | 1441 | 0.30 | 0.15 | 0.26 | 0.20 | −0.29 | 3.04 | 3.71 | −3.10 | −8.19 | 1.85 | 3.89 | 7.47 | 2.74 | 3.81 | −0.01 | −6.63 |
| Non-Smoker & High Sleep | 1436 | −0.07 | −0.13 | −0.01 | 0.01 | 0.15 | −4.93 | −7.67 | 2.83 | 6.01 | −1.30 | −3.77 | −4.23 | −12.06 | −0.94 | 4.94 | 7.96 |
| Inactive Smokers | 1323 | −0.53 | −0.35 | −0.58 | −0.47 | −0.04 | −0.43 | −3.22 | 5.82 | 7.87 | −1.05 | −4.91 | −7.73 | 7.36 | 4.51 | −3.60 | −8.37 |
| Active & Med Alcohol | 1306 | 0.37 | 0.21 | 0.34 | 0.21 | −0.31 | 3.58 | 0.21 | −3.53 | −8.26 | −1.55 | 5.21 | 10.42 | 6.65 | 5.37 | −3.26 | −8.85 |
| Smoker & Low Alcohol | 1157 | −0.53 | −0.34 | −0.55 | −0.50 | 0.11 | −0.80 | −11.50 | 11.62 | 10.34 | −6.69 | −6.89 | −8.60 | 12.09 | 5.08 | −6.20 | −11.07 |
| Smoker & High Alcohol | 1144 | −0.18 | −0.17 | −0.22 | −0.17 | −0.40 | 1.82 | 8.59 | 2.90 | 0.85 | −0.36 | 0.83 | −3.39 | 5.62 | 6.55 | −3.30 | −8.97 |
| Inactive & Low Sleep | 992 | −0.50 | −0.39 | −0.48 | −0.60 | 0.46 | −4.63 | −7.67 | 2.80 | 4.22 | −3.56 | −1.07 | −3.92 | 0.51 | −0.65 | −0.32 | 0.35 |
| Active & High Fruit | 992 | 0.47 | 0.30 | 0.45 | 0.24 | −0.38 | 1.72 | −13.82 | −3.15 | −7.27 | −2.65 | 7.09 | 7.17 | 4.75 | 4.29 | −2.03 | −7.11 |
| Low Alcohol & Low Sleep | 954 | −0.56 | −0.45 | −0.51 | −0.60 | 0.50 | −4.29 | −13.25 | 6.17 | 8.49 | −3.00 | −5.47 | −6.68 | −0.41 | 0.08 | −0.23 | 0.47 |
| Nonsedentary Non-Smokers | 920 | 0.16 | 0.06 | 0.16 | 0.10 | −0.18 | 3.90 | 0.47 | −0.13 | −0.97 | −2.10 | 2.13 | 2.39 | 11.30 | −1.46 | −6.33 | −3.61 |
| High Alcohol & Low Sleep | 806 | −0.02 | −0.13 | −0.02 | −0.17 | −0.09 | −2.35 | 4.13 | −0.46 | −4.94 | 2.33 | 1.86 | 0.57 | −2.87 | −0.36 | 2.90 | 0.23 |
| Active & High Alcohol | 792 | 0.46 | 0.27 | 0.41 | 0.28 | −0.41 | 2.29 | 9.11 | −4.66 | −11.17 | 1.20 | 8.88 | 8.27 | −2.84 | 2.22 | 4.50 | −3.98 |
| Med Alcohol & High Sleep | 576 | −0.02 | −0.13 | −0.02 | 0.06 | 0.09 | −3.89 | −8.48 | 0.93 | 4.85 | −0.76 | −1.03 | −4.50 | −7.97 | 3.59 | 1.95 | 2.33 |
| Nonsedentary & Med Fruit | 521 | 0.17 | 0.03 | 0.11 | 0.14 | −0.21 | 6.34 | −0.92 | 0.09 | 0.77 | −4.42 | 2.00 | 1.85 | 13.34 | −3.21 | −7.47 | −2.76 |
| Smoker & High Fruit | 494 | −0.08 | −0.06 | −0.09 | −0.10 | −0.18 | −0.57 | −17.12 | 2.02 | 1.30 | 0.20 | 0.41 | −4.39 | 10.03 | 8.69 | −7.41 | −11.41 |
| Nonsedentary Med Sleep | 450 | 0.22 | 0.12 | 0.16 | 0.10 | −0.21 | 3.50 | −2.43 | −1.23 | −0.69 | −4.73 | 2.78 | 4.52 | 11.80 | −0.44 | −5.40 | −6.06 |
| Smoker & Low Sleep | 448 | −0.69 | −0.62 | −0.69 | −0.90 | 0.12 | −2.70 | −2.89 | 14.64 | 8.12 | −9.29 | −7.40 | −7.23 | 15.09 | 5.05 | −7.55 | −12.70 |
| Nonsedentary & Med Alcohol | 442 | 0.28 | 0.13 | 0.22 | 0.17 | −0.23 | 6.87 | 1.80 | −2.50 | −5.47 | −1.95 | 6.30 | 5.98 | 21.09 | −0.10 | −11.18 | −9.90 |
| High Alcohol & High Sleep | 441 | 0.10 | −0.05 | 0.14 | 0.16 | −0.12 | −3.30 | 5.78 | −1.36 | −4.30 | 3.79 | −0.45 | 1.95 | −13.96 | −2.29 | 5.85 | 10.30 |
| Inactive & High Sleep | 436 | −0.36 | −0.37 | −0.29 | −0.21 | 0.37 | −6.00 | −9.65 | 3.73 | 6.48 | 1.23 | −6.22 | −5.90 | −11.29 | 0.80 | 2.29 | 8.11 |
| Active & Low Alcohol | 410 | 0.08 | 0.07 | 0.07 | 0.09 | −0.23 | −0.50 | −11.05 | 0.43 | 2.30 | −0.47 | 1.05 | −3.70 | 4.29 | 0.20 | −0.72 | −3.87 |
| Active & Low Fruit | 386 | 0.12 | 0.09 | 0.13 | 0.10 | −0.24 | −0.55 | 28.10 | −1.01 | −0.48 | −2.31 | 2.43 | 2.62 | −1.59 | −0.91 | 0.18 | 2.23 |
| Low Alcohol & High Sleep | 342 | −0.28 | −0.30 | −0.29 | −0.28 | 0.41 | −6.60 | −21.61 | 9.83 | 15.97 | −6.79 | −8.23 | −10.19 | −10.41 | −1.59 | 8.76 | 3.14 |
| Nonsedentary & Low Fruit | 279 | −0.12 | −0.12 | −0.09 | −0.17 | −0.06 | 2.69 | 20.08 | 3.29 | 1.29 | 0.29 | −1.95 | −2.95 | 9.28 | 1.33 | −5.48 | −5.24 |
| Inactive & Nonsedentary | 254 | −0.16 | −0.13 | −0.13 | −0.17 | 0.04 | 2.96 | 4.05 | 3.78 | 4.55 | −7.81 | 2.29 | −3.46 | 12.78 | −4.83 | −6.47 | −1.57 |
| Nonsedentary & High Fruit | 225 | 0.26 | 0.19 | 0.30 | 0.13 | −0.34 | 3.50 | −20.21 | −2.11 | −3.80 | −1.40 | 3.00 | 7.19 | 14.69 | 3.56 | −7.40 | −10.94 |
| Nonsedentary & Low Alcohol | 223 | −0.19 | −0.25 | −0.13 | −0.15 | 0.02 | 2.70 | −6.50 | 2.40 | 6.69 | −3.80 | −2.65 | −3.39 | 13.71 | −3.30 | −6.81 | −3.70 |
| Nonsedentary & High Alcohol | 220 | 0.27 | 0.12 | 0.24 | 0.07 | −0.44 | 5.12 | 6.35 | 1.15 | −4.71 | −2.04 | 2.55 | 4.48 | −0.29 | −0.64 | 1.60 | −0.77 |
| Active & Low Sleep | 189 | 0.01 | −0.22 | 0.06 | −0.29 | −0.19 | −1.71 | −3.60 | 2.27 | −7.93 | 5.75 | −0.60 | 1.64 | −1.86 | 2.92 | 2.53 | −3.69 |
| Smoker & High Sleep | 188 | −0.44 | −0.52 | −0.56 | −0.41 | −0.11 | −0.61 | −3.89 | 13.48 | 8.65 | −6.80 | −6.89 | −8.91 | 0.40 | 8.43 | −1.59 | −7.33 |
| Active Smokers | 149 | −0.12 | −0.10 | −0.11 | −0.25 | −0.29 | 4.02 | −2.12 | 6.41 | 1.03 | −5.88 | 2.46 | −1.62 | 4.67 | 12.97 | −2.59 | −15.14 |
| Nonsedentary Smokers | 121 | −0.26 | −0.32 | −0.39 | −0.35 | −0.28 | 8.47 | 8.75 | 6.73 | 9.26 | −7.78 | −5.43 | −4.61 | 18.43 | 3.54 | −10.18 | −11.89 |
| Active & High Sleep | 64 | 0.23 | 0.21 | 0.14 | 0.33 | −0.22 | 1.31 | −2.23 | 0.58 | −3.49 | −9.96 | 6.44 | 3.49 | −1.20 | 7.06 | −6.21 | 0.25 |
| Nonsedentary High Sleep | 36 | −0.08 | −0.13 | 0.07 | −0.02 | −0.09 | 0.27 | 6.46 | 5.44 | 1.20 | −2.84 | −0.33 | −2.59 | −3.98 | −7.00 | 9.93 | 0.94 |

[1] Standardized Means

[2] Profile Sample % - Overall Sample %

Variable Names: Gen.H = General Health, Men.H = Mental Health, LifeSat = Life Satisfaction, BMI = Body Mass Index, No CC = No Chronic Conditions, Income Levels = <$20k/ $20-$49k/ $50-$99k/ $100-$149k/ $150k+, Age Groups = 45-54/ 55-64/ 65-74/ 75-85

**Table 4**. Behavioural combinations (top and bottom five ranked by counts)

| | | Health Indicators | | | | | | Sociodemographics | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Profile** | **N** | **Gen.H[1]** | **Men.H[1]** | **H.Age[1]** | **LifeSat[1]** | **BMI[1]** | **No CC[2]** | **Male[2]** | **<$20k[2]** | **$20-$49k[2]** | **$50-$99k[2]** | **$100-$149k[2]** | **$150k+[2]** | **45-54[2]** | **55-64[2]** | **65-74[2]** | **75-85[2]** |
| Sedentary Non-Smokers | 42400 | 0.06 | 0.04 | 0.05 | 0.05 | 0.02 | −0.14 | −0.03 | −1.15 | −1.15 | 0.62 | 0.71 | 1.05 | −1.32 | −0.35 | 1.00 | 0.57 |
| Sedentary Med Sleep | 22981 | 0.13 | 0.06 | 0.09 | 0.05 | 0.01 | 0.06 | 1.48 | −1.68 | −4.35 | 0.30 | 2.36 | 3.69 | −0.85 | 1.01 | 1.34 | −1.60 |
| Non-Smoker & Med Sleep | 22372 | 0.15 | 0.08 | 0.11 | 0.06 | 0.02 | −0.06 | 1.35 | −1.94 | −4.66 | 0.16 | 2.53 | 4.15 | −1.17 | 0.16 | 1.53 | −0.62 |
| Sedentary & Med Alcochol | 18999 | 0.10 | 0.06 | 0.06 | 0.08 | −0.02 | 1.55 | 1.25 | −2.68 | −4.43 | 1.53 | 2.60 | 3.59 | 4.97 | 1.86 | −2.17 | −4.77 |
| Non-Smoker & Med Alcohol | 18881 | 0.12 | 0.08 | 0.09 | 0.10 | −0.01 | 1.49 | 1.31 | −2.91 | −4.66 | 1.31 | 3.00 | 3.92 | 4.81 | 1.17 | −2.06 | −4.03 |
| Nonsedentary Smokers | 121 | −0.26 | −0.32 | −0.39 | −0.35 | −0.28 | 8.47 | 8.75 | 6.73 | 9.26 | −7.78 | −5.43 | −4.61 | 18.43 | 3.54 | −10.18 | −11.89 |
| Active & High Sleep | 64 | 0.23 | 0.21 | 0.14 | 0.33 | −0.22 | 1.31 | −2.23 | 0.58 | −3.49 | −9.96 | 6.44 | 3.49 | −1.20 | 7.06 | −6.21 | 0.25 |
| Active & Nonsedentary | 61 | 0.37 | 0.26 | 0.33 | 0.33 | −0.35 | 8.33 | 11.56 | 2.53 | −10.69 | −8.81 | 5.95 | 10.89 | 19.70 | −5.77 | −3.73 | −10.30 |
| Nonsedentary Low Sleep | 59 | −0.17 | −0.27 | −0.14 | −0.50 | −0.02 | 0.41 | −6.73 | 6.19 | −5.16 | 7.28 | −1.75 | −1.84 | 22.95 | 6.98 | −18.32 | −11.72 |
| Nonsedentary High Sleep | 36 | −0.08 | −0.13 | 0.07 | −0.02 | −0.09 | 0.27 | 6.46 | 5.44 | 1.20 | −2.84 | −0.33 | −2.59 | −3.98 | −7.00 | 9.93 | 0.94 |

[1] Standardized Means

[2] Profile Sample % - Overall Sample %

Variable Names: Gen.H = General Health, Men.H = Mental Health, LifeSat = Life Satisfaction, BMI = Body Mass Index, No CC = No Chronic Conditions, Income Levels = <$20k/ $20-$49k/ $50-$99k/ $100-$149k/ $150k+, Age Groups = 45-54/ 55-64/ 65-74/ 75-85

**Table 5.** Behavioural combinations (top and bottom five ranked by health indicators)

| | | Health Indicators | | | | | | Sociodemographics | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Profile** | **N** | **Gen.H[1]** | **Men.H[1]** | **H.Age[1]** | **LifeSat[1]** | **BMI[1]** | **No CC[2]** | **Male[2]** | **<$20k[2]** | **$20-$49k[2]** | **$50-$99k[2]** | **$100-$149k[2]** | **$150k+[2]** | **45-54[2]** | **55-64[2]** | **65-74[2]** | **75-85[2]** |
| Active & High Alcohol | 792 | 0.46 | 0.27 | 0.41 | 0.28 | −0.41 | 2.29 | 9.11 | −4.66 | −11.17 | 1.20 | 8.88 | 8.27 | −2.84 | 2.22 | 4.50 | −3.98 |
| Active & Med Sleep | 1571 | 0.41 | 0.24 | 0.36 | 0.21 | −0.29 | 1.81 | 2.01 | −3.57 | −8.27 | −3.10 | 5.60 | 11.06 | 2.00 | 4.22 | 0.41 | −6.72 |
| Active & Nonsedentary | 61 | 0.37 | 0.26 | 0.33 | 0.33 | −0.35 | 8.33 | 11.56 | 2.53 | −10.69 | −8.81 | 5.95 | 10.89 | 19.70 | −5.77 | −3.73 | −10.30 |
| Active & Med Alcohol | 1306 | 0.37 | 0.21 | 0.34 | 0.21 | −0.31 | 3.58 | 0.21 | −3.53 | −8.26 | −1.55 | 5.21 | 10.42 | 6.65 | 5.37 | −3.26 | −8.85 |
| Active Non-Smokers | 2665 | 0.36 | 0.21 | 0.33 | 0.22 | −0.31 | 2.03 | 1.07 | −3.27 | −7.21 | −0.15 | 4.99 | 7.20 | 2.81 | 2.82 | −0.62 | −5.10 |
| Inactive & Low Sleep | 992 | −0.50 | −0.39 | −0.48 | −0.60 | 0.46 | −4.63 | −7.67 | 2.80 | 4.22 | −3.56 | −1.07 | −3.92 | 0.51 | −0.65 | −0.32 | 0.35 |
| Smoker & Low Alcohol | 1157 | −0.53 | −0.34 | −0.55 | −0.50 | 0.11 | −0.80 | −11.50 | 11.62 | 10.34 | −6.69 | −6.89 | −8.60 | 12.09 | 5.08 | −6.20 | −11.07 |
| Inactive Smokers | 1323 | −0.53 | −0.35 | −0.58 | −0.47 | −0.04 | −0.43 | −3.22 | 5.82 | 7.87 | −1.05 | −4.91 | −7.73 | 7.36 | 4.51 | −3.60 | −8.37 |
| Low Alcohol & Low Sleep | 954 | −0.56 | −0.45 | −0.51 | −0.60 | 0.50 | −4.29 | −13.25 | 6.17 | 8.49 | −3.00 | −5.47 | −6.68 | −0.41 | 0.08 | −0.23 | 0.47 |
| Smoker & Low Sleep | 448 | −0.69 | −0.62 | −0.69 | −0.90 | 0.12 | −2.70 | −2.89 | 14.64 | 8.12 | −9.29 | −7.40 | −7.23 | 15.09 | 5.05 | −7.55 | −12.70 |

[1] Standardized Means

[2] Profile Sample % - Overall Sample %

Variable Names: Gen.H = General Health, Men.H = Mental Health, LifeSat = Life Satisfaction, BMI = Body Mass Index, No CC = No Chronic Conditions, Income Levels = <$20k/ $20-$49k/ $50-$99k/ $100-$149k/ $150k+, Age Groups = 45-54/ 55-64/ 65-74/ 75-85

**Table 6**. Behavioural combinations (top and bottom five ranked by chronic conditions)

| | | Health Indicators | | | | | | Sociodemographics | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Profile** | **N** | **Gen.H[1]** | **Men.H[1]** | **H.Age[1]** | **LifeSat[1]** | **BMI[1]** | **No CC[2]** | **Male[2]** | **<$20k[2]** | **$20-$49k[2]** | **$50-$99k[2]** | **$100-$149k[2]** | **$150k+[2]** | **45-54[2]** | **55-64[2]** | **65-74[2]** | **75-85[2]** |
| Nonsedentary Smokers | 121 | −0.26 | −0.32 | −0.39 | −0.35 | −0.28 | 8.47 | 8.75 | 6.73 | 9.26 | −7.78 | −5.43 | −4.61 | 18.43 | 3.54 | −10.18 | −11.89 |
| Active & Nonsedentary | 61 | 0.37 | 0.26 | 0.33 | 0.33 | −0.35 | 8.33 | 11.56 | 2.53 | −10.69 | −8.81 | 5.95 | 10.89 | 19.70 | −5.77 | −3.73 | −10.30 |
| Nonsedentary & Med Alcochol | 442 | 0.28 | 0.13 | 0.22 | 0.17 | −0.23 | 6.87 | 1.80 | −2.50 | −5.47 | −1.95 | 6.30 | 5.98 | 21.09 | −0.10 | −11.18 | −9.90 |
| Nonsedentary & High Alcohol | 220 | 0.27 | 0.12 | 0.24 | 0.07 | −0.44 | 5.12 | 6.35 | 1.15 | −4.71 | −2.04 | 2.55 | 4.48 | −0.29 | −0.64 | 1.60 | −0.77 |
| Active Smokers | 149 | −0.12 | −0.10 | −0.11 | −0.25 | −0.29 | 4.02 | −2.12 | 6.41 | 1.03 | −5.88 | 2.46 | −1.62 | 4.67 | 12.97 | −2.59 | −15.14 |
| Sedentary High Sleep | 1511 | −0.09 | −0.16 | −0.06 | −0.01 | 0.12 | −4.55 | −7.87 | 3.33 | 5.72 | −1.43 | −3.70 | −4.50 | −11.11 | 1.09 | 4.07 | 5.85 |
| Inactive & Low Sleep | 992 | −0.50 | −0.39 | −0.48 | −0.60 | 0.46 | −4.63 | −7.67 | 2.80 | 4.22 | −3.56 | −1.07 | −3.92 | 0.51 | −0.65 | −0.32 | 0.35 |
| Non-Smoker & High Sleep | 1436 | −0.07 | −0.13 | −0.01 | 0.01 | 0.15 | −4.93 | −7.67 | 2.83 | 6.01 | −1.30 | −3.77 | −4.23 | −12.06 | −0.94 | 4.94 | 7.96 |
| Inactive & High Sleep | 436 | −0.36 | −0.37 | −0.29 | −0.21 | 0.37 | −6.00 | −9.65 | 3.73 | 6.48 | 1.23 | −6.22 | −5.90 | −11.29 | 0.80 | 2.29 | 8.11 |
| Low Alcohol & High Sleep | 342 | −0.28 | −0.30 | −0.29 | −0.28 | 0.41 | −6.60 | −21.61 | 9.83 | 15.97 | −6.79 | −8.23 | −10.19 | −10.41 | −1.59 | 8.76 | 3.14 |

[1] Standardized Means

[2] Profile Sample % - Overall Sample %

Variable Names: Gen.H = General Health, Men.H = Mental Health, LifeSat = Life Satisfaction, BMI = Body Mass Index, No CC = No Chronic Conditions, Income Levels = <$20k/ $20-$49k/ $50-$99k/ $100-$149k/ $150k+, Age Groups = 45-54/ 55-64/ 65-74/ 75-85

The prevalence of people living without any chronic conditions ranged from 16.52% (8.47% above the 8.06% sample average) for a small group of non-sedentary and younger individuals to 1.46% (6.6% below the 8.06% sample average) for those who consume low amounts of alcohol and sleep more than nine hours a day. The most common health behaviour associated with a greater prevalence of people living without chronic conditions was non-sedentary behaviour. Interestingly, two of the top five included smokers, although confounds with younger age brackets are evident. In most instances, the top five were associated with more males than the overall sample while the bottom five was associated with females in all instances. In the bottom five, all behaviour combinations included sleeping greater than nine hours a day or less than five hours a day.

**Table 7**. Behavioural combinations (top and bottom five ranked by income)

| | | Health Indicators | | | | | | Sociodemographics | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Profile | N | Gen.H[1] | Men.H[1] | H.Age[1] | LifeSat[1] | BMI[1] | No CC[2] | Male[2] | <$20k[2] | $20-$49k[2] | $50-$99k[2] | $100-$149k[2] | $150k+[2] | 45-54[2] | 55-64[2] | 65-74[2] | 75-85[2] |
| Active & Med Alcohol | 1306 | 0.37 | 0.21 | 0.34 | 0.21 | −0.31 | 3.58 | 0.21 | −3.53 | −8.26 | −1.55 | 5.21 | 10.42 | 6.65 | 5.37 | −3.26 | −8.85 |
| Active & Med Sleep | 1571 | 0.41 | 0.24 | 0.36 | 0.21 | −0.29 | 1.81 | 2.01 | −3.57 | −8.27 | −3.10 | 5.60 | 11.06 | 2.00 | 4.22 | 0.41 | −6.72 |
| Non-Smoker & High Alcohol | 11129 | 0.22 | 0.13 | 0.20 | 0.17 | −0.18 | −0.04 | 11.13 | −3.70 | −6.30 | 2.80 | 3.64 | 4.68 | −7.47 | −1.15 | 4.69 | 3.84 |
| High Alcohol & Med Sleep | 6578 | 0.24 | 0.14 | 0.19 | 0.15 | −0.17 | −0.00 | 10.93 | −3.71 | −8.96 | 1.88 | 4.80 | 7.07 | −6.76 | 0.72 | 4.82 | 1.13 |
| Active & High Alcohol | 792 | 0.46 | 0.27 | 0.41 | 0.28 | −0.41 | 2.29 | 9.11 | −4.66 | −11.17 | 1.20 | 8.88 | 8.27 | −2.84 | 2.22 | 4.50 | −3.98 |
| Smoker & Low Sleep | 448 | −0.69 | −0.62 | −0.69 | −0.90 | 0.12 | −2.70 | −2.89 | 14.64 | 8.12 | −9.29 | −7.40 | −7.23 | 15.09 | 5.05 | −7.55 | −12.70 |
| Smoker & High Sleep | 188 | −0.44 | −0.52 | −0.56 | −0.41 | −0.11 | −0.61 | −3.89 | 13.48 | 8.65 | −6.80 | −6.89 | −8.91 | 0.40 | 8.43 | −1.59 | −7.33 |
| Smoker & Low Alcohol | 1157 | −0.53 | −0.34 | −0.55 | −0.50 | 0.11 | −0.80 | −11.50 | 11.62 | 10.34 | −6.69 | −6.89 | −8.60 | 12.09 | 5.08 | −6.20 | −11.07 |
| Low Alcohol & High Sleep | 342 | −0.28 | −0.30 | −0.29 | −0.28 | 0.41 | −6.60 | −21.61 | 9.83 | 15.97 | −6.79 | −8.23 | −10.19 | −10.41 | −1.59 | 8.76 | 3.14 |
| Nonsedentary Smokers | 121 | −0.26 | −0.32 | −0.39 | −0.35 | −0.28 | 8.47 | 8.75 | 6.73 | 9.26 | −7.78 | −5.43 | −4.61 | 18.43 | 3.54 | −10.18 | −11.89 |

[1] Standardized Means

[2] Profile Sample % - Overall Sample %

Variable Names: Gen.H = General Health, Men.H = Mental Health, LifeSat = Life Satisfaction, BMI = Body Mass Index, No CC = No Chronic Conditions, Income Levels = <$20k/ $20-$49k/ $50-$99k/ $100-$149k/ $150k+, Age Groups = 45-54/ 55-64/ 65-74/ 75-85

The five behavioural combinations most strongly associated with higher incomes each included high physical activity or high levels of alcohol consumption while four of the top five combinations associated with lower annual incomes included smoking. Each of the top five combinations associated with higher incomes contained more males while four of the bottom five combinations contained more females.

**Table 8**. Behavioural combinations (top and bottom five ranked by sex)

| | | Health Indicators | | | | | | Sociodemographics | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Profile | N | Gen.H[1] | Men.H[1] | H.Age[1] | LifeSat[1] | BMI[1] | No CC[2] | Male[2] | <$20k[2] | $20-$49k[2] | $50-$99k[2] | $100-$149k[2] | $150k+[2] | 45-54[2] | 55-64[2] | 65-74[2] | 75-85[2] |
| High Alcohol & Low Fruit | 2799 | −0.02 | −0.03 | −0.02 | −0.02 | −0.10 | 0.34 | 30.18 | −1.70 | −2.33 | 3.22 | 0.58 | 1.31 | −6.26 | −2.10 | 3.32 | 4.94 |
| Active & Low Fruit | 386 | 0.12 | 0.09 | 0.13 | 0.10 | −0.24 | −0.55 | 28.10 | −1.01 | −0.48 | −2.31 | 2.43 | 2.62 | −1.59 | −0.91 | 0.18 | 2.23 |
| Med Alcohol & Low Fruit | 4309 | −0.09 | −0.05 | −0.11 | −0.07 | 0.09 | 2.29 | 23.93 | −1.17 | −1.24 | 2.90 | 0.24 | −0.19 | 4.76 | 0.21 | −1.12 | −3.95 |
| Non-Smoker & Low Fruit | 9789 | −0.13 | −0.08 | −0.11 | −0.10 | 0.14 | 0.04 | 20.41 | 0.67 | 1.89 | 0.80 | −1.47 | −1.83 | −1.73 | −2.18 | 1.50 | 2.32 |
| Nonsedentary & Low Fruit | 279 | −0.12 | −0.12 | −0.09 | −0.17 | −0.06 | 2.69 | 20.08 | 3.29 | 1.29 | 0.29 | −1.95 | −2.95 | 9.28 | 1.33 | −5.48 | −5.24 |
| Smoker & High Fruit | 494 | −0.08 | −0.06 | −0.09 | −0.10 | −0.18 | −0.57 | −17.12 | 2.02 | 1.30 | 0.20 | 0.41 | −4.39 | 10.03 | 8.69 | −7.41 | −11.41 |
| Nonsedentary & High Fruit | 225 | 0.26 | 0.19 | 0.30 | 0.13 | −0.34 | 3.50 | −20.21 | −2.11 | −3.80 | −1.40 | 3.00 | 7.19 | 14.69 | 3.56 | −7.40 | −10.94 |
| Inactive & High Fruit | 1766 | −0.02 | 0.01 | 0.01 | 0.00 | 0.15 | −2.06 | −20.56 | −0.46 | −0.70 | 0.24 | −0.30 | −0.73 | −1.45 | −1.08 | 1.40 | 1.04 |
| Low Alcohol & High Sleep | 342 | −0.28 | −0.30 | −0.29 | −0.28 | 0.41 | −6.60 | −21.61 | 9.83 | 15.97 | −6.79 | −8.23 | −10.19 | −10.41 | −1.59 | 8.76 | 3.14 |
| Low Alcohol & High Fruit | 1972 | 0.01 | 0.04 | 0.03 | 0.01 | 0.08 | −1.72 | −23.09 | 0.16 | 3.18 | 2.10 | −2.29 | −4.17 | 1.03 | 0.81 | −0.73 | −1.21 |

[1] Standardized Means

[2] Profile Sample % - Overall Sample %

Variable Names: Gen.H = General Health, Men.H = Mental Health, LifeSat = Life Satisfaction, BMI = Body Mass Index, No CC = No Chronic Conditions, Income Levels = <$20k/ $20-$49k/ $50-$99k/ $100-$149k/ $150k+, Age Groups = 45-54/ 55-64/ 65-74/ 75-85

The distribution of sexes varied across behavioural combinations from 79.97% male (49.79% sample average + 30.18% deviation) who consumed low amounts of fruit/vegetables and high amounts of alcohol, to 26.7% male (23.09% less than the sample average) for those who consume high amounts of fruits/vegetables and low amounts of alcohol.  Each combination with the most males contained low fruit consumption and four of the five combinations with the most females contained high fruit consumption. Although sex-based trends in alcohol consumption and fruit/vegetable consumption were evident from single-item behavioural associations, the combination of alcohol and fruit/vegetable consumption exacerbated these differences.

## 7.4 Discussion

A examination of the sociodemographic factors and health indicators associated with behavioural combinations has demonstrated that accounting for more than one health behaviour can reveal variability and associations not evident when considering behaviours in isolation. However, the number of behavioural combinations which can reasonable be included in static tables is not ideal and only accounts for combinations of two behaviours. This approach is also susceptible to the general limitations for cross-tabulations (e.g., third variable problems) and cross-sectional data (e.g., not possible to establish directionality of associations). An interactive dashboard which enables easy selection, filtering, and comparisons of multiple health behaviours and frequencies could be of more use to researchers aiming to understand a particular population of interest based on their health behaviours and sociodemographic contexts.

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