Gender Differences in Chronic Disease Risk Behaviours and their Association with Body Mass Index: Cross-sectional and Longitudinal Multilevel Analyses

Among a Large Sample of Youth.

by

Nour Hammami

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Doctor of Philosophy
in
Public Health and Health Systems

Waterloo, Ontario, Canada, 2019

©Nour Hammami 2019

Examining Committee Membership

The following served on the Examining Committee for the thesis. The decision of the Examining Committee is by majority vote.

External Examiner DR. PATTI-JEAN NAYLOR

Associate Professor

School of Exercise Science, Physical and Health Education

University of Victoria

Supervisor DR. ASHOK CHAURASIA

Assistant Professor

School of Public Health and Health Systems

University of Waterloo

Internal Member(s) DR. PHILIP BIGELOW

Associate Professor

School of Public Health and Health Systems

University of Waterloo

DR. SCOTT LEATHERDALE

Professor

School of Public Health and Health Systems

University of Waterloo

Internal/External Member DR. JENNIFER DEAN

Assistant Professor School of Planning University of Waterloo

Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

This thesis consists in part of three manuscripts that have been submitted for publication. Exceptions to sole authorship:

Chapter 5:

Hammami, N., Chaurasia, A., Bigelow, P., & Leatherdale, S. T. (2019). A gender-stratified, multilevel latent class assessment of chronic disease risk behaviours' association with BMI among youth in the COMPASS study. *Preventive Medicine*, 126(C). https://doi.org/10.1016/j.ypmed.2019.105758.

Chapter 6:

Hammami, N., Chaurasia, A., Bigelow, P., & Leatherdale, S.T. (under review). Gender differences in the longitudinal association between youth's multilevel latent classes of chronic disease risk behaviours and Body Mass Index. *Pediatric Obesity*.

Chapter 7:

Hammami, N., Chaurasia, A., Bigelow, P., & Leatherdale, S.T. Exploring differences among youth who are victims of bullying and youth who are not: their chronic disease risk behaviours and their longitudinal association with Body Mass Index. Intended for the *International Journal of Obesity*.

As lead author of these three chapters, I was responsible for developing the research questions, conducting background research, leading the study designs, conducting the statistical analyses, interpreting the results, and writing the initial drafts of the manuscripts. My co-authors provided guidance during each step of the research and provided feedback on draft manuscripts.

Abstract

Obesity has become a worldwide concern due to the escalating number of individuals who have overweight or obesity. The prevalence of overweight/obesity among youth aged 12-17 years old was 37% in 2012-2013, as reported in the Canadian Health Measures Survey, affecting approximately one in four youth in Canada. The Senate of Canada released a report in 2016 which advocated for obesity to be prioritized on a federal and provincial level by calling for a National Campaign to Combat Obesity among all provinces and urging Health Canada to work with the provinces to address the 21 recommendations provided in the report.

Many factors contribute to the high overweight/obese rates, of which personal factors play a dominant role in preventing obesity and some are modifiable. Chronic disease risk behaviours (CDRB) are associated with obesity among youth include: physical activity (PA), binge drinking behaviour, cigarette smoking, dietary habits and sedentary behaviour. Some subgroups of youth are at a disadvantage relative to their peers because they engage in poorer CDRB and have higher rates of overweight/obesity compared with their peers. For example, youth who are victims of bullying (VoB) are reported to engage in more substance use and are found to be at higher odds of overweight/obesity than their non-VoB (NVoB) peers. CDRB and overweight/obesity track from adolescence into adulthood, making adolescence an optimal phase for interventions.

The purpose of this dissertation was to conduct a gender-specific examination in the effect that latent classes of chronic disease risk behaviours have on Body Mass Index among youth (i) at the same time point (using repeated, cross-sectional analyses), as well (ii) as over time (using transitional, longitudinal analyses). Since youth who are VoB engage in more substance use than their peers and have higher rates of overweight/obesity, this dissertation also sought (iii) to investigate whether there were differences in the longitudinal association between consecutive bullying status and BMI among youth. Three research studies were conducted to address these three research objectives among a large sample of youth in Ontario, Canada.

This dissertation used data from the 'Cohort Study on Obesity, Marijuana Use, Physical Activity, Alcohol Use, Smoking and Sedentary Behaviour' (COMPASS) Study.

COMPASS's student questionnaire collects information on youth's health behaviours and health outcomes. This dissertation included youth participating in the COMPASS Study during 2013-2014 (Wave 1), 2014-2015 (Wave 2) and 2015-2016 (Wave 3) from Ontario, Canada. Multilevel latent class analysis (MLCA) was used to identify chronic disease risk behaviour latent classes. To assess for gender differences, the MLCA was stratified by gender (i.e., reported for females and males separately). Gender-specific, mixed-effects regression models were used to assess the nature of the association of Body Mass Index (BMI) on the latent classes. Each of these regression models were reported two times: with BMI (as a continuous variable) and as weight status (i.e., BMI as a binary variable).

The first manuscript (i.e., Chapter 5) found that males were more physically active; however, they had more engagement in substance use (binge drinking, marijuana use and cigarette smoking) and had a higher prevalence of *overweight/obesity relative to their female counterparts*. The MLCA found that both genders have similar overall latent classes: active experimenters (ACE), inactive clean youth (INC) and inactive substance users (INSU). The repeated cross-sectional regression analyses found that youth in latent classes with substance use are associated with higher BMI and higher odds of an overweight/obese weight status among females and males. INC males were associated with lower odds of overweight/obesity relative to active males who experimented with substance use (ACE). As for females, the class with the highest proportion of youth using substances (INSU) were associated with higher odds of overweight/obesity relative to their active experimenting peers (ACE).

The second manuscript (i.e., Chapter 6) used the latent classes that were identified in Chapter 5, in a transitional, gender-specific, mixed-effects regression model. The gender-stratified models showed that male inactive clean youth (i.e., INC) were associated with a 0.29 kg/m² higher (continuous) BMI (95% C.I.=0.057, 0.53) and higher odds of overweight/obesity by 72% (OR=1.72, 95% C.I.=1.2, 2.4) for weight status at follow-up, relative to active experimenters. No significant associations were detected among females.

The third manuscript (i.e., Chapter 7) assessed whether there were gender differences among VoB and NVoB in their association with BMI in a longitudinal analysis. VoB were found to engage in more physical activity and substance use than their NVoB

peers. The longitudinal, transitional, gender-specific, mixed-effects models were consistent in showing that there are gender differences in the effect of bullying on BMI. Among female youth, repeated bullying was associated with a 51% increase in the odds of having overweight/obesity at follow-up (95% C.I.=1.03, 2.23). Among male youth, being a VoB at the previous wave only, was associated with a 60% increase in the odds of overweight/obesity (95% C.I.=1.11, 2.29).

This dissertation emphasizes the importance of gender stratification in chronic disease risk behaviour, BMI and bullying research among youth. Females and males have different factors associated with BMI as well as with changes in BMI over time. Furthermore, gender-stratification is essential since using results from the models that adjusted for gender would misinform prevention programs since they downplay the effect of the associations being studied. This research will be valued among school programs, policy-makers and other researchers engaged in youth health, as it provides evidence that school-programs and population-level initiatives are warranted that focus on substance use and bullying prevention and that encourage PA engagement among youth.

Acknowledgements

I acknowledge that we are living and working on the traditional territory of the Attawandaron (also known as Neutral), Anishinaabe and Haudenosaunee peoples. The University of Waterloo is situated on the Haldimand Tract, the land promised to the Six Nations that includes six miles on each side of the Grand River.

It is a testament to this great country we live in that provides us with opportunities to follow our dreams and pursue our passions; Canada, you are great.

I owe my deep appreciation to the University of Waterloo and the individuals working behind the scenes whose work contributed to achieving the title of most innovative university in Canada for 27 consecutive years. You are giants; we produce the work we do because of your efforts.

To my three mentors at the School of Public Health and Health Systems (SPHHS): Doctors Ashok Chaurasia, Scott Leatherdale and Philip Bigelow, each of you contributed to my growth, progression and to this research; for those reasons, I thank you.

Ashok, you always made time for me, you were patient through my questions, explained with enthusiasm when I needed direction and gave me the space to do self-learning to make this dissertation my own. You encouraged me to ask myself questions and to pursue every research question I had. You are dedicated to teaching your students, arming them with the statistical theory, methods and applications that they need and that their mind can comprehend. Thank you for your supervision: the time you invested in me, the knowledge you armed me with and the opportunities you encouraged me to pursue – all of which contributed to my growth as an independent researcher.

Scott, you saw my enthusiasm in wishing to pursue population health research and welcomed me in your area of research early on. I learned the artistry behind scientific writing and the critical thinking from your example. I also witnessed the passion in teaching you have with your students, ensuring theoretical and applied concepts are being learned. I will always draw inspiration from how you shatter the conventional box in teaching, research and applied public health initiatives. Thank you for being a true trailblazer and providing us novel researchers with such research opportunities.

Phil, it started with you, your saying *yes* to supervising my studies. Your support was a balance in knowing when I needed your advice, when I needed to figure things out on my own and when I needed a simple morale boost. Thank you for your thoughtful edits and comments on the manuscripts and for always having my best interest in mind.

Through the combination of your efforts, I consider myself a public health researcher today. Each of you provided me with a unique set of skills that completed my experience as a researcher worthy of this doctorate degree. The energy and time you dedicate to your students is a small glimpse of your generosity of heart that I had the pleasure of witnessing throughout my years at SPHHS.

I also want to thank my internal/external member Dr. Jennifer Dean and my external examiner Dr. Patti-Jean Naylor for their interest in my research and the time they dedicated to this work; I greatly appreciated your insightful feedback.

There are a few people at SPHHS I also want to acknowledge. Carol West-Seebeck and Doris Makowich, I'll fondly remember the lovely conversations we had on our breaks. Chad Bredin and Kate Battista, thank you for always providing me access to the data I required. Trevor Bain, thank you for having an open door (and email) policy for my many software related inquiries and always being more than willing to find solutions for these issues with me.

I am most grateful for your endless support through all means possible, my family. This degree would not have been possible without you: Dad and Mom – by my side at every step. I couldn't have dreamed of everything you have provided for me; I am forever grateful for your endless love, trust, support, advice and patience. My brother, Dr. Ahmad Hammami, you've been my - life and research - coach since (literally) day one. I am thankful for your generous, loving spirit; you've been a support and lifeline like no other. My sister Salwa and brother Mohammad, each of you supported me in your distinct, loving way during these years. You kept my feet on the ground and mind in check by reminding me of the life beyond my research with your regular video calls, messages and pictures of my beloved nieces and nephews. My nieces and nephews, you always remind me that the future is bright; every one of your smiles reminded me why I undertook a project dealing with prevention research among youth: to help bring you closer to that bright future. Maher and Rouwane, I am grateful and thankful to have you as the perfect additions to our family – your presence in my life, love and support are dear to my heart.

I've collected a few gems on my path; a special note to my (self-selected) home team and support system. Mira Chaar, you believed in my dreams, and in me, from day one; I am grateful for your beautiful spirit, in every way. Farah Afra, Jasmin Bhawra, Patricia Moghames and Sarah Aleyan, your support has been priceless. I am grateful, and I value you: for your unrelenting presence and for the loving, fierce, kind-hearted women that you are. I wouldn't hesitate to turn to any of you in times of need – whether it be research, evaluation or life-related. I look forward to watching the paths meant for you and roads you will pave to greatness.

A note to you, reading: keep at it – curiosity and persistence will take you: *Above & Beyond.*

Finally, to my Eternal Refuge – God.

All praise be to You: for answering my prayers, calming my heart, keeping my head focused and providing me with the tools I needed for this journey.

I am thankful, grateful and humbled with Your choices for me.

Through You and by You all things are possible.

Table of Contents

Examining Committee Membership	11
Author's Declaration	iii
Statement of Contributions	iv
Abstract	v
Acknowledgements	viii
Table of Contents	X
List of Tables	xiv
List of Figures	xvi
List of Abbreviations	xvii
Chapter 1 Introduction	1
Chapter 2 Background	4
2.1 Obesity in Canada	4
2.1.1 Health risks	4
2.1.2 The Canadian Senate's position on obesity	5
2.1.3 Measures of obesity	5
2.1.4 Obesity is multifactorial	6
2.2 Chronic Disease Risk Behaviours among Youth in Canada	7
2.2.1 Physical activity	7
2.2.2 Alcohol consumption	8
2.2.3 Cigarette smoking	10
2.2.4 Sedentary behaviour	11
2.2.5 Fruit and vegetable intake	12
2.2.6 Youth who are Victims of Bullying	13
2.3 Multi-Component Approach to Obesity	14
2.3.1 Co-occurring behaviours	14
2.4 Review of the Scientific Literature	16
2.4.1 Chronic disease risk behaviour latent classes among youth	16
2.4.2 Chronic disease risk behaviour latent classes and weight status	17
2.5 Theoretical approach: Problem Behaviour Theory	20
2.6 The COMPASS Study (Host Study)	22
2.7 Gap in the Scientific Literature	24

Chapter 3 Study Objectives and Research Questions	26
3.1 Dissertation Purpose	26
3.2 Study One (Chapter 5)	26
3.2.1 Research questions	26
3.2.2 Hypotheses	26
3.3 Study Two (Chapter 6)	27
3.3.1 Research questions	27
3.3.2 Hypotheses	28
3.4 Study Three (Chapter 7)	28
3.4.1 Research questions	28
3.4.2 Hypotheses	28
Chapter 4 General Methods	30
4.1 Data Source: The COMPASS Study	30
4.1.1 Ethics and recruitment	30
4.1.2 Sampling and response rate	31
4.1.3 COMPASS Student Questionnaire (Cq)	31
4.2 Study Measures	33
4.2.1 Weight status (outcome variable)	33
4.2.2 Chronic disease risk behaviours (predictor variables)	33
4.2.3 Bullying status (predictor variable)	35
4.3 Statistical Analyses	36
4.3.1 Data sampling	36
4.3.2 Study One (Chapter 5)	36
4.3.3 Study Two (Chapter 6)	38
4.3.4 Study Three (Chapter 7)	39
Chapter 5 A gender-stratified, multilevel latent class assessment of chronic disbehaviours' association with BMI among youth in the COMPASS study	
Overview	44
5.1 Introduction	45
5.2 Methods	46
5.2.1 Design	46
5.2.2 Participants	47
5.2.3 Data collection	47

5.2.4 Measures	47
5.2.5 Statistical analyses	49
5.3 Results	50
5.3.1 Study participants and characteristics	51
5.3.2 Gender differences	51
5.3.3 Multilevel latent class analysis (MLCA)	53
5.3.4 Association between latent classes of chronic disease risk behaviou	
5.4 Discussion	58
5.4.1 Strengths and limitations	59
5.4.2 Recommendations	60
Chapter 6 Gender differences in the longitudinal association between multilevelasses of chronic disease risk behaviours and Body Mass Index among youth	
Overview	63
6.1 Introduction	64
6.2 Methods	65
6.2.1 Participants	66
6.2.2 Measures	66
6.2.3 Statistical analyses	67
6.3 Results	68
6.3.1 Study participants	68
6.3.2 BMI category transitions	69
6.3.3 Latent class transitions	71
6.3.4 Longitudinal regression analyses	72
6.4 Discussion	73
6.4.1 Strengths and limitations	76
6.4.2 Conclusion	77
Chapter 7 Exploring gender differences in the longitudinal association between the chronic disease risk behaviours with Body Mass Index among a sample of Canada.	f youth in
Overview	79
7.1 Introduction	80
7.2 Methods	81
7.2.1 Design	81

7.2.2 Participants and procedures	82
7.2.3 Measures	82
7.2.4 Statistical analyses	83
7.3 Results	85
7.3.1 Participant characteristics	85
7.3.2 Differences in chronic disease risk behaviours by bullying state	us86
7.3.3 Longitudinal analyses	88
7.4 Discussion	93
7.4.1 Recommendations	95
7.4.2 Strengths and limitations	96
7.4.3 Conclusion	97
Chapter 8 General Discussion	98
8.1 Overview	98
8.2 Summary of key findings	99
8.2.1 Findings and discussion for each of the three studies	100
8.2.2 Overall findings from the three studies	106
8.3 Overall Strengths	108
8.4 Overall Limitations	110
8.5 Overall Implications	112
8.5.1 Implications for public health	112
8.5.2 Implications for school programs	114
8.6 Directions for Future Research	115
8.7 Overall Conclusions	117
References	118
Appendix A Conceptual Framework for Problem Behaviour Theory	142
Appendix B COMPASS Student Questionnaire	143
Appendix C Supplementary Material for Chapter 5	155
Appendix D Supplementary Material for Chapter 6	161

List of Tables

Table 4.1 The chronic disease risk behaviour (CDRB), its corresponding public health
guideline and relevant question(s) from the COMPASS student questionnaire (Cq)34
Table 5.1 Descriptive results for youth across years 2013-2015 among youth participating
in COMPASS in Ontario, Canada. Percentages and sample size [%(n)] are reported for
categorical variables, mean and standard deviation are reported for continuous variables. 50
Table 5.2 Fit statistics for the multilevel latent class analysis among female youth in 2013
participating in COMPASS from Ontario, Canada53
Table 5.3 Latent classes' adjusted estimates (and 95% confidence intervals) from the
regression models where Body Mass Index (BMI; as a binary and continuous measure) is
regressed onto the student latent classes, among female and males, participating in
COMPASS across years 2013-2015 in Ontario, Canada57
Table 6.1 Summary statistics for longitudinal outcomes and covariates among youth
participating in COMPASS (Ontario, Canada) by gender in Waves 1, 2 and 3. Percentages
and sample size are reported for categorical variables, mean and standard deviation are
reported for continuous variables
Table 6.2 Transitions in weight status (binary body mass index) [%(n)] across consecutives
waves (Waves 1 to 2 and Waves 2 to 3) and by gender among youth participating in
COMPASS (Ontario, Canada)70
Table 6.3 Transitions in latent classes [%(n)] across gender in Waves 1 and 2 and Waves 2
and 3 among youth participating in COMPASS (Ontario, Canada)71
Table 6.4 Adjusted regression estimates (and 95% confidence intervals) from the
regression models where Body Mass Index (BMI; as a binary and continuous measure) is
regressed onto latent class at the previous wave, among female and males, participating in
COMPASS across Waves 1, 2 and 3 in Ontario, Canada
Table 7.1 Summary statistics for longitudinal outcomes and covariates among youth
participating in COMPASS by bullying status in Waves 1, 2 and 3. Percentages and sample
size are reported for categorical variables, mean and standard deviation are reported for
continuous variables
Table 7.2 Transitions in bullying status [%(n)] across consecutives waves (Waves 1 to 2
and Waves 2 to 3) among youth participating in COMPASS in Ontario, Canada88

Table 7.3 Transitions in weight status (binary BMI) [%(n)] across consecutives waves
(Waves 1 to 2 and Waves 2 to 3) and by bullying status among youth participating in
COMPASS in Ontario, Canada89
Table 7.4 Transitions in latent classes [%(n)] across consecutives waves (Waves 1 to 2 and
Waves 2 to 3) and by bullying status among youth participating in COMPASS in Ontario,
Canada90
Table 7.5 Adjusted regression estimates (and 95% confidence intervals) from the
regression models where Body Mass Index (BMI; as a binary and continuous measure) is
regressed onto bullying status at the previous wave, among female and males, participating
in COMPASS across Waves 1, 2 and 3 in Ontario, Canada91
Table 7.6 Adjusted regression estimates (and 95% confidence intervals) from the
regression models where Body Mass Index (BMI; as a binary and continuous measure) is
regressed onto consecutive bullying status, among female and males, participating in
COMPASS across Waves 1, 2 and 3 in Ontario, Canada92
Supplementary Table 1 Results from the chi-square tests assessing for differences across
gender in chronic disease risk behaviours across years 2013-2015 among youth
participating in COMPASS in Ontario, Canada
Supplementary Table 2 Fit statistics for the multilevel latent class analysis among male
youth in 2013 participating in COMPASS from Ontario, Canada156
Supplementary Table 3 Fit statistics for the multilevel latent class analysis among female
youth in 2014 participating in COMPASS from Ontario, Canada157
Supplementary Table 4 Fit statistics for the multilevel latent class analysis among male
youth in 2014 participating in COMPASS from Ontario, Canada158
Supplementary Table 5 Fit statistics for the multilevel latent class analysis among female
youth in 2015 participating in COMPASS from Ontario, Canada159
Supplementary Table 6 Fit statistics for the multilevel latent class analysis among male
youth in 2015 participating in COMPASS from Ontario, Canada160
Supplementary Table 7 Cross-tables showing Body Mass Index (BMI) status (categorical)
transitions [%(n)] across gender in Waves 1 and 2 and Waves 2 and 3161

List of Figures

Figure 5.1 The chronic disease risk behaviours and weight status of female and male youth
(in percentages) who participated in COMPASS across years 2013-2015 in Ontario,
Canada
Figure 5.2 Distribution of youth latent classes in school latent classes from the multilevel
latent class analysis models for females and males, participating in COMPASS across the
years 2013-2015
Figure 7.1 The chronic disease risk behaviours and weight status of youth who are victims
of bullying and non-victims of bullying (in percentages) who participated in COMPASS
across Waves 1, 2 and 3 in Ontario, Canada
Supplementary Figure 1 Problem Behaviour Theory conceptual framework. Adapted from
"Problem Behaviour Theory: A Half-Century of Research on Adolescent Behaviour and
Development" by R. Jessor, in "The developmental science of adolescence: History
through autobiography." New York: Psychology Press. Pp. 250. Reprinted with
permission

List of Abbreviations

ACE Active experimenters BMI Body Mass Index

CDRB Chronic disease risk behaviours
CHMS Canadian Health Measures Survey

C.I. Confidence Interval

CIHR Canadian Institute of Health Research

COMPASS Cohort Study on Obesity, Marijuana Use, Physical Activity, Alcohol

Use, Smoking and Sedentary Behaviour

Cq The COMPASS student questionnaire CSEP Canadian Society for Exercise Physiology

CSTADS Canadian Student Tobacco, Alcohol and Drugs Survey

HBSC Health Behaviour in School-aged Children

ICC Intra-class Correlation Coefficient

INC Inactive clean youth
INSU Inactive substance users

Kg Kilograms

LCA Latent Class Analysis
LTA Latent Transition Analysis

M Meters

NVoB Non-Victims of Bullying

OR Odds Ratio

PA Physical Activity

PBT Problem Behaviour Theory

PHAC Public Health Agency of Canada

SES Socio-economic status

TV Television

U.S. United States of America

VoB Victims of Bullying

WHO World Health Organization

Chapter 1 Introduction

Youth who have overweight or obesity have a higher risk of metabolic diseases (such as Type 2 Diabetes and the Metabolic Syndrome), cardiovascular disturbances, are reported to experience psychological complaints and are often bullied (Maggio et al., 2014). Furthermore, childhood obesity tracks into adulthood (Lloyd, Langley-Evans, & McMullen, 2012) increasing the risk of adult type 2 diabetes, hypertension and coronary heart disease (Park, Falconer, Viner, & Kinra, 2012). Between the years 2012 and 2013, one in three Canadian children and youth were reported to have overweight or obesity. The prevalence was higher among youth 12-17 years old at 37% (Statistics Canada, 2015).

Chronic disease risk behaviours (CDRB) are modifiable behaviours that are associated with a higher chronic disease risk. Some CDRBs are also associated with a high, or increase in, weight status (measured via body mass index, BMI) among youth, including: not enough physical activity (PA) (Mei et al., 2016), binge drinking behaviour (Battista & Leatherdale, 2017), a dietary intake that exceeds one's needs (Berkey et al., 2000) and cigarette smoking (Delk, Creamer, Perry, & Harrell, 2018). Associations between these CDRB and obesity, or increasing BMI, have been found individually (i.e., when assessing each behaviour with obesity) and when evaluating the role health behaviours have as a cumulative effect on obesity (Leech, McNaughton, & Timperio, 2014). Observing the cumulative effect that CDRB have on obesity, and on increases in BMI, signify a shift from assessing the extent to which a single behaviour contributes to obesity to evaluating classes of CDRB and how they are associated with obesity. The latter closely reflects behaviours as they occur among youth and the nature of the underlying patterns between behaviours (McAloney, Graham, Law, & Platt, 2013).

The underlying classes of CDRB may differ across sub-populations of youth if they engage in CDRB differently. For example, female and male youth engage in CDRB differently (Leech et al., 2014; Nuutinen et al., 2017; Te Velde et al., 2007) and report their weight and height differently (Arbour-Nicitopoulos, Faulkner, & Leatherdale, 2010; Sherry, Jefferds, Grummer-Strawn, et al., 2007). Therefore, investigations that address

CDRB and BMI among youth need to take into consideration that females and males cannot be treated as one population with the same characteristics; they should be treated as two populations with distinct characteristics and behaviours.

Behaviours are not static; individuals change habitual behaviours and adopt new behaviours; thus, longitudinal tracking of the changes that occur during a critical phase of growth such as adolescence is needed. Patterns of CDRB are reported to set in during the transition from adolescence to early adulthood identifying this as a critical time for interventions. (Gordon-Larsen, Nelson, & Popkin, 2004; Gordon-Larsen, The, & Adair, 2010; Quick, Wall, Larson, Haines, & Neumark-Sztainer, 2013; Watts, Mason, Loth, Larson, & Neumark-Sztainer, 2016).

Additionally, about four out of five adolescents who fall in the obese category, continue to be have obesity as adults (Freedman et al., 2005). Longitudinal studies and research examining CDRB, the change in these risk factors during adolescence and their relationship with increases in BMI and weight status are sparse. Since health habits are shaped in adolescence, this is an optimal time to intervene because environmental and social interventions would be possible when collaborating with schools.

The Canadian Institute of Health Research (CIHR) and Health Canada funded (2012-2021) the 'Cohort Study on Obesity, Marijuana Use, Physical Activity, Alcohol Use, Smoking and Sedentary Behaviour' (COMPASS) Study. The COMPASS study is a prospective, cohort study designed to collect longitudinal, hierarchical data from secondary schools and their students (grades 9 to 12) pertaining to student health behaviours, school policies and the built environment in Canada (Leatherdale, Brown, et al., 2014). COMPASS provides data that allows for the identification of associations between health behaviours and weight status over time.

The purpose of this dissertation was to examine gender differences in chronic disease risk behaviour classes and their association with BMI among youth in Canada in cross-sectional and longitudinal analyses and to examine differences in these associations between youth who are victims of bullying and youth who are not, using data from the COMPASS host study. Three chapters of this dissertation (Chapters 5, 6 and 7) were dedicated to answering the aforementioned research questions, in the form of three

research studies.

As for the remaining chapters, Chapter 1 is an introduction and overview to the dissertation's topic and scope. Chapter 2 provides a background and review of the scientific literature pertaining to the dissertation's scope. This chapter starts with reviewing the state of obesity in Canada among youth and continues to describe the Canadian Senate's position on obesity. Next, evidence is presented that obesity is multifactorial and that several chronic disease risk behaviours are independently associated with obesity. This chapter continues to provide scientific evidence that CDRB co-occur and mentions statistical methods that group youth based on their homogenous patterns of CDRB. This is followed by a review of studies from the scientific literature that assessed the association between such homogenous classes of youth's CDRB and BMI. The theoretical approach of this dissertation (Problem Behaviour Theory) is then described and an overview of the COMPASS host study is provided. Finally, this chapter ends with identifying gaps in the literature.

Chapter 3 outlines the research questions that this dissertation addresses via the three research studies (Chapters 5, 6 and 7) that are included in this dissertation. It also provides hypotheses for each research question based on findings from previous literature.

Chapter 4 addresses the general methods of the dissertation. It provides a brief overview of the COMPASS host study, details the three studies' measures (outcome and predictor variables), and describes the statistical analyses that were included in the three studies (Chapters 5, 6 and 7).

Chapter 8 begins by providing an overview of the dissertation's discussion. This chapter goes on to include a discussion for each of the three research studies' findings, then continues to present a discussion on the overall findings from the three studies. Next, strengths and limitations of the dissertation are outlined. This is followed by detailing the implications that this dissertation has for public health and for school programs. The chapter ends with suggesting areas for future research and overall conclusions.

Chapter 2 Background

This chapter will begin by reviewing chronic disease risk behaviours (CDRB) associated with BMI (and overweight/obesity) among youth. This chapter will continue to review the scientific literature regarding CDRB classes among youth. Then, the underlying theoretical approach for the dissertation will be introduced, the Problem Behaviour Theory. This will be followed with an overview of the COMPASS host study. The chapter will conclude by identifying gaps in the literature.

2.1 Obesity in Canada

Obesity has become a worldwide concern due to the escalating number of individuals who have overweight or obesity. Approximately 62.1% of adults in Canada had overweight or obesity according to objective measurements as reported from the Public Health Agency of Canada (PHAC) (2011). Among children (ages 5 to 11 years old) 26% had overweight or obesity between the years 2012 and 2013 based on objective, national data from the Canadian Health Measures Survey (CHMS). The prevalence of overweight/obesity was higher among youth aged 12-17 years old than in children at 37%, in the CHMS, affecting approximately one in four youth (Statistics Canada, 2015).

2.1.1 Health risks

Obesity is a state of excess body fat beyond healthy levels; reaching a state where a person's health is adversely affected (Adab, Pallan, & Whincup, 2018). Excess body fat causes metabolic changes by releasing inflammatory markers in the body. This places the individual at a higher risk of chronic diseases such as diabetes, cancer and cardiovascular diseases (Monteiro & Azevedo, 2010). An obese state significantly increases the risk of morbidity and mortality (Raj & Kumar, 2010). Youth classified with overweight or with obesity have similar future risks of chronic diseases (Peirson et al., 2015).

Children and youth who have overweight or obesity are at a higher risk of developing a myriad of health issues than their counterparts that include: metabolic diseases, cardiovascular disturbances, obstructive sleep apnea, musculoskeletal problems, psychological complaints and asthma (Maggio et al., 2014; Public Health England, n.d.).

Children and youth with obesity may face several risk factors, as a result of obesity's inflammation, with each component worsening with increasing obesity levels (Raj & Kumar, 2010). Not only does obesity affect youth at one point in time, children and youth with overweight/obesity are at a higher risk of becoming adults with obesity than their counterparts and maintaining obesity-related diseases through adulthood (Statistics Canada, 2015).

2.1.2 The Canadian Senate's position on obesity

The Senate of Canada's Committee on Social Affairs, Science and Technology released a report titled "Obesity in Canada" in March 2016. The report states that obesity-related chronic diseases are increasing at alarming rates and this is causing health care (direct) and loss in productivity (indirect) costs. Direct and indirect costs were estimated to cost Canadians between \$4.6 billion to \$7.1 billion annually (Senate of Canada, 2016).

This report places obesity prevention programs and initiatives on the policy agenda in Canada. The report urges the federal government to act by promoting healthy weight statuses to Canadians by calling for a National Campaign to Combat Obesity among all provinces and urges Health Canada to work with the provinces to address the twenty-one recommendations provided in the report. Movement in the obesity prevention initiatives are expected, as some of the recommendations in the report include a tax on sugar-sweetened beverages and a ban on the advertising of food and drink to children (Senate of Canada, 2016) as well as the recent revisions to Canada's food guide (Health Canada, 2019).

2.1.3 Measures of obesity

Children and youth in Canada have high and increasing levels of overweight and obesity, almost three-fold increases since 1980 (Senate of Canada, 2016). Statistics Canada reported that one in three children or youth (5 to 17 years old) have overweight (19.8%) or obesity (11.7%) from 2009 to 2011 based on measurements reported by trained professionals from the CHMS (Roberts, Shields, de Groh, Aziz, & Gilbert, 2012).

Body Mass Index (BMI) is the most commonly used measure of adiposity in population-based studies; it is a measurement based on a ratio of an individual's weight

(in kilograms) to height (in meters) $\left(BMI = \frac{weight \, (kilograms)}{[height \, (meters)]^2}\right)$ (Adab et al., 2018). Among youth, BMI is standardized for age and sex as displayed in the World Health Organization's (WHO) Child Growth Standards (World Health Organization, 2007).

To calculate BMI, weight and height information need to be collected. Objective measurements (i.e., measuring weight and height by a trained individual) deliver higher estimates of obesity than self-reported (subjective) measures of weight and height; however, each method has its strengths and weaknesses. Objective measures are relatively labor intensive, while subjective measures have been reported to underestimate BMI (Chau et al., 2013; Gorber, Shields, Tremblay, & McDowell, 2008).

Among Canadian youth, objective measurements of BMI collected in 2012-2013 indicate that among boys aged 12-17 years, 23% had overweight and 21% had obesity, amounting to a total of 44% of male youth having overweight/obesity. The numbers were lower among 12-17 year old girls with a reported 18% having overweight and 12% having obesity, for a total of 30% of female youth having overweight/obesity (Statistics Canada, 2015). On the other hand, self-reported BMI among Canadian youth in 2013 were lower than the objective measures, 27.8% of Canadian boys aged 12-17 years had overweight/obesity, while 15.4% of girls in the same age range had overweight/obesity, based on self-reported measures (Statistics Canada, 2015).

With regards to weight and height measurements in population studies, objective measures may be more reliable; however, they have been reported to achieve up to a two-time higher refusal in participation rate than self-measured weight and height among youth (Chau et al., 2013). There is no gold standard in collecting weight and height information as each presents different errors and biases; the use of objective weight and height measures is recommended, especially among children and youth (Roberts et al., 2012). However, self-reported weight and height remain valuable when they are the only available data (Sherry, Jefferds, Grummer-Strawn, et al., 2007).

2.1.4 Obesity is multifactorial

Many factors contribute to the high prevalence of overweight/obesity such as: economic growth, the wide-spread availability of energy-dense, nutrient-poor food,

mechanized transportation, socio-economic and hereditary factors, among others (Hruby & Hu, 2015). However, personal factors play a dominant role in preventing obesity, and these are modifiable (Hruby & Hu, 2015).

In this dissertation, the focus is the association between obesity and modifiable personal behaviours – referred to from hereon as chronic disease risk behaviours (CDRB).

2.2 Chronic Disease Risk Behaviours among Youth in Canada

Chronic disease risk behaviours that are associated with obesity among youth include: PA, binge drinking behaviour, cigarette smoking, dietary habits and sedentary time (Battista & Leatherdale, 2017; Conry et al., 2011; Deliens, Clarys, De Bourdeaudhuij, & Deforche, 2013; Delk et al., 2018; Sisson, Krampe, Anundson, & Castle, 2016).

Public health guidelines are in place for CDRB (e.g., PA, alcohol use, sedentary behaviour and diet) to support disease prevention and control (Saunders, Chaput, & Tremblay, 2014; World Health Organization, 2015). A reportedly large proportion of youth in Canada, do not meet these guidelines (Faught, Gleddie, Storey, Davison, & Veugelers, 2017; Government of Canada, Health Canada, Healthy Environments and Consumer Safety Branch, 2012; Leatherdale, 2015; Leatherdale & Burkhalter, 2012; Melkevik et al., 2015; Minaker & Hammond, 2016; L. V. Moore, Thompson, & Demissie, 2017; Pearson et al., 2017; Shi, Lenzi, & An, 2015).

A specific group of youth are at a disadvantage of meeting public health guidelines and standards are youth who are victims of bullying. Recent evidence shows that victims of bullying have different engagement in CDRB and rates of overweight/obesity than their counterparts (Moore et al., 2017).

2.2.1 Physical activity

2.2.1.1 Rates in Canada

Janssen, Roberts and Thompson (2017) reported that among a nationally representative sample of youth (10-17 years old) in Canada, 70.2% of females and 58.4%

of male youth were found to not meet public health guidelines for PA. These youth participated in the WHO Health Behaviour in School-aged Children (HBSC) study in 2013-2014 (Janssen et al., 2017).

2.2.1.2 Independent association with obesity

In a systematic review of objectively measured PA among children and youth, total PA had favorable physical, psychological, social and cognitive health indicators (Poitras et al., 2016). There was strong evidence as to favorable relationships between PA, adiposity, several cardiometabolic measures (blood pressure, cholesterol and insulin resistance) and physical fitness (aerobic fitness, muscular strength and endurance). The authors also found favorable associations between the current guidelines for PA on adiposity and quality of life. These findings emphasize the preventative role PA plays in obesity and chronic disease prevention. (Poitras et al., 2016).

2.2.1.3 Physical activity guidelines

Public health guidelines refer to recommendations that intend to support healthy lifestyles as well as ameliorate the risk of diseases. A guideline that accounts for a person's 24-hour movement (i.e., PA, sleep duration and screen time) has been disseminated in Canada; but traditionally, PA is used a measure of energy expenditure (Tremblay et al., 2016).

The Canadian Society for Exercise Physiology (CSEP) placed the current guidelines for PA levels among youth to achieve optimal health benefits. The guideline recommends that youth aged 12-17 years old engage in 60 minutes of moderate-to-hard activity daily and hard activity on at least three out of the last seven days and participate in activities that strengthen muscles and bone at least three days per week (Tremblay et al., 2016).

2.2.2 Alcohol consumption

2.2.2.1 Rates in Canada

Alcohol drinking habits of youth in Canada are reported from two studies that used national datasets in Canada. A reported 25% of youth engaged in binge drinking

behaviour, consuming five or more drinks at one occasion, once a month or more (Leatherdale & Rynard, 2013). Similar findings are reported from the Canadian Student Tobacco, Alcohol and Drugs Survey (CSTADS) in 2016-2017, although they measured an episode of binge drinking behaviour within the last 12 months: 24% of youth in grades 7 to 12 reported binge drinking behaviour in the past 12 months (Health Canada, 2018b).

2.2.2.2 Independent association with obesity

The energy content of one gram of alcohol (approximately seven calories per gram) is higher than the energy content provided by protein and carbohydrates (four calories per gram); yet, less than that of fat (nine calories per gram) (Sayon-Orea, Martinez-Gonzalez, & Bes-Rastrollo, 2011). Calories from alcohol are unnecessary as alcohol is nutritionally void. Among youth, findings from Battista and Leatherdale (2017) suggest that one binge drinking episode in the past 30 days, accumulated over one year, is calorically equivalent to 2 kilograms of fat, purely from alcohol.

Additional findings support that heavy drinking (defined as greater than thirty grams of alcohol per day or approximately two to three drinks) is associated with higher BMI as well as weight gain over time (Traversy & Chaput, 2015). However, light to moderate drinking does not seem to be associated with weight gain (Traversy & Chaput, 2015). Similar results were reported from a systematic review; the review cited that the choice of alcohol may also affect weight gain, with spirit consumption being positively associated with weight gain (Sayon-Orea et al., 2011).

2.2.2.3 Alcohol consumption standards

Since drinking is illegal in the provinces of Alberta, Manitoba and Québec under the age of 18 years old and illegal in the rest of Canada ¹ under the ages of 19 years old, there are no official guidelines or cut-off values for alcoholic drinking under this age.

With alcoholic drinking, binge drinking specifically is of concern since it refers to when

¹ Including the following: British Columbia, New Brunswick, Newfoundland and Labrador, Northwest Territories, Nova Scotia, Nunavut, Ontario, Prince Edward Island, Saskatchewa and Yukon.

the blood alcohol concentration (BAC) is at 0.08 g/dL: a level associated with acute impairment in motor coordination and cognitive functioning (Chung, Creswell, Bachrach, Clark, & Martin, 2018). Typically, the binge drinking definitions used for adults are also used for adolescents: 5 or more drinks for males and 4 or more drinks for females; however, these are suggested to be too high among children and adolescents who reach the BAC level of 0.8 g/dL with lower amounts of alcohol due to having a smaller body size (Chung et al., 2018). Donovan (2009) used estimated BAC to suggest that among youth ages 14 to 15, 4 or more drinks for males and 3 or more drinks for females would deliver a BAC of 0.8 g/dL or higher.

With no clear cutoff for binge drinking among youth, previous research reported using a single number for binge drinking among female and male youth; binge drinking was classified as five or more drinks on one occasion during the last 30 days. (Leatherdale, 2015; Leatherdale & Rynard, 2013). Research that used this conservative cutoff were studies that used COMPASS survey as well as the Youth Smoking Survey/Canadian Student Tobacco, Alcohol and Drugs Survey (Leatherdale, 2015; Leatherdale & Rynard, 2013).

2.2.3 Cigarette smoking

2.2.3.1 Rates in Canada

The latest findings on the prevalence of smoking among youth in grades 7 to 12 in Canada are from 2016-2017. These findings report that 3% are current cigarette smokers, unchanged from 2014-2015, with no detectable gender differences (Health Canada, 2018b). Youth in Canada use more tobacco products as they grow older: among youth in grade 10, 1.3% were found to be current smokers, in grade 11, 2.0% were found to be current smokers and in in grade 12, 3.2% were found to be current smokers (Health Canada, 2018a).

2.2.3.2 Independent association with obesity

There are mixed findings from the literature to support an association between cigarette smoking and obesity and theoretical understandings of this relationship are still underway (Delk et al., 2018). Although not conclusive, there is evidence to support that

that substance users (including smokers) are most likely to have overweight/obesity than their non-smoking counterparts (Delk et al., 2018; H. I. Lanza, Pittman, & Batshoun, 2017; Zeller, Reiter-Purtill, Peugh, Wu, & Becnel, 2015).

2.2.3.3 Cigarette smoking standards

As with binge drinking, no 'safe' levels of cigarette smoking are available; therefore, no cutoffs exist since all guidelines do not recommend smoking. Researchers have used standards to classify individuals as current smokers, or not. The measure validated by Wong, Shields, Leatherdale, Malaison and Hammond (2012) is widely used and accepted. As such, youth who reported ever smoking 100 cigarettes and any smoking in the previous 30 days were classified as current smokers otherwise they are considered non-smokers (Wong et al., 2012).

2.2.4 Sedentary behaviour

2.2.4.1 Rates in Canada

In two representative studies, most youth in Canada were found to exceed the recommended two hours of recreational screen time. Leatherdale & Ahmed (Leatherdale & Ahmed, 2011) found that 50.9% exceeded the time frame among youth participating in the Youth Smoking Survey (2008-2009). A more recent study (2013-2014) reported by Janssen, Roberts & Thompson (2017) found that among a national sample of youth (10-17 years old) in Canada, 91.1% of female and 91.9% of male youth exceeded the two-hour time frame as a part of the WHO HBSC sample.

2.2.4.2 Independent association with obesity

Sedentary behaviour is associated with cardio-metabolic diseases and physiological problems. A systematic review reported a dose-response relation between increased sedentary behaviour among youth and unfavorable body composition, and decreased fitness. The review also cited a meta-analysis that found that interventions aimed at decreasing sedentary time found a significant, negative BMI change (Tremblay et al., 2011).

Additionally, there are gender differences in the association between sedentary

behaviour and obesity. Prolonged bouts of sedentary behaviour and time spent playing video/computer games were found to be positively associated with a higher adiposity among males; while this association was not identified among female youth – indicating that there are gender differences in the association between sedentary behaviours and obesity and future research should take this into consideration (Shakir, Coates, Olds, Rowlands, & Tsiros, 2018).

2.2.4.3 Sedentary behaviour guidelines

As for the public health guideline for sedentary behaviours, CSEP advise that youth between the ages of 5-17 years old should limit their recreational screen time (a measure of sedentary behaviour) to no more than two hours per day for health benefits (Tremblay et al., 2016). This time limit is also recommended by the American Academy of Pediatrics (American Academy of Pediatrics, n.d.).

2.2.5 Fruit and vegetable intake

2.2.5.1 Rates in Canada

Among a nationally representative sample of Canadian youth, 93.6% of youth in Canada were found to not meet their fruit and vegetable recommended intake in 2010-2011 (Leatherdale & Rynard, 2013). More male youth reported inadequate intake (94.7%) than their female counterparts (92.7%). More recent findings from 2012-2013 indicate similar rates: 90.1% of youth in Canada in grades 6-12 did not meet their fruit and vegetable recommended intake (Minaker & Hammond, 2016). Younger students (grade 6) had higher odds of meeting the recommendation than older students in grades 8-12. Students with more spending money and those achieving higher marks academically were more likely to meet the recommendation than their counterparts (Minaker & Hammond, 2016).

2.2.5.2 Independent association with obesity

Fruits and vegetables are widely accepted as playing an important role in a healthy diet and in cancer and cardiovascular disease prevention (Agudo, 2005). Findings in the scientific literature indicate that there is an inverse relationship between fruit and

vegetable consumption and weight status, even after controlling for confounding factors that include demographic, socioeconomic and lifestyle factors (Heo et al., 2011). The consumption of more than three servings of fruits and vegetables daily was found to be inversely associated with abdominal obesity among children and adolescents. (Funtikova, Navarro, Bawaked, Fito, & Schroder, 2015).

2.2.5.3 Fruit and vegetable guidelines

Canada's food guide is hosted by Health Canada. This initiative aims to guide food selection and promote the nutritional health of Canadians. Meeting the food guide's recommendations maintains an adequate intake of vitamin, mineral and nutrient needs as well as reduce the risk of obesity and chronic diseases such as diabetes, cardiovascular diseases, osteoporosis and certain types of cancer (Health Canada, 2019).

Fruit and vegetable recommendations differ by age group and gender. Canada's food guide recommends seven servings of fruits and vegetable for female youth and eight servings of fruits and vegetables for male youth (ages 14-18 years) per day (Health Canada, 2019).

2.2.6 Youth who are Victims of Bullying

Youth who are VoB have poorer CDRB than their non-victims of bullying (NVoB) peers during adolescence. This is especially apparent in their substance use behaviours including: alcohol use, tobacco use and illicit drug use (Hertz, Everett Jones, Barrios, David-Ferdon, & Holt, 2015; S. E. Moore et al., 2017). VoB also have poorer mental health than their counterparts (e.g., depression, anxiety and psychotic symptoms) (Arseneault, Bowes, & Shakoor, 2010).

Youth who are VoB are characterized as youth who (i) have been intentionally targeted by their peers, (ii) have an imbalance of power with their perpetrator and (iii) have been exposed to this behaviour repeatedly (Gaete et al., 2017). The prevalence of VoB among youth ranged between 10 to 35% in a review and meta-analysis across a multitude of countries (Moore et al., 2017).

Bullying differs across the genders in prevalence as well as in the type of

bullying. Females are more likely to be verbally and relationally bullied, while males are more likely to be physically bullied (Janssen, Craig, Boyce, & Pickett, 2004; Priesman, Newman, & Ford, 2018).

A recent review and meta-analysis found that being bullied is associated with a higher BMI in cross-sectional studies (Moore et al., 2017). Longitudinal studies have mixed results on whether victimization is associated with increases in BMI during adolescence (Lee & Vaillancourt, 2018a; Mamun, O'Callaghan, Williams, & Najman, 2013). A possible mechanism is explained by the General Strain Theory (Hay, Meldrum, & Mann, 2010). Youth who are VoB may resort to a collection of CDRB (internalizing behaviours) such as problematic eating behaviours (among females) and several substance use behaviours (among males) and when dealing with strain (i.e., being bullied) (Hay et al., 2010).

2.3 Multi-Component Approach to Obesity

Research on CDRB indicates that they cluster and form patterns. An individual is likely to have more than one CDRB at one time point that has a beneficial or detrimental effect on their wellbeing (Prochaska, Velicer, Prochaska, Delucchi, & Hall, 2006).

Assessing for the co-occurrence of chronic disease risk behaviours reflects a lifestyle approach to evaluating health determinants.

A study using COMPASS data assessed youth's compliance to CDRB public health guidelines/standards in Ontario, Canada. The CDRB include the following: PA, binge drinking, cigarette smoking, sedentary behaviour, dietary intake and marijuana use. Leatherdale (2015) found that 20.0% of youth had overweight/obesity, a majority (53.1%) were physically inactive, 22.9% had binge drinking behaviour, 16.5% were current marijuana users, 5.5% were current smokers, 96.7% were highly sedentary and 95.1% had inadequate fruit and vegetable intake. Leatherdale (2015) reports that youth tended to engage in more than one CDRB at the same time, with the mean number of cooccurring behaviours being 3.2 (± 1.1).

2.3.1 Co-occurring behaviours

Some CDRB co-occur more closely than others; for example, diet and PA are two

closely related behaviours and they are both closely associated with obesity (Sisson et al., 2016). Furthermore, co-occurrence research indicates that PA is also inversely associated with substance use behaviours. A study from longitudinal, national data across Canada found that increases in PA participation were associated with decreases in tobacco use over time (DeRuiter, Cairney, Leatherdale, & Faulkner, 2014). deRuiter et al. (2014) also found that declines in alcohol consumption were associated with decreases in tobacco use over the seven cycles (1994-2007) that the Canadian National Population Health Survey was collected indicating the substance use behaviours also tend to co-occur.

Recent investigations group individuals into underlying, homogenous classes of CDRB using statistical methods such as cluster analysis and latent class analysis (LCA). These techniques separate subjects into classes based on their CDRB characteristics (McAloney et al., 2013). For example, a study in the U.S. assessed for youth and young adults' underlying (or latent) classes of CDRB using the CDRB: PA, binge drinking, marijuana use, tobacco use, doctor visitations and fast food intake (Skalamera & Hummer, 2016). They identified four latent classes: a healthy class (they had: high PA, low smoking, binge drinking, marijuana use and fast food intake), a mixed healthy/unhealthy class (had: high fast food and physical inactivity, moderate smoking, low binge drinking and marijuana use) and an unhealthy class (had: high smoking, binge drinking and marijuana use, moderate fast food, physical inactivity) (Skalamera & Hummer, 2016). Arranging CDRB into latent classes helps researchers and policy makers understand how youth engage in different health behaviours and which CDRB tend to co-occur and form underlying profiles.

Additionally, identifying CDRB that are closely associated and co-occur is informative as to which behaviours can be addressed individually, (i.e., ones that are not closely related with other CDRB), and which CDRB co-occur and therefore may benefit from a multi-component or multi-behaviour intervention. In another study, deRuiter, Cairney, Leatherdale and Faulkner (2016) evaluated the prevalence of PA, alcohol consumption and smoking in different arrangements among a national sample of the Canadian population longitudinally. The authors found that the most prevalent combination was physical inactivity and smoking, while less than 3% of the population in

Canada engaged in all three risk behaviours: physical inactivity, smoking and excessive alcohol consumption (DeRuiter et al., 2016). Research that elucidates the co-occurrence of chronic disease risk behaviours is valuable for informing policy.

Understanding the association between chronic disease risk behaviours furthers knowledge in creating effective, evidence-based interventions that target behaviour change. From an intervention standpoint, multi-component interventions may be more cost-effective and efficient since behaviours that are closely related will be addressed simultaneously (DeRuiter et al., 2014; Leech et al., 2014). Assessing the co-occurrence of CDRB will also direct policy-makers as to the CDRB classes that need to be addressed – as they will be more prevalent, or they will be associated with detrimental health outcomes. Multi-component research provides grounds to study and analyze chronic disease risk behaviours and their association with covariates and health outcomes such as overweight/obesity.

2.4 Review of the Scientific Literature

The following section will further examine findings from the scientific literature on chronic disease risk behaviours' latent classes among youth. This section will begin by comparing identified latent classes for chronic disease risk behaviours in the scientific literature. This section will be followed by a review of the associations between the latent classes and weight status among cross-sectional and longitudinal studies.

2.4.1 Chronic disease risk behaviour latent classes among youth

Research evaluating the co-occurrence and the nature of the relationship of different CDRB is on the rise. Statistical methods are used to group participants into CDRB classes based on their behaviours to identify homogenous groups (or classes) of individuals. Insight into the underlying relationships between chronic disease risk behaviours and which are likely to co-occur is an approach that is increasingly accepted as it addresses the multivariate and interactive influences of the participants' behaviour (Leech et al., 2014).

A limited number of studies assessed such CDRB classes among youth that include a combination of substance use (i.e., alcohol, marijuana use or smoking) as well

as behaviours that are more traditionally associated with obesity (i.e., dietary intake, physical activity or sedentary behaviour). Fourteen studies included a similar combination of CDRB were identified from the scientific literature (Boone-Heinonen, Gordon-Larsen, & Adair, 2008; Busch, Van Stel, Schrijvers, & De Leeuw, 2013; Fleary, 2017; Kang et al., 2014; Kritsotakis, Psarrou, Vassilaki, Androulaki, & Philalithis, 2016; Lamont, Woodlief, & Malone, 2014; Landsberg et al., 2010; Laska, Pasch, Lust, Story, & Ehlinger, 2009; Laxer et al., 2017; Luo, Agley, Hendryx, Gassman, & Lohrmann, 2015; C. A. Magee, Caputi, & Iverson, 2013; Mistry, McCarthy, Yancey, Lu, & Patel, 2009; Silva et al., 2014a; Skalamera & Hummer, 2016).

Among these studies, there were three prominent, most popular classes of CDRB. The first class was a high substance use class of youth. Approximately one-third of youth belonged to a class with high substance use, as reported from studies in Canada, the Netherlands, Germany and the U.S.; youth in this class tended to engage in higher alcohol use and smoking behaviours than their peers (Busch et al., 2013; Fleary, 2017; Kang et al., 2014; Landsberg et al., 2010; Laxer et al., 2017; Luo et al., 2015; Skalamera & Hummer, 2016).

The second prominent class is one where close to 40% of youth engaged in low substance use behaviours; however, they also had low PA, poor dietary habits and high sedentary time. The main culprit behaviour across the studies, in this class, was physical inactivity among youth as seen in studies from the U.S. and Germany (Kang et al., 2014; Landsberg et al., 2010; Laska et al., 2009; Luo et al., 2015).

The final class that was reported, among more than half of male and one-third of female youth, was a mixed class. Youth in this class were physically active but had (i) moderate alcohol use patterns (Landsberg et al., 2010; Mistry et al., 2009) or (ii) moderate smoking habits (Skalamera & Hummer, 2016) or (iii) a combination of alcohol use patterns and cigarette smoking or marijuana use habits (Laska et al., 2009; Laxer et al., 2017; Mistry et al., 2009).

2.4.2 Chronic disease risk behaviour latent classes and weight status

The practical significance of identifying latent classes of CDRB is that they

enable researchers to then measure the association of these classes with health outcomes, such as overweight/obesity. Certain classes may be at a higher risk of negative health outcomes. Such associations can inform interventions and policies as to who needs interventions the most, (i.e., the classes that are most closely associated with detrimental health outcomes) resulting in targeting interventions and policies to the groups and individuals who are in need.

The follow sections review the literature's findings on associations between latent classes of CDRB and weight status, as well as with changes in weight status.

2.4.2.1 Cross-sectional findings: latent classes and obesity

Certain latent classes have been found to be associated with a BMI weight status of overweight/obesity. These latent classes are characterized by physical inactivity, poor dietary intake and sedentary behaviour (Busch et al., 2013; Huh et al., 2011; Magee, Caputi, & Iverson, 2013). Among college students in the U.S., 68.6% of those identified in class one (characterized by physical inactivity, an unhealthy diet, and low engagement in binge drinking behaviours) were categorized with overweight/obesity (Kang et al., 2014). Across all the study's classes, the prevalence of overweight/obesity was highest in this class.

Research also suggests an association between latent classes with substance use and overweight/obesity. In Kang et al.'s (2014) study, second to class one, 36.6% of youth in class four (characterized by physical inactivity, binge drinking, high tobacco use and a poor dietary intake), had overweight/obesity (Kang et al., 2014). Two other studies also used PA and substance use in their clustering patterns to observe associations with weight status. Youth who engaged in substance use had the highest prevalence (Busch et al., 2013) and high odds of having overweight/obesity (Laxer et al., 2017).

2.4.2.2 Longitudinal findings: latent classes and obesity

Substance use and PA are CDRB that reportedly track from adolescence into adulthood, as does weight status (e.g., overweight/obesity). As such, adolescence is a prime stage where the determinants of overweight/obesity should be understood and addressed before CDRB habits, and overweight/obesity, become set in adulthood (Sisson

et al., 2016; Suppli et al., 2013).

Longitudinal associations between latent classes and BMI have not been extensively studied. Findings from studies suggest that youth's BMI tends to increase over time, these increases are associated with latent classes where youth use substances and that older youth tend to engage in less healthy CDRB compared with their younger counterparts (Boone-Heinonen et al., 2008; de Winter, Visser, Verhulst, Vollebergh, & Reijneveld, 2016; Deforche, Van Dyck, Deliens, & De Bourdeaudhuij, 2015; Huang, Lanza, & Anglin, 2013; Laxer et al., 2018).

2.4.2.2.1 CDRB latent classes are associated with overweight/obesity

BMI reportedly increases over time, and this increase is different across the genders. Females were seen to have a lower increase in BMI compared to male youth transitioning from high-school to college over a year and a half (Deforche et al., 2015).

There is evidence that CDRB latent classes with smoking behaviour play a role in BMI increases. Among male youth in the U.S., only the *Junk Food & Smoking* cluster was associated with prevalent or incident obesity (Boone-Heinonen et al., 2008). Among young adults, also from the U.S., 24% of those in the smoking trajectory were found to have an increasing obesity trajectory, which was higher than the alcohol and marijuana trajectories. The increased marijuana trajectory also had a high risk of belonging to the increasing obesity trajectory compared to those in the low marijuana trajectory (Huang, Lanza, Wright-Volel, & Anglin, 2013). Similar results were reported from another study; the only pathway that was significant for substance use at time-one to percent body fat at time-two was among adolescents who smoked cigarettes (Pasch, Velazquez, Cance, Moe, & Lytle, 2012). The authors explain that there is a relationship between substance use and obesity that is mediated through energy balance, the clustering of CDRB and social influences (Pasch et al., 2012).

2.4.2.2.2 Other factors to consider in the longitudinal relationship between latent classes and BMI

Although BMI is reported to increase over time, the class with the healthiest BMI at baseline is not necessarily the healthiest BMI class at all time points. Among youth in

Germany, the latent class characterized by low PA, low substance use (smoking and alcohol) and moderate media time had the lowest BMI at baseline (Landsberg et al., 2010). However, after four years, the latent class characterized by high PA, medium substance use (low smoking and moderate alcohol use) and low media time had the lowest BMI and it was the class with the lowest incidence of obesity over the four years (Landsberg et al., 2010).

Other factors to consider are that risk factors that cause increases in BMI differ across age and gender. A longitudinal analysis assessed CDRB and changes in BMI one year apart. Among a national sample of U.S. youth, there were differences in the CDRB associated with BMI across the genders (Berkey et al., 2000). Among female youth, fewer hours of PA, a higher calorie intake and more hours of TV/video games predicted annual BMI increases (Berkey et al., 2000). As for males, annual BMI increases were associated with less PA and more TV/video game time (Berkey et al., 2000). The authors also found that older youth reported attending the gym once more per week than their younger counterparts; yet, they had more screen time and higher BMIs (Berkey et al., 2000). Another study also found that as youth grow older they engage in more risky behaviours (de Winter et al., 2016).

2.5 Theoretical approach: Problem Behaviour Theory

The Problem Behaviour Theory explains the theoretical underpinnings of how and why CDRB co-occur. Jessor and Jessor developed the Problem Behaviour Theory (PBT) in 1977; the theory suggests that behaviours are a result of the interaction between person and environment (Jessor & Jessor, 1977). Problem behaviours are considered actions that are inappropriate or undesirable by the larger society or legal norms of the society and authority and that warrant exercise of social control. These may include: drug-use behaviour, social protest behaviour and sexual behaviour. Conventional behaviours are those that are socially approved, normatively expected, and considered appropriate for adolescents and youth. These may include academic achievement as measured by grade point average. (Jessor & Jessor, 1977).

PBT focuses on three systems of psychosocial influence, which when combined

generate a state called 'proneness' that specifies the likelihood of problem behaviour. The three systems are: the personality, the perceived environment, and the behaviour system. The personality system deals with cognitive-social variables including the individual's controls to participate in a behaviour and their own belief or control structure. The perceived environment consists of the individual's perceptions about their parents, peers and teacher's supports and controls. The behaviour system addresses the individual's meaning of the act, its social definition, its relation to age and status, the context of its occurrence and its time in history. Each system is composed of variables that either control against the involvement in problem behaviours (protective factors) or are instigations for engaging in problem behaviours (risk factors). The interrelations of the systems determine the level of proneness of an individual to engage in problem behaviour due to their set of personality variables and perceived environment variables. (Donovan, 2005; Jessor & Jessor, 1977).

Researchers later added upon problem behaviours to include pro-social behaviour, health-compromising and health-enhancing behaviours to the theory. A conceptual framework of PBT is available in Appendix A. (Begg & Gulliver, 2008; Costa & Jessor, n.d.; Jessor, 1991; Jessor & Jessor, 1977; Ndugwa et al., 2011).

The theory suggests that individuals who engage in one problem behaviour are at a higher risk of being involved in other problem behaviours due to the shared meanings and functions of these behaviours, as well as the social influences surrounding them. (Jessor & Jessor, 1977). As reviewed from the scientific literature, behaviours cluster and some more than others – PBT explains that the behaviours may share similar social-cognitive determinants. For example, strong associations have been reported from the scientific literature between diet and exercise, and between alcohol and smoking. Such findings suggest that health-promoting behaviours influence each other, that health-risk behaviours are closely related and that behaviours influence the future engagement in similar behaviour (Jessor, 2014; Lippke, Nigg, & Maddock, 2012).

The theory also observes that longitudinally, there is a developmental increase in the engagement in problem behaviours among high-school students as time progresses, and a decrease in the engagement in conventional behaviours (Jessor, 2014). This

observation is also cited in the scientific literature as previously mentioned.

Jessor and Jessor's PBT has been tested for behaviours such as alcohol use, drug use, tobacco use, problematic internet use and unsafe sexual behaviour (Begg & Gulliver, 2008; De Leo & Wulfert, 2013). PBT has also been tested across Asian, European, North American and Eurasian countries (Vazsonyi et al., 2010) and among minority/vulnerable populations (Mobley & Chun, 2013).

One such group among youth are those who are victims of bullying. A study assessed the relationship between youth involved with bullying and their engagement in problem behaviours (i.e., cigarette smoking, drinking alcohol, breaking or damaging others' property, etc.) (Lester, Cross, & Shaw, 2012). The authors found that youth who are victims of bullying had a higher engagement with problem behaviours over time, as their victimization increased. Lee and Vaillancourt (2018b) explained these observations by suggesting that: being victimized has an internalizing effect, by integrating other people's attitudes into one's own self-image. When bullied, youth tend to blame themselves and in turn this affects how they see their bodies, causing a lower self-esteem and body-esteem (Lee & Vaillancourt, 2018b). If self-esteem is not gained through socially acceptable methods, Kaplan (1976) suggested that one will turn to deviant behaviour (such as problem behaviours and substance use) to gain self-esteem and attention; thus, low self-esteem (e.g., triggered by being a victim of bullying) is suggested as a motivating factor for deviant/problem behaviour (Wing Lo, Cheng, Wong, Rochelle, & Kwok, 2012).

2.6 The COMPASS Study (Host Study)

The primary objective of the 'Cohort Study on Obesity, Marijuana Use, Physical Activity, Alcohol Use, Smoking and Sedentary Behaviour' (COMPASS) Study is to effectively guide and improve the health of youth through research and practice (Leatherdale, Brown, et al., 2014). COMPASS is designed to strengthen capacities to advance youth's health and lifestyle behaviours and to engage researchers by utilizing natural experiments to generate evidence-based practice and practice-based evidence. It also aims to strengthen knowledge of health inequities among high-risk groups of youth

(e.g., Aboriginal youth), health related outcomes and to foster partnerships between researchers and knowledge users through primary prevention actions and evidence-based practice. The COMPASS study was initiated in 2012-2013 and renewed for nine years through support by a bridge grant from the CIHR Institute of Nutrition, Metabolism and Diabetes through the "Obesity - Interventions to Prevent or Treat" priority funding awards and an operating grant from the CIHR Institute of Population and Public Health. (Leatherdale, Brown, et al., 2014).

COMPASS uses a four staged, cyclical process to achieve its objectives:

- (1) it enables the investigation of current youth health behaviours as well as the school's-built environment, programs and policies;
- (2) the data is used for knowledge translation by providing the school with a yearly report and a dedicated knowledge broker;
- (3) COMPASS staff inform intervention activities deemed a priority by the school's stakeholders; and
- (4) the impact of school interventions can be evaluated.

COMPASS collects data via a two-stage cluster sample of school boards and secondary schools (teaching grades 9-12, with a student population of at least 100 students per grade) (Leatherdale, Brown, et al., 2014).

Students complete COMPASS's student questionnaire (Cq) to document their health behaviours and outcomes. The questionnaire collects information on youth's physical activity, dietary, sedentary behaviour, tobacco use, alcohol and marijuana use habits. It addresses both science-based and practice-based (e.g., obesity, bullying, among others) concerns. The questionnaire takes 30-40 minutes to complete and is machine-readable. Students in participating schools complete the questionnaire each year that the COMPASS Cq is being collected. (Leatherdale, Brown, et al., 2014).

The Cq has been collected since the COMPASS study's initiation in 2012-2013 and can be linked for a longitudinal sample. The Cq includes five questions that were specifically designed to enable linking of the questionnaires across the four time points to a specific individual by a six-digit alpha-numeric code (Qian, Battista, Bredin, Brown, &

Leatherdale, 2015).

2.7 Gap in the Scientific Literature

With the high overweight/obesity rates among youth in Canada, a novel approach to study determinants of overweight/obesity is through identifying classes of chronic disease risk behaviours and assessing their effect on weight status – rather than evaluating the effect of each CDRB individually on weight status. Although this has been attempted before (Laxer et al., 2017, 2018), the limitation with previous research is that it did not stratify for gender.

Female and male youth have differences at a biological, psychological, and social level. There are biological differences in behaviours which are also accompanied with other socializing agents (e.g., peers, community) that contribute to female and male youth engaging in different behaviours (Ngun, Ghahramani, Sánchez, Bocklandt, & Vilain, 2011). This is of importance since females and males engage in CDRB differently (Harvey, Faulkner, Giangregorio, & Leatherdale, 2017; Leech et al., 2014), have different BMIs (Roberts et al., 2012), report BMI differently (Arbour-Nicitopoulos et al., 2010; Sherry, Jefferds, Grummer-Strawn, et al., 2007), and likely have different CDRB predictors of BMI (Boone-Heinonen et al., 2008; Nuutinen et al., 2017; Te Velde et al., 2007).

Additionally, longitudinal studies that track the association between CDRB and subsequent BMI are scarce. The scientific literature reports that as youth progress through secondary school, CDRB are poorer and BMI increases. Identifying which classes of CDRB are associated with increases in BMI over time inform as to which are problematic and need interventions. Such results will also indicate which classes of youth are prone to increases in BMI and will provide evidence-based knowledge to direct early prevention efforts as a part of CDRB prevention programs and policies.

Intervening during adolescence is paramount because youth who were categorized with overweight/obese move to having 'healthier' BMI categories, while reportedly few adults have decreases in BMI. Findings from adults in the U.S. report that over 18 years, BMI increased by 13%, with only 1.9% of females and 0.5% of males following a

trajectory that resulted in a one unit (kg/m²) decrease in BMI (Malhotra, Østbye, Riley, & Finkelstein, 2013). Findings from youth in Spain, show that 26% of youth classified as obese transitioned to having an overweight BMI (Devis-Devis et al., 2017). These findings emphasize that healthy weight loss and maintenance interventions should be implemented during adolescence since decreases in BMI are reported during adolescence.

When discussing CDRB, BMI and gender differences, a population of youth are at a distinct disadvantage relative to their peers. Youth who are victims of bullying face victimization by their peers and this influences the CDRB they engage in. It is unclear whether the act of victimization contributes to increases in BMI among youth who are VoB, or if the increased in BMI are mediated through VoB's increased engagement in poor CDRB such as substance use.

Chapter 3 Study Objectives and Research Questions

3.1 Dissertation Purpose

The purpose of this dissertation was to identify gender differences in chronic disease risk behaviour (CDRB) latent classes and their association with BMI in cross-sectional and longitudinal analyses among youth in Canada. Furthermore, this dissertation presents evidence as to whether there are differences in these associations among youth who are victims of bullying and those who are not. The following section describes the three research studies that were conducted to meet these objectives. This section also drew on the scientific literature and presented hypotheses regarding each study's research questions.

3.2 Study One (Chapter 5)

3.2.1 Research questions

The objective in this study was to identify gender-specific latent classes of CDRB and assess the latent class's associations with BMI in a cross-sectional design for youth in grades 9 to 12 in Wave 1 (2013-2014), Wave 2 (2014-2015) and Wave 3 (2015-2016) of the COMPASS study, cross-sectionally (i.e., at each separate time point) in Ontario, Canada. This objective was answered through the research questions below:

- a) What are the percentages of youth not meeting the public health guidelines for: physical activity, binge drinking, marijuana use and cigarette smoking?
- b) What is the number and composition of the latent classes that best represents CDRBs (physical activity, binge drinking, marijuana use and smoking), for females and males?
- c) To what extent are the latent classes associated with weight status, cross-sectionally, when controlling for ethnicity and grade, as per gender-stratified regression analyses?

3.2.2 Hypotheses

a) Regarding the percentages of youth not meeting public health guidelines and standards, it is was expected that approximately: 50% of youth will not meet the PA

public health guideline, 30% would be considered binge drinkers, 30% would be considered marijuana users, and 10-15% would be considered cigarette smokers (Alamian & Paradis, 2012; Carson, Pickett, & Janssen, 2011; Leatherdale, 2015; Leatherdale & Rynard, 2013; Mejia et al., 2013; Plotnikoff et al., 2009). Gender differences were expected for PA, with possible gender differences for binge drinking and marijuana use (Berkey et al., 2000).

- b) As for the latent class analysis, the optimal number of latent classes was expected to be three to five classes, with four profiles being most likely the optimum number. The latent classes were likely to include one (or more) of the following classes: (1) high substance use, (2) low PA and low substance use, and (3) a mixed class of the two sets of behaviours with smoking or alcohol the predominant substance use behaviour. As for gender, female and male youth were expected to have different classes. (Busch et al., 2013; Kang et al., 2014; Landsberg et al., 2010; Laska et al., 2009; Luo et al., 2015; Mistry et al., 2009; Skalamera & Hummer, 2016).
- c) Based on previous research, inactive youth were expected to have a higher risk of having overweight/obesity compared with their more active peers, as were substance users compared with their non-substance using peers (Laxer et al., 2017; Nuutinen et al., 2017; Spengler, Mess, Mewes, Mensink, & Woll, 2012).

3.3 Study Two (Chapter 6)

3.3.1 Research questions

In this study, the objective was to assess whether CDRB latent classes (that were identified in study one) were associated with BMI longitudinally (at follow-up), in gender-specific analyses, among youth in grades 9 to 12 in Wave 1 (2013-2014), Wave 2 (2014-2015) and Wave 3 (2015-2016) of the COMPASS study in Ontario, Canada. This study had the following research questions:

- a) Are there transitions in BMI status from one year to the next?
- b) To what extent are the latent classes of CDRB associated with BMI longitudinally, as per gender-stratified transition regression analyses?

3.3.2 Hypotheses

- a) An overall increase in average BMI is expected in the following year, as BMI is on an increasing trajectory during this age (Haerens, Vereecken, Maes, & De Bourdeaudhuij, 2010; Rodd & Sharma, 2016). Although most youth (about 75%) are expected to remain in their BMI category, some transitions were expected. Similar to previous findings from Spain, it is predicted that approximately 25% of youth with obesity will transition to having an overweight BMI in the following year. (Devis-Devis et al., 2017; Huang, Lanza, & Anglin, 2013).
- b) As for the impact of the latent classes on BMI, an increase in BMI was expected among youth who are physically inactive (Haerens et al., 2010). Based on previous research, it was also expected that youth in a class with smoking will have increases in BMI (Huang, Lanza, & Anglin, 2013; H. I. Lanza, Grella, & Chung, 2014; Pasch et al., 2012).

3.4 Study Three (Chapter 7)

3.4.1 Research questions

Study three's main objective was to assess the relationship between being a victim of bullying with BMI longitudinally, among female and male youth, in grades 9 to 12 in Wave 1 (2013-2014), Wave 2 (2014-2015) and Wave 3 (2015-2016) of the COMPASS study in Ontario, Canada. The following research questions addressed this objective:

- a) Are there differences in CDRB (physical activity, binge drinking, marijuana use and smoking) across youth who are victims of bullying and those who are not?
- b) Are there transitions in bullying status, in BMI, and in latent classes among youth who are victims of bullying and those who are not across a one-year time frame?
- c) To what extent is bullying (at the previous wave and consecutive bullying status) associated with BMI longitudinally? Does this differ among female and male youth?

3.4.2 Hypotheses

a) Youth who are victims of bullying were expected to have higher substance use behaviours than their non-bullied peers (Gaete et al., 2017; Piggott et al., 2018).

- b) Some CDRB will track across time, these include: cannabis use, physical inactivity and an overweight/obese weight status (de Winter et al., 2016). Changes in latent class memberships will be highly variable depending on the latent classes identified. It is expected that a selection of adolescents (at least 8-10%) will change class memberships. (Tomczyk, Pedersen, Hanewinkel, Isensee, & Morgenstern, 2016).
- c) Being a victim of bullying was expected to be associated with a higher BMI one year later. It was predicted that there will be differences across the genders, with a stronger relationship between bullying and BMI among female youth. (Mamun et al., 2013; Moore et al., 2017; Wang, Li, Li, & Seo, 2018).

Chapter 4 General Methods

This dissertation is a secondary analysis using data from the COMPASS study (2012-2021). The following section will describe: the sampling and response data from COMPASS, the COMPASS student questionnaire (Cq) and the variables of interest used in this dissertation. It will also present a brief overview of the statistical methods used in the three studies.

4.1 Data Source: The COMPASS Study

4.1.1 Ethics and recruitment

The University of Waterloo Office of Research Ethics and School Board and School committees approved all procedures. School boards and schools that endorse passive consent were purposefully sampled from Ontario and Alberta, Canada. After a school board granted approval, schools were approached. Schools with at least 100 students per grade in grades 9 to 12 were invited to participate.

Parents approved participation by passive consent. Passive consent was obtained by sending an information sheet to the student's parent/guardian. The sheet requested from the caregiver to call a toll-free number or e-mail the recruitment officer if they did not want their child to participate. COMPASS uses passive consent: (1) because it is appropriate to use given its research design, (2) to ensure there is a sufficient sample to answer research questions and most importantly (3) to protect the anonymity of students taking part in the COMPASS questionnaire. Research examining youth substance use does not encourage the use of active consent procedures since youth are less likely to participate in active consent studies of this nature. This may reduce the participation of the very students that programs are trying to help (i.e. substance users). (Thompson-Haile, Bredin, & Leatherdale, 2013).

Active consent has been reported in the literature to have an impact on students who participate in school-based research. Active consent would require students to list and sign their names, grade-level and teacher's name when participating in the research study. Passive consent will require the recording of the names and details of students not

30

participating; thus, the COMPASS team does not have the names of participating students. This ensures confidentiality in the submissions. Age and gender also play a factor: students who are older, and reportedly males, are less likely to participate in active consent protocols compared with passive consent studies; passive consent reduces this potential bias. (Thompson-Haile et al., 2013).

Assent was obtained from all students on the day that they completed the survey. Students could withdraw from participation at any time. The COMPASS Student Questionnaire assured anonymity and confidentiality by asking students not to record their names on the survey. Participants were also asked to seal their booklet in an envelope before submitting it to the project staff. Individual student responses were not communicated back to the school or other personnel.

4.1.2 Sampling and response rate

COMPASS spans from 2012 to 2021; this dissertation used data from the school years: 2013-2014 (Wave 1), 2014-2015 (Wave 2) and 2015-2016 (Wave 3).

Schools were recruited in Waves 1, 2 and 3 reaching a sample of greater than eighty schools across Ontario and Alberta and more than 40,000 participating students each year. In Wave 1, the sample size was 45,298 students from 89 schools from the two provinces. In Wave 2, 42,355 students participated in the Cq from 89 schools from the two provinces. In Wave 3, 40,436 students took part in the Cq from 81 participating schools from the two provinces.

Parent permission rates from the passive consent were at 99%. Participation from students was 79.1% in 2013 (n=41734), 78.4% in 2014 (n=39013) and 79.9% from 2015 (n=37106) in Ontario; the primary reason for non-participation was absence from school.

4.1.3 COMPASS Student Questionnaire (Cq)

4.1.3.1 Questionnaire design

The Cq was designed to collect quantitative health data on a large-scale. The questionnaire is a twelve-page, machine-readable booklet that was completed in classrooms by secondary school students in approximately 30 to 45 minutes. The

complete questionnaire is available in Appendix B.

The questionnaire collected health behaviour data on youth such as: participation in PA, sedentary behaviour, dietary habits, and experiences with tobacco, alcohol and marijuana. The Cq asked for youth's weight and height as well as socio-demographic characteristics including age, spending money, ethnicity and gender. The Cq also inquired about social (family and peer) influences regarding smoking and physical activity participation. Other information included data on student academic outcomes, academic ambitions, bullying and the student's intentions to change behaviours.

The questionnaire has a "Physical activity" section that asked for minutes of hard PA and moderate PA performed over the last seven days, school participation in sports and days of muscle conditioning over the past seven days. A "Healthy Eating" section followed and inquired on eating habits, for example, the number of days that they eat breakfast and consumption of fruits and vegetables.

The next section is titled "Your experience with smoking" and asked about smoking habits, initiation and accessibility, if the student had ever smoked more than one-hundred whole cigarettes in their life, smoking habits in the last thirty days and peer smoking habits.

The next section addressed "Alcohol and Marijuana Use". It defined a measure of a standard drink at the beginning of the page and proceeded to ask about alcohol consumption including the number of times in the last twelve months when they had 5 or more drinks of alcohol. This section also inquired about use of marijuana and age when first used marijuana.

The last section is entitled "Your school and you" and asked about feelings of school connectedness, bullying behaviour (perpetrators and victims of), school support for health behaviours, academic achievement, number of classes skipped when not supposed to and frequency of going to class without homework complete.

4.2 Study Measures

4.2.1 Weight status (outcome variable)

Weight status was determined by Body Mass Index (BMI) from youth's self-reported weight and height using the formula $\left(BMI = \frac{weight\ (kg)}{[height\ (m)]^2}\right)$, where weight is in kilograms and height is in meters. The World Health Organization's (WHO) age- and sex-specific cut-off points (ages 13–18 years old) were used to classify BMI categorically (World Health Organization, 2007). The measures used to determine BMI in COMPASS have previously been validated (ICC= 0.84) (Leatherdale & Laxer, 2013). BMI was used as a (i) continuous outcome, as well as a (ii) binary outcome for comparative purposes. A binary BMI (*overweight /obese* versus *normal*) was considered because existing literature have shown that youth classified as *overweight* or *obese* have similar future risks of chronic diseases (Peirson et al., 2015).

4.2.2 Chronic disease risk behaviours (predictor variables)

The CDRB that formulated the latent classes are: physical activity, current binge drinking, current marijuana use and current cigarette smoking. These CDRB were measured against national standards and public health guidelines to facilitate comparison across Canadian adolescents and to keep in line with other similar research. The responses were dichotomized as follows: youth *met* the public health guideline (or standard) for that CDRB versus youth *did not meet* the public health guideline (or standard). A full list of the CDRBs, their corresponding public health guideline (or standard) and the respective measure as it is collected from the COMPASS student questionnaire are available in Table 4.1.

4.2.2.1 Physical activity

PA was measured from the Cq through youth's answers to three questions: (i) "How many minutes of hard PA you did on each of the last seven days." (ii) "How many minutes of moderate PA you did on each of the last seven days." And (iii) "On how many days in the last seven days did you do exercises to strengthen or tone your muscles?".

The definitions of hard and moderate PA were provided in the Cq. Minutes of hard PA

and minutes of moderate PA reported in the Cq have been found to be valid (Leatherdale, Laxer, & Faulkner, 2014).

In compliance with the Canadian Society for Exercise Physiology's (CSEP) 24-Hour Movement Guidelines for PA among youth 12-17 years old (Tremblay et al., 2016), youth who (i) performed 60 minutes of moderate-to-hard activity (MVPA) daily; and on at least three out of the last seven days participated in (ii) hard activity and (iii) activities that strengthen muscles and bone were considered to meet PA guidelines; otherwise they did not (Tremblay et al., 2016).

Table 4.1 The chronic disease risk behaviour (CDRB), its corresponding public health guideline and relevant question(s) from the COMPASS student questionnaire (Cq).

CDRB	Measures	Corresponding Questions (Q) from the Cq
Physical activity	The CSEP guidelines for youth 12-17 years old were used: students who performed 60 minutes of moderate-to-hard activity daily and hard activity on at least three out of the last seven days and participated in activities that strengthened muscles and bone at least three days per week were considered active; otherwise they were considered not active (Tremblay et al., 2016).	Minutes of hard PA (Q10), minutes of moderate PA (Q11). Measure of strength/resistance training (Q18).
Current binge drinking	Consistent with the national standards used in previous research, binge drinking was classified as five or more drinks on one occasion during the last month (Leatherdale, 2015; Leatherdale & Burkhalter, 2012).	Binge drinking (Q46).
Current marijuana use	Consistent with the national standards used in previous research, marijuana use of once a month was considered a current marijuana user (Leatherdale, 2015; Leatherdale & Burkhalter, 2012).	Marijuana use (Q48).
Current cigarette smoking	The measure that Wong et al. (2012) validated for current smoking was used: students who reported ever smoking 100 cigarettes and any smoking in the previous 30 days were classified as current cigarette smokers, otherwise they were classified as non-smokers.	Smoked more than 100 cigarettes (Q37). Any smoking in the past 30 days (Q39).

4.2.2.2 Substance use

Regarding alcohol consumption, youth were asked: "In the last 12 months, how often did you have 5 drinks of alcohol or more on one occasion?". Consistent with previous research, youth were current binge drinkers if they had five or more drinks at least once in the last month otherwise they were not (Leatherdale, 2015; Leatherdale & Burkhalter, 2012).

As for smoking, the Cq asked: (i) "Have you ever smoked 100 or more whole cigarettes in your life?" and (ii) "On how many of the last 30 days did you smoke one or more cigarettes?". To distinguish current cigarette smokers, the measure validated by Wong and colleagues (2012) was used: students who reported (i) ever smoking 100 cigarettes and (ii) any smoking in the previous 30 days were classified as current smokers otherwise they were considered non-smokers.

The Cq asked youth about their marijuana use as such: "In the last 12 months, how often did you use marijuana or cannabis? (a joint, pot, weed, hash)". Youth who used marijuana once a month were considered current marijuana users, otherwise they were non-current users (Leatherdale, 2015; Leatherdale & Burkhalter, 2012).

4.2.2.3 Other chronic disease risk behaviours

Additional CDRB including sedentary behaviour and diet (fruit and vegetable intake) were considered for this analysis. These variables were not included in this analysis because most youth did not meet guidelines for sedentary behaviour (96.1%) (Milicic, Piérard, DeCicca, & Leatherdale, 2017) nor fruit and vegetable intake (94.7%) (Harvey et al., 2017) in previous COMPASS studies; therefore, these CDRB were excluded from these studies due to a floor effect.

4.2.3 Bullying status (predictor variable)

In the Cq, youth replied to the question "In the last 30 days, how often have you been bullied by other students?" using the following selections: "I have not been bullied by other students in the last 30 days" or "less than once a week" or "about once a week" or "2 or 3 times a week" or "daily or almost daily". To be considered not a victim of

bullying (NVoB), the answer: "I have not been bullied by other students in the last 30 days" had to be selected, otherwise youth were classified as VoB.

Furthermore, an interaction variable was reported to assess changes in bullying status across two-time points (will be referred to as *consecutive bullying status*) as such: bullying status at the previous wave crossed with bullying status at follow-up (four categories were possible: VoB/VoB, VoB/NVoB, NVoB/VoB, NVoB/NVoB). This variable was used in the regression model as it provided evidence as to whether sustained bullying, or changes in bullying status are associated with changes in BMI.

4.3 Statistical Analyses

This section is an overview of the statistical methods that were used in each of the three studies. A detailed description of the analyses can be found in the chapter corresponding to the study in this dissertation: chapter 5 for study one, chapter 6 for study two and chapter 7 for study three.

4.3.1 Data sampling

This dissertation is a multilevel investigation based on secondary analysis from the COMPASS Cq. Three waves of the COMPASS study (Waves 1, 2 and 3) were utilized for cross-sectional as well as longitudinal analyses. The cross-sectional analysis (study one) used the three waves of data unlinked, assessing chronic disease risk behaviours at each separate time point (i.e., in a repeated cross-sectional design). The conclusions made explored associations among Grade 9-12 students at each wave independently to assess the reliability of these findings across the three years (Makel, Plucker, & Hegarty, 2012). The longitudinal analysis (studies two and three) used the same three waves of data (Waves 1, 2 and 3); however, youth's participation was linked for the longitudinal analysis (Bredin & Leatherdale, 2013).

4.3.2 Study One (Chapter 5)

The objective of this study (i.e., Chapter 5) was to identify gender differences in latent classes of CDRB and evaluate the association of the latent classes to BMI and weight status among youth in grade 9 to 12 in Waves 1, 2 and 3 of the COMPASS study.

Youth were identified as meeting or not meeting the public health guidelines (or standard) via frequencies for the CDRB: PA, binge drinking, marijuana use and cigarette smoking. The CDRB latent classes were identified using a multilevel latent class analysis (MLCA) for females and males. The multilevel mixed-effects regression models regressed BMI (as a continuous and as a binary variable, separately) onto the latent classes and accounted for the clustered nature of the data in gender-stratified analyses.

The gender-specific, multilevel mixed-effects regression model regressed BMI onto the latent classes, adjusting for ethnicity and grade as seen below in the models with BMI as a continuous outcome (Model 1.1) and as weight status (a binary outcome variable) (Model 1.2). This analysis was repeated for each of the three waves independently to assess for the finding's reliability across the three waves. The results from the models are presented in Chapter 5.

The mixed-effects linear model is given by

$$BMI_{i,j} = \beta_0 + \beta_1 Latent \ class_{i,j} + \beta_2 Grade_{i,j} + \beta_3 Ethnicity_{i,j}$$
 where,

Latent $class_{i,j} = subject \ i$'s latent class at the j-th year; $Grade_{i,j} = subject \ i$'s grade-level at the j-th year;

 $Ethnicity_{i,j} = subject \ i$'s self-identified ethnicity at the j-th year.

The mixed-effects binary model is given by

$$\zeta_{i,j} = \beta_0 + \beta_1 Latent \ class_{i,j} + \beta_2 Grade_{i,j} + \beta_3 Ethnicity_{i,j}$$

$$\tag{1.2}$$

where,

$$\zeta_{i,j} = log\left(\frac{Pr(Binary\ BMI_i = Overweight/Obese)_{i,j}}{Pr(Binary\ BMI_i = Healthy)_{i,j}}\right)$$
 with

Weight $status_{i,j} = binary BMI (normal versus overweight/obese)$ at the j-th year;

Latent $class_{i,j} = subject i$'s latent class at the j-th year;

 $Grade_{i,j} = subject \ i's \ grade-level \ at \ the \ j-th \ year;$

 $Ethnicity_{i,j} = subject \ i's \ self-identified \ ethnicity \ at \ the \ j-th \ year.$

4.3.3 Study Two (Chapter 6)

The purpose of this study was to assess the extent to which lagged latent classes of CDRB were associated with BMI (as a continuous and as a binary variable, separately) among youth in grades 9-12 in Waves 1, 2 and 3 of the COMPASS study in gender-stratified analyses. This study is addressed in Chapter 6.

The analysis measured transitions in binary BMI across the two years via McNemar's test. Using the latent classes identified from study one, the multilevel mixed-effects models regressed BMI on lagged latent classes of CDRB. All mixed-models adjusted for the following predictors: BMI (at the previous wave), ethnicity (at baseline), grade (at current wave) and year, while accounting for the three-level hierarchical structure of the data: schools (level 3) enrolled students (level 2) over the three waves of the study (level 1). The outcome variable BMI was used as a continuous outcome (Model 2.1) and as weight status (a binary outcome) (Model 2.2) for comparative purposes. The results from the models are presented in Chapter 6.

The longitudinal mixed-effects linear model conducted is given by

$$BMI_{i,j} = \beta_0 + \beta_1 Latent \ class_{i,j-1} + \beta_2 \ BMI_{i,j-1} + \beta_3 Grade_{i,j} + \beta_4 Ethnicity_i + \beta_5 Year$$
 (2.1)

where,

Latent $class_{i,j-1} = subject \ i$'s latent class at the previous wave (j-1);

 $BMI_{i,j-1} = subject \ i$'s BMI at the previous wave (j-1);

 $Grade_{i,j} = subject \ i's \ grade-level \ at the j-th \ year;$

 $Ethnicity_i = subject\ i$'s self-identified ethnicity at baseline;

 $Year = categorical \ variable \ specifying \ the \ data \ collection \ year (2013, 2014 \ or 2015).$

The mixed-effects binary model conducted is given by

$$\zeta_{i,j} = \beta_0 + \beta_1 Latent \ class_{i,j-1} + \beta_2 \ BMI_{i,j-1} + \beta_3 Grade_{i,j} + \beta_4 Ethnicity_i + \beta_5 Year$$
 (2.2)

where.

$$\zeta_{i,j} = log\left(\frac{\Pr(Binary\ BMI_i = Overweight/Obese)_{i,j}}{\Pr(Binary\ BMI_i = Healthy)_{i,j}}\right) \ \ \text{with}$$

$$Weight\ status_{i,j} = \text{binary\ BMI}\ (normal\ versus\ overweight/obese)\ \text{at\ the}}$$

$$\text{j-th\ year;}$$

$$Latent\ class_{i,j-1} = subject\ i\text{'s\ latent\ class\ at\ the\ previous\ wave\ (j-1);}$$

 $BMI_{i,j-1} = subject \ i's \ BMI \ at the previous wave (j-1);$

 $Grade_{i,j} = subject i$'s grade-level at the j-th year;

 $Ethnicity_i = subject\ i$'s self-identified ethnicity at baseline;

 $Year = categorical \ variable \ specifying \ the \ data \ collection \ year (2013, 2014 \ or$ 2015).

4.3.4 Study Three (Chapter 7)

The purpose of this study was to investigate whether victims of bullying engage in CDRB differently than their peers, and whether being a victim of bullying is associated with BMI longitudinally. This study is detailed in Chapter 7.

To address this objective, exploratory analysis via chi-square tests measured differences in CDRB engagement across bullying status. Additionally, McNemar tests were used to assess transitions in consecutive bullying status, BMI and in the latent classes. Gender-specific, multilevel mixed-effects regression models were used to regress bullying status on BMI longitudinally, controlling for latent class, and BMI at the previous wave, as well as ethnicity at baseline, grade at follow-up and year. Bullying status was used as: (i) a main effect in the model (i.e., victim of bullying at the previous wave; Models 3.1 and 3.2) and as (ii) an interaction term of consecutive bullying status (i.e., bullying status at the previous wave crossed with bullying status at follow-up; Models 3.3 and 3.4) as previously described in Section 4.2.3. Additionally, this study assessed for BMI as a continuous outcome (Models 3.1 and 3.3) and weight status (BMI as a binary outcome; Models 3.2 and 3.4). The results from the models are presented in Chapter 7.

The mixed-effects linear model that used bullying at the previous wave (i.e., bullying as a

main effect) conducted is given by

$$BMI_{i,j} = \beta_0 + \beta_1 Latent \ class_{i,j-1} + \beta_2 Latent \ class_{i,j} + \beta_3 \ BMI_{i,j-1} + \beta_4 Grade_{i,j} + \beta_5 Ethnicity_i + \beta_6 Year + \beta_7 Bullying \ status \ at \ the \ previous \ wave_{i,j-1}$$
 (3.1)

where,

Latent class_{i,j-1} = subject i's latent class at the previous wave (j-1);

Latent $class_{i,j} = subject\ i$'s latent class at the j-th year (j);

 $BMI_{i,j-1} = subject \ i$'s BMI at the previous wave (j-1);

 $Grade_{i,j} = subject \ i$'s grade-level at the j-th year;

 $Ethnicity_i = subject \ i's \ self-identified \ ethnicity \ at \ baseline;$

 $Year = categorical \ variable \ specifying \ the \ data \ collection \ year (2013, 2014 \ or 2015);$

Bullying status at the previous wave_{i,j-1} = subject i's bullying status at the previous wave (j-1).

The mixed-effects binary model that used *bullying at the previous wave* (i.e., bullying as a main effect) conducted is given by

 $\zeta_{i,j} = \beta_0 + \beta_1 Latent \ class_{i,j-1} + \beta_2 Latent \ class_{i,j} + \beta_3 \ BMI_{i,j-1} + \beta_4 Grade_{i,j} + \beta_5 Ethnicity_i + \beta_6 Year + \beta_7 Bullying \ status \ at the \ previous \ wave_{i,j-1}$ (3.2) where,

$$\zeta_{i,j} = log\left(\frac{\Pr(Binary\ BMI_i = Overweight/Obese)_{i,j}}{\Pr(Binary\ BMI_i = Healthy)_{i,j}}\right)\ \text{with}$$

Weight $status_{i,j} = binary BMI (normal versus overweight/obese)$ at the j-th year;

Latent $class_{i,j-1} = subject i$'s latent class at the previous wave (j-1);

 $Latent\ class_{i,j} = subject\ i$'s latent class at the j-th year (j);

 $BMI_{i,j-1} = subject \ i$'s BMI at the previous wave (j-1);

 $Grade_{i,j} = subject i$'s grade-level at the j-th year;

 $Ethnicity_i = subject \ i's \ self-identified \ ethnicity \ at \ baseline;$

Year = categorical variable specifying the data collection year (2013, 2014 or 2015);

Bullying status at the previous wave_{i,j-1} = subject i's bullying status at the previous wave (j-1).

The mixed-effects linear model that used *consecutive bullying status* (i.e., bullying as an interaction term) conducted is given by

$$\begin{split} \mathrm{BMI}_{i,j} = & \beta_0 + \beta_1 Latent\ class_{i,j-1} + \beta_2 Latent\ class_{i,j} + \beta_3\ BMI_{i,j-1} + \\ & \beta_4 Grade_{i,j} + \beta_5 Ethnicity_i + \beta_6 Year\ + \\ & \beta_7 Bullying\ status\ at\ the\ previous\ wave_{i,j-1}\ + \\ & \beta_8 Bullying\ status\ at\ follow\ up_{i,j} + \\ & \beta_9\ Bullying\ status\ at\ the\ previous\ wave_{i,j-1}\ \times Bullying\ status\ at\ follow\ up_{i,j} \end{split}$$

where,

Latent $class_{i,j-1} = subject \ i$'s latent class at the previous wave (j-1);

Latent $class_{i,j} = subject\ i$'s latent class at the j-th year (j);

 $BMI_{i,j-1} = subject \ i$'s BMI at the previous wave (j-1);

 $Grade_{i,j} = subject \ i$'s grade-level at the j-th year;

 $Ethnicity_i = subject \ i's \ self-identified \ ethnicity \ at \ baseline;$

 $Year = categorical \ variable \ specifying \ the \ data \ collection \ year (2013, 2014 \ or 2015);$

Bullying status at the previous wave_{i,j-1} = subject i's bullying status at the previous wave (j-1);

Bullying status at follow $up_{i,j}$ = subject i's bullying status at the j-th year;

Bullying status at the previous wave $_{i,j-1}$ \times

Bullying status at follow $up_{i,j} = subject\ i$'s bullying status as an interaction term: bullying status at the previous wave crossed with bullying status at follow-up (i.e., VoB/VoB, VoB/NVoB, NVoB/NVoB).

The mixed-effects binary model that used *consecutive bullying status* (i.e., bullying as an interaction term) conducted is given by

 $\zeta_{i,j} = \beta_0 + \beta_1 Latent\ class_{i,j-1} + \beta_2 Latent\ class_{i,j} + \beta_3\ BMI_{i,j-1} + \beta_4 Grade_{i,j} + \beta_5 Ethnicity_i + \beta_6 Year + \beta_7 Bullying\ status\ at\ the\ previous\ wave_{i,j-1} + \beta_8 Bullying\ status\ at\ follow\ up_{i,j} +$

 β_9 Bullying status at the previous wave_{i,j-1} × Bullying status at follow up_{i,j} (3.4)

where,

$$\zeta_{i,j} = log\left(\frac{\Pr(Binary\ BMI_i = Overweight/Obese)_{i,j}}{\Pr(Binary\ BMI_i = Healthy)_{i,j}}\right)$$
 with

 $Weight\ status_{i,j} = \text{binary BMI}\ (normal\ versus\ overweight/obese)$ at the j-th year;

Latent class_{i,j-1} = subject i's latent class at the previous wave (j-1);

Latent $class_{i,j} = subject\ i$'s latent class at the j-th year (j);

 $BMI_{i,i-1} = subject \ i$'s BMI at the previous wave (j-1);

 $Grade_{i,j} = subject \ i$'s grade-level at the j-th year;

 $Ethnicity_i = subject \ i's \ self-identified \ ethnicity \ at \ baseline;$

Year = categorical variable specifying the data collection year (2013, 2014 or 2015);

Bullying status at the previous wave_{i,j-1} = subject i's bullying status at the previous wave (j-1);

Bullying status at follow $up_{i,j}$ = subject i's bullying status at the j-th year;

Bullying status at the previous wave_{i,j-1} \times

Bullying status at follow $up_{i,j} = subject\ i$'s bullying status as an interaction term: bullying status at the previous wave crossed with bullying status at follow-up (i.e., VoB/VoB, VoB/NVoB, NVoB/NVoB).

Chapter 5 A gender-stratified, multilevel latent class assessment of chronic disease risk behaviours' association with BMI among youth in the COMPASS study.

Status: Published in *Preventive Medicine*: doi:10.1016/j.ypmed.2019.105758.

Authors: Nour Hammami, MSc ; Ashok Chaurasia, PhD ; Philip Bigelow, PhD ; Scott T. Leatherdale PhD.

School of Public Health and Health Systems, University of Waterloo, Waterloo, ON, Canada

Overview

Purpose: This paper sought to examine chronic disease risk behaviour latent classes and their association with body mass index (BMI), assessing for gender differences.

Methods: Participants were youth (n=116,086; grades 9-12) enrolled in the COMPASS study (Ontario, Canada) during 2013, 2014, 2015. Multilevel latent class analysis was used to identify underlying, homogenous classes of youths' engagement in physical activity, smoking, binge drinking and marijuana use. Adjusted multilevel models regressed BMI on the latent classes controlling for ethnicity and grade.

Results: Three latent classes were identified: active experimenters (ACE), inactive clean youth (INC) and inactive substance users (INSU). This study found that gender differences are apparent in chronic disease risk behaviour latent classes and their association with BMI. INC males (OR=0.85, 95% CI=0.78, 0.93) were associated with lower odds of overweight/obesity relative to active males who experimented with substance use. As for females, the class with the highest proportion of youth using substances were associated with higher odds (Females: OR=1.2, 95% CI=1.1, 1.4) of overweight/obesity relative to their active experimenting peers.

Conclusions: As such, youth in latent classes with substance use are associated with higher BMI and weight status. Successful interventions may include school policies/programs that limit screen time use, as they were seen to have a positive effect on PA engagement and including social-influences approaches for substance use. Future research and interventions should be gender-specific as our results show that different latent classes are associated with obesity across genders.

Keywords: Chronic disease risk behaviours; youth; latent class analysis; body mass index; weight status; obesity; Canada.

5.1 Introduction

Children and youth in Canada have high and increasing levels of overweight and obesity (Senate of Canada, 2016). Overweight/obesity increases a person's risk of chronic diseases such as diabetes, cancer and cardiovascular diseases (Monteiro & Azevedo, 2010; Peirson et al., 2015). One in three children were classified with overweight (19.8%) or obesity (11.7%) from 2009 to 2011 among a representative sample of youth in Canada (Roberts et al., 2012). Recently, The Senate of Canada suggested a national campaign to combat obesity, and estimated that overweight/obesity cost Canadians between \$4.6 billion to \$7.1 billion annually (Senate of Canada, 2016).

Obesity has many determining and influencing factors, of which, certain chronic disease risk behaviours (CDRB) have been associated with a higher obesity risk (Cancer Care Ontario & Public Health Ontario, 2012). For example, physical activity (PA) has a preventative role in obesity and chronic disease prevention. Also independently associated with obesity, as well as weight gain over time, is heavy drinking among youth (Traversy & Chaput, 2015). Public health guidelines are in place for CDRB (e.g., PA and diet) to support disease prevention and control (World Health Organization, 2015). A reportedly large proportion of youth in Canada, do not meet these guidelines (Faught et al., 2017; Leatherdale & Burkhalter, 2012).

Furthermore, associations between CDRB and elevated weight status are reportedly compounded when youth engage in more than one CDRB (Leech et al., 2014). Recent investigations use techniques such as latent class analysis (LCA), to separate subjects into homogeneous classes based on their CDRB characteristics. These classes are then used in regression analyses to evaluate associations with weight status. Youth with overweight or obesity face a similar risk of obesity-related chronic diseases (Peirson et al., 2015); thus, they are often grouped in these analyses (Laxer et al., 2017).

One such study by Laxer et al., (2017) grouped CDRB to identify latent classes among youth from the COMPASS study in 2012. The authors found that the latent

classes with the highest risks of overweight/obesity were inactive screenagers ² relative to their health conscious ³ peers (Laxer et al., 2017). Although insightful, this research did not account for school effect when identifying the latent classes; this plays a factor since youth may have different CDRB latent classes depending on the schools they attend. A statistical analysis method that takes this into consideration is multilevel latent class analysis (MLCA) (Allison et al., 2016; Henry and Muthén, 2010). Another limitation with this study was the lack of gender-stratified analyses despite evidence that gender differences in weight status and CDRB exist.

Female and male youth engage in CDRB differently (Leech et al., 2014; Nuutinen et al., 2017; Te Velde et al., 2007). Males are more active and engage in more substance use than females (Harvey et al., 2017; Schilling et al., 2017), furthering the position that gender-stratified analyses should be implemented in these investigations. Furthermore, prevention and intervention efforts may need to be gender-specific to address the needs of each of the genders as they are different.

As such, we conducted gender-stratified analyses to (i) identify latent classes based on youths' CDRB (physical activity, smoking, binge drinking and marijuana use), and (ii) to evaluate associations between CDRB latent classes and weight status among youth in Ontario, Canada. We chose to test the replicability of our findings by adopting a repeated cross-sectional analyses using three years of data (Makel et al., 2012).

5.2 Methods

5.2.1 Design

This study used data from youth in Ontario (Canada) who participated in three waves 2013 (2013-2014), 2014 (2014-2015) and 2015 (2015-2016) of the COMPASS study. COMPASS is a hierarchical cohort study that collects data from secondary schools and students in Canada. Additional details on COMPASS are available elsewhere in print

-

² This class has the lowest PA and moderate sedentary time relative to their peers.

³ This class had higher PA than their peers, had the highest breakfast habits, low intake of fast food, snacks, sugar-sweetened beverages and were the least sedentary compared with their peers.

(Leatherdale, Brown, et al., 2014) and online (http://www.compass.uwaterloo.ca).

5.2.2 Participants

Students in grades 9-12 participated from 79 schools in 2013, 78 schools in 2014 and 72 schools in 2015. Participation from students was 79.1% in 2013 (n=41734), 78.4% in 2014 (n=39013) and 79.9% from 2015 (n=37106); the primary reason for non-participation was absence from school.

5.2.3 Data collection

COMPASS used active information with passive consent: an information sheet was sent to parents/guardians that requested them to contact the recruitment officer if they did not want their child to participate. Informed consent (assent) was obtained from all students included in the study. Students self-administered the student questionnaire (Cq), did not record their names and sealed their responses before submission. Individual student responses were not communicated. The University of Waterloo Office of Research Ethics and School Board and School committees approved all procedures.

5.2.4 Measures

5.2.4.1 Weight status (outcome variable)

Weight status was estimated via BMI using the traditional formula: weight (in kilograms) divided by height (in meters) squared, from the Cq's self-reported information. Self-reported BMI was found to have substantial concurrent validity (ICC=0.84) with COMPASS data (Leatherdale & Laxer, 2013).

This study used BMI as a continuous variable as well as a binary variable (*normal* verses *overweight/obesity*) for comparative reasons. The World Health Organization's (WHO) growth references were used in classifying BMI (World Health Organization, 2007). Previous literature reports that youth with overweight or obesity have a similar risk of future chronic diseases; therefore, these two classes were grouped in the binary BMI analyses (Peirson et al., 2015). Extreme BMI values at the 1 and 99% were omitted for each of the three years. For example, in 2013, rather than a BMI range of 10.0-49.9 kg/m², our analyses included youth with BMI values between 15.6-37.6 kg/m².

Since our analyses excluded youth with missing BMI (2013: 22.9%, n=9398; 2014: 25.0%, n=9633; 2015: 26.3%, n=9619), we conducted a Wilcoxon-Mann-Whitney test to assess for differences in the distribution of BMI among this study's youth (with BMI information) in 2013 and among a national sample of youth in the Canadian Health Measures Survey (CHMS) (Roberts et al., 2012). CHMS is a national survey where health measures (including weight and height) are collected by trained individuals (Roberts et al., 2012). Our results found that there are no significant differences in the prevalence of BMI among youth in this study's analysis and among youth in CHMS (p>0.05). Stratification by BMI categories and by genders also did not result in significant differences across the samples.

5.2.4.2 Chronic disease risk behaviours (variables for latent class analysis)

Four CDRB were included: PA, current cigarette use, current binge drinking behaviour and current marijuana use. PA was classified as meeting or not meeting the respective public health guideline (Tremblay et al., 2016). Guidelines are not available for substance use behaviours; thus, standards based on cut-off points used in similar research were used to classify youth as currently engaging (or not) in the behaviour (Laxer et al., 2017; Wong et al., 2012).

5.2.4.2.1 Physical activity (PA)

PA was measured as: how much time, in the last week, was spent on *hard PA*, *moderate PA* and *how many days included strengthening or toning muscles*. The Cq's minutes of hard and moderate PA have been previously validated (Leatherdale, Laxer, et al., 2014).

In compliance with the Canadian Society for Exercise Physiology's 24-Hour Movement Guidelines for PA (Tremblay et al., 2016), youth who on at least three of the last seven days participated in (i) hard activity and (ii) activities strengthening muscles and bones and (iii) in the last seven days performed sixty minutes of moderate-to-hard activity daily, were considered to meet PA guidelines; otherwise they did not (Tremblay et al., 2016).

5.2.4.2.2 Substance use behaviors

To distinguish current cigarette smokers, the Cq asked youth: (i) if they ever smoked 100 or more whole cigarettes in their life and (ii) how many days they smoked one or more cigarettes in the past 30 days. Students who reported both (i) ever smoking 100 cigarettes and (ii) any smoking in the previous 30 days were classified as current smokers otherwise they not (Wong et al., 2012).

To assess binge drinking behaviour, youth answered the following question: *how often they had 5 drinks of alcohol or more on one occasion, during the past 12 months.*Current binge drinking was classified as five or more drinks at least once in the last month otherwise they were not (Leatherdale, 2015; Leatherdale & Burkhalter, 2012).

The Cq asked youth to report marijuana use by answering: *how often they used marijuana or cannabis during the past 12 months*. Youth using marijuana in the last month were classified current marijuana users, otherwise they were not (Leatherdale, 2015; Leatherdale & Burkhalter, 2012).

5.2.5 Statistical analyses

5.2.5.1 Descriptive analyses

Descriptive statistics and bivariate analysis (via Pearson's χ^2 tests) were calculated separately for years 2013-2015.

5.2.5.2 Multilevel latent class analysis (MLCA) to determine latent classes

MLCA grouped the CDRB into latent classes reflecting underlying patterns; a detailed explanation of the MLCA is provided by Henry & Muthén (2010). Unlike a LCA, a MLCA takes into account that youth from the same school are dependent. Two MLCAs were conducted in our study, one for females and one for males. Since we used four binary variables in our MLCA, it is not possible to identify more than three student latent classes (Muthén & Muthén, 2009); therefore, models with one to three latent classes were examined for the purpose of our analysis. The appropriate number of classes was chosen by assessing: lowest Bayesian Information Criterion (BIC), highest entropy and the interpterability of the classes, as recommended by previous research (Henry and

Muthén, 2010; Lanza et al., 2007). MLCA was conducted in Mplus (Muthén & Muthén, 2018), while the SAS 9.4 (SAS Institute Inc., 2013) was used for all regression analyses with significance level of 5%.

5.2.5.3 Regression analyses to assess associations between latent classes and BMI

We regressed BMI (outcome variable) on the latent classes (predictor variable) via mixed-effects models (linear for continuous BMI, and logistic for binary BMI), for each year separately, adjusting for grade and ethnicity (Mejia et al., 2013). These models accounted for the clustering of students within schools.

5.3 Results

Table 5.1 Descriptive results for youth across years 2013-2015 among youth participating in COMPASS in Ontario, Canada. Percentages and sample size [%(n)] are reported for categorical variables, mean and standard deviation are reported for continuous variables.

	2013	2014	2015		
Individuals	n=41103	n=38440	n=36543		
Schools	n=79	n=78	n=72		
Gender					
Female	49.1 (19176)	49.1 (17866)	48.0 (16516)		
Male	50.9 (19898)	50.9 (18546)	52.0 (17911)		
Grade					
Grade 9	27.0 (11056)	27.3 (10425)	27.5 (9981)		
Grade 10	25.7 (10507)	26.8 (10240)	25.8 (9385)		
Grade 11	24.7 (10085)	24.4 (9353)	24.9 (9030)		
Grade 12	22.6 (9243)	21.5 (8217)	21.8 (7914)		
Ethnicity					
White	74.6 (30390)	73.6 (28056)	71.5 (25918)		
Non-white	25.4 (10358)	26.4 (10044)	28.5 (10325)		
Weight status [categorized Body Mass Index (BMI)]					
Normal	57.4 (23591)	55.0 (21163)	54.0 (19714)		
Overweight/Obese	19.7 (8114)	20.0 (76.44)	19.7 (7210)		
Missing BMI	22.9 (9398)	25.0 (9633)	26.3 (9619)		
BMI (continuous BMI)	22.1 ± 3.7	22.2 ± 3.8	22.2 ± 3.8		
Physical activity (PA) status					
Meets PA guidelines	30.1 (12330)	30.0 (11489)	30.2 (10988)		
Does not meet PA guidelines	69.9 (28631)	70.0 (26818)	69.8 (25412)		
Currently a binge drinker			· ,		

No	76.4 (31289)	77.9 (29820)	79.2 (28809)
Yes	23.6 (9661)	22.1 (8480)	20.8 (7586)
Currently a marijuana user			
No	83.3 (33390)	83.4 (31338)	83.9 (29888)
Yes	16.7 (6703)	16.6 (6228)	16.1 (5750)
Currently a smoker			
No	88.1 (36216)	88.5 (34004)	87.9 (31724)
Yes	11.9 (4887)	11.5 (4436)	12.1 (4353)

5.3.1 Study participants and characteristics

Table 5.1 presents descriptive summary statistics of the participant's behaviours and characteristics. Of the 41103 youth participating in 2013, BMI could not be calculated for 22.9% (n=9398) of youth, with similar rates for 2014 and 2015 (2014: 25.0%, n=9633; 2015: 26.3%, n=9619). Since BMI is the outcome of interest, youth with missing BMI were excluded (10.4% Females; 10.8% Males; 1.6% missing gender or BMI in 2013).

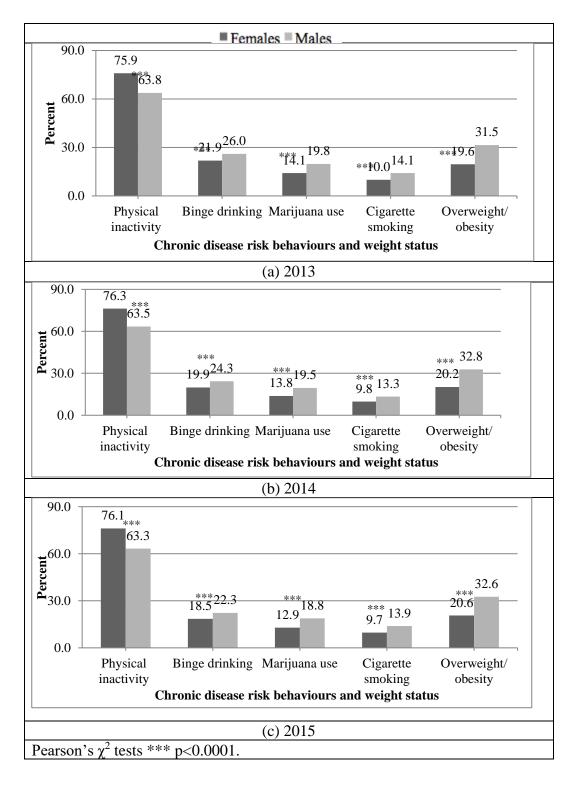
Table 5.1 displays that the sample was evenly split across genders in 2013 (Females=49.1%, Males=50.9%), with similar estimates from 2014 and 2015 (2014: Females=49.1%, Males=50.9%; 2015: Females=48.0%, Males=52.0%). Most youth did not meet PA guidelines (2013=69.9%, 2014=70.0%, 2015=69.8%). As for substance use, in 2013, 23.6% reported binge drinking (2014=22.1%, 2015=20.8%), 16.7% reported marijuana use (2014=16.6%, 2015=16.1%), and 11.9% reported smoking (2014=11.5%, 2015=12.1%).

5.3.2 Gender differences

Results from our analyses indicate that there are differences in CDRB engagement across gender. Figure 5.1 displays the percentage of youth not meeting public health guidelines for females and males across 2013-2015. Males meet PA guidelines more than their female counterparts; however, males consistently reported engaging in higher substance use. Males also reported higher overweight/obesity than females. Pearson's χ^2 tests showed that these gender differences are significant (p<.0001) as presented in Appendix C, supplementary table 1. As such, the remaining analyses were

gender-stratified.

Figure 5.1 The chronic disease risk behaviours and weight status of female and male youth (in percentages) who participated in COMPASS across years 2013-2015 in Ontario, Canada.



5.3.3 Multilevel latent class analysis (MLCA)

5.3.3.1 MLCA fit statistics

Table 5.2 displays the fit statistics for the MLCA among female youth in 2013. The fit statistics for male youth in 2013 and for females and males in 2014 and 2015 are available in Appendix C, supplementary tables 2-6. These tables show the fixed effects LCA models (i.e., not multilevel), the MLCA, as well as the MLCA with a continuous factor on student (level 1) latent class indicators (Henry and Muthén, 2010). Consistently, the MLCA models had the lowest BIC and highest entropy, suggesting that school heterogeneity should be accounted for in the clustering of students' CDRB.

Model selection was based on lowest BIC, highest entropy as well as the interpretability of the classes. For example, among females in 2013, the model with 4 school and 3 student latent classes has the lowest BIC; however, its entropy was relatively lower than other models that have a higher but comparable BIC. We selected the model with 3 school and 2 student latent classes since its entropy is high and its BIC is close to the model with the lowest BIC. Decisions regarding choosing the final MLCA model were conducted in a similar fashion for supplementary tables 2-6 and in line with previous literature (Allison et al., 2016; Henry and Muthén, 2010).

5.3.3.2 MLCA findings

Figure 5.2 shows the distribution of female and male youth in their respective (multilevel) latent classes across 2013-2015. The left panel, (Figures 2a, c, e) shows latent classes for females and the right panel (Figures 2b, d, f) for males for 2013-2015, respectively. The final models had either two or three student latent classes, and three or four school latent classes, as is evident in Figure 2. Although the number of classes differed (over the years within the gender groups), the classes had similar defining characteristics; therefore, the same latent class names were used for both genders across the three years.

Table 5.2 Fit statistics for the multilevel latent class analysis among female youth in

 ${\bf 2013\ participating\ in\ COMPASS\ from\ Ontario,\ Canada.}$

-	Number of student (level 1) latent classes						
	1	2	3				
Fixed effects model							
Number of free parameters	4	9	14				
Log-likelihood	-35118.9	-32082.1	-32054.5				
BIC	70277.4	64253.1	64247.4				
Entropy	1	0.807	0.927				
Random effects nonparametric multilevel latent class analysis models							
2 school (level 2) latent classes							
Number of free parameters	5	11	17				
Log-likelihood	-35118.9	-31993.1	-31892.6				
BIC	70287.2	64094.9	63953.2				
Entropy	0.937	0.811	0.776				
3 school (level 2) latent classes							
Number of free parameters	6	13	20				
Log-likelihood	-35118.9	-31973.8	-31833.3				
BIC	70297.1	64076.1	63864.1				
Entropy	0.024	0.833	0.81				
4 school (level 2) latent classes							
Number of free parameters	7	15	23				
Log-likelihood	-35118.9	-31971.3	-31807				
BIC	70307	64090.8	63841.2				
Entropy	0.027	0.788	0.816				
Random effects nonparametric	multilevel late	ent class analysi	is models with a				
continuous factor on level 1 latent class indicators							
2 school (level 2) latent classes							
Number of free parameters		15	21				
Log-likelihood		-31780.7	-31751.5				
BIC		63709.5	63710.4				
Entropy		0.816	0.761				
3 school (level 2) latent classes							
Number of free parameters		17	24				
Log-likelihood		-31763.4	-31721				
BIC		63694.8	63680.8				
Entropy							
шиору		0.840	0.697				
4 school (level 2) latent classes		0.840	0.697				
		0.840	0.697 27				
4 school (level 2) latent classes							
4 school (level 2) latent classes Number of free parameters		19	27				

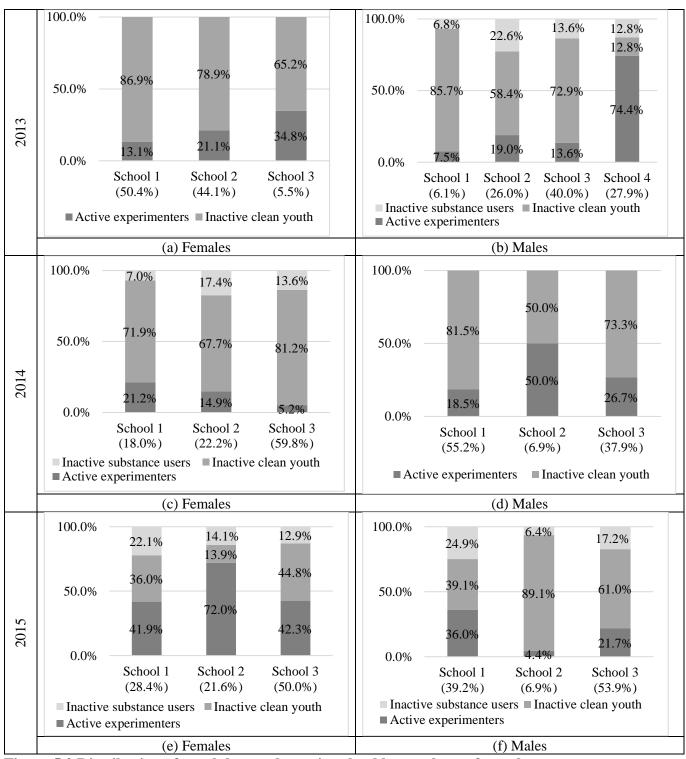


Figure 5.2 Distribution of youth latent classes in school latent classes from the multilevel latent class analysis models for females and males, participating in COMPASS across the years 2013-2015.

The first group were the most active, however they engaged in some substance use; hence, labeled 'active experimenters' (ACE). This group had the highest rates of both females and males, who met PA guidelines across the three years. In 2013, 15.9% of females and 16.2% of males were ACE. The second group were the least likely to meet PA guidelines and did not engage in substance use; hence, labeled 'inactive clean youth' (INC). In 2013, 84.1% of females and 71.1% of males were INC. The third and final group had the lowest proportion of youth who met PA guidelines and had the highest rates of engaging in substance use; hence labeled 'inactive substance users' (INSU). In 2013, 12.7% of males were INSU; the model for females did not have this latent class as the best fit model for females in 2013 was for two student level classes.

Our analyses show gender differences as females and males have different best fitted latent class models for 2013 and 2014. Only in 2015 does the model with three school- and three student- latent classes fit the data consistently for both genders; even so, the proportion of students in the classes are different across genders. Collins and Lanza (2010) suggest that when the probabilities differ across groups, constraining them to be equal will misspecify the model. Therefore, we choose to use the best fit MLCA models specific to the respective year and gender in our regression analyses.

5.3.4 Association between latent classes of chronic disease risk behaviours and BMI

Table 5.3 presents findings from the gender-stratified regression models that regressed BMI onto the latent classes while adjusting for grade and ethnicity. Our models used BMI as a binary (Models 1-3 and 7-9) and as a continuous outcome variable (Models 4-6 and 10-12) for 2013, 2014 and 2015.

Among males, only INC youth were associated with a lower BMI relative to their ACE counterparts in 2013, 2014 and 2015 (Models 7, 8, and 10-12). INC were associated with 15% lower odds of overweight/obesity for the binary BMI (OR=0.85, CI=0.78, 0.93) relative to their ACE counterparts as seen in 2013 and 2014 (Models 7 and 8, respectively). Similarly, INC males were associated with a lower (continuous) BMI by 0.50 kg/m² (CI= -0.68, -0.35) relative to their ACE counterparts in 2013, 2014 and 2015 (as seen in Models 10, 11 and 12, respectively). These findings suggest that INC males are associated with lower odds of overweight/obesity by 15% (for binary BMI) and a

lower (continuous) BMI by 0.50 kg/m^2 relative to their ACE peers; as reported from two, or all three years of observation.

As for females, only INSU were associated with a higher BMI relative to their ACE peers as seen in 2015 (Models 3 and 6). In 2015, INSU females were associated with higher odds of overweight/obesity for the binary BMI by 20% (CI= 1.1, 1.4) (Model 3), and were found to be associated with a 0.25 kg/m 2 (CI= 0.04, 0.45) higher (continuous) BMI than their ACE peers (Model 6).

Table 5.3 Latent classes' adjusted estimates (and 95% confidence intervals) from the regression models where Body Mass Index (BMI; as a binary and continuous measure) is regressed onto the student latent classes, among female and males, participating in COMPASS across years 2013-2015 in Ontario, Canada.

	Odds ratios from the logistic regression, with weight status (binary BMI) as an outcome ^a			eta coefficients from the linear regression, with continuous BMI as an outcome			
	2013	2014	2015	2013	2014	2015	
			F	Females			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	
ACE (l	Ref.)						
INC	0.75***	0.98	1.2**	-0.46***	-0.20	0.12	
	(0.67, 0.84)	(0.84, 1.1)	(1.1, 1.3)	(-0.62, -0.31)	(-0.42, 0.02)	(-0.04, 0.28)	
INSU	N/A	1.1 (0.95, 1.4)	1.2** (1.1, 1.4)	N/A	0.0001 (-0.27, 0.27)	0.25* (0.04, 0.45)	
				Males			
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	
ACE (Ref.)							
INC	0.85**	0.85**	0.91	-0.51***	-0.50***	-0.50***	
	(0.78, 0.93)	(0.78, 0.94)	(0.82, 1.0)	(-0.68, -0.35)	(-0.67, 0.32)	(-0.69, -0.32)	
INSU	0.96 (0.85, 1.09)	N/A	1.04 (0.92, 1.2)	-0.005 (-0.23, 0.22)	N/A	0.050 (-0.17, 0.27)	

^a The category 'normal BMI' served as the reference category in the outcome variable. All models were adjusted for grade and ethnicity.

ACE: Active experimenters (Ref.); INC: Inactive clean youth; INSU: Inactive substance users. N/A indicates that this latent class was not identified during this year among youth.

5.4 Discussion

Among this large sample of youth, we identified that substance use is fairly common, youth tend to be inactive, and that it is important to consider gender differences when examining the clustering of risk behaviours associated with youth overweight/obesity. Building from previous research that identified CDRB classes associated with overweight/obesity (Laxer et al., 2017); our use of a MLCA allowed us to take into account the dependent nature of student observations within schools, and showed that – although student latent classes are similar across genders and years – schools have an effect on the distribution of youth in CDRB latent classes. We were also able to identify that there are gender differences in the risk of overweight/obesity associated with different group memberships.

Youth engage in CDRB differently across genders, as is reported from previous literature, and is seen in our study. Our descriptive results show that more males met the PA guidelines; yet, they also reported higher rates of current substance use and overweight/obesity, relative to females. These findings are consistent with the scientific literature (Croisant, Laz, Rahman, & Berenson, 2013; Kritsotakis et al., 2016; Silva et al., 2014b; Simen-Kapeu & Veugelers, 2010). Among youth in Germany, males had the highest odds of being in CDRB clusters with illicit substance use relative to females (Schilling et al., 2017). Male youth smoked and used marijuana up to three times more than females in Texas (Croisant et al., 2013). Even though we identified gender differences in meeting the guidelines, the latent classes we identified had similar characteristics over the years and across genders.

Our regression findings suggest that there are gender differences in the association of the latent classes with BMI and that youth in latent classes with substance use are associated with higher BMI and weight status. Inactive clean male youth (INC) were found to be associated with lower odds of overweight/obesity, and were associated with a lower BMI, compared with their male counterparts who experimented with substance use, even though they were more active (ACE). Furthermore, female youth who were inactive and had the highest proportion of substance users (INSU) were associated with a higher BMI, and higher risk of overweight and obesity than their active

peers who experiment with substance use (ACE).

In agreement with our findings, other research (Berkey et al., 2000; Delk et al., 2018; Laxer et al., 2017) reports that substance users (specifically smokers) are most likely to have overweight/obesity. The general CDRB profile of smokers is likely placing youth at a higher weight status. Youth who smoke have been found to engage in less health promoting behaviours (e.g., PA and healthy diet) and consume more energy-dense foods compared to their peers, in the U.S.A. (Larson, Story, Perry, Neumark-Sztainer, & Hannan, 2007).

Our MLCA classified youth's latent classes within homogeneous classes of schools showing that schools play a factor in student latent classes since the distribution of student latent classes differs across schools. It is well reported that environmental factors (e.g., school) have an effect on student behaviours (Fletcher, Bonell, & Hargreaves, 2008). Linking student latent classes to the respective school provides grounds for researchers to further study the characteristics of the schools (e.g., school climate, built environment and policies) that report high prevalence of student classes with CDRB to optimize prevention and intervention efforts to those who need it most.

5.4.1 Strengths and limitations

Strengths of this study include a large sample size (n=116,086) and our use of a person-centered approach (i.e., MLCA) to group individuals rather than forcing predefined classes. Furthermore, MLCA took into account the nesting of youth within schools and generated latent classes for schools based on their similarities of youths' latent classes. Our MLCA findings are different from previous studies (Laxer et al., 2017) that only used LCA while ignoring the heterogeneity of schools – making their models prone to overfitting. Our study also accounted for gender as a confounder by stratifying by gender in the MLCA and the multilevel regression analyses both of which accounted for the clustering of the data.

Given the above contributions of this research, there are some limitations. This is a cross-sectional study; however, three years of data were incorporated to observe if the findings are replicated over more than one year. Second, the results are not generalizable

to all Canadian youth since COMPASS used purposeful sampling (Leatherdale, Brown, et al., 2014); yet, these results provide insights into associations that warrant further exploration. Finally, the data is self-reported, making missing information inevitable, since students may forgo certain questions. Consistent with previous research, 23% of youth in this study did not report weight, height, or both and were not included in the analyses (Sherry, Jefferds, & Grummer-Strawn, 2007). In contrast with previous research (Sherry, Jefferds, & Grummer-Strawn, 2007), there were no gender differences in missing BMI in our findings. It cannot be dismissed that some associations may be attenuated in our findings due to observations with missing BMI (Little & Rubin, 2002); although we found that youth who were included in our analysis had similar BMI prevalence rates as a national sample of youth in Canada who had objectively measured weight and height.

5.4.2 Recommendations

Population-wide interventions that encourage activity and the use of less substances are necessary. School-based substance use prevention efforts that used a comprehensive social-influences approach have reported to be successful (Skara & Sussman, 2003). Such successful substance use prevention models can be used for obesity prevention programs (Sakuma, Riggs, & Pentz, 2012).

Increases in PA and decreases in smoking co-occur and may influence binge drinking habits as well (DeRuiter et al., 2014). Effective school interventions include increasing opportunities for PA and reducing opportunities for electronic devices (Van Kann et al., 2017; Vasques et al., 2014). A recent natural experiment found that schools that implemented PA policies/programs saw lower screen time use among students, than schools without PA policies/programs, in Alberta and Ontario, Canada (Katapally, Laxer, Qian, & Leatherdale, 2018).

Our MLCA results are important to school-based interventions as we were able to identify potential culprit classes of CDRBs among youth, in their respective schools. Interventions should be gender-specific as our results show that different latent classes are associated with obesity across genders. As such, researchers and school officials

should combine efforts and look further into why certain schools have higher substance use, or less PA, and frame targeted interventions that address the needs of the youth in that school. COMPASS employs such systems with its participating schools, bridging research and practice.

Chapter 6 Gender differences in the longitudinal association between multilevel latent classes of chronic disease risk behaviours and Body Mass Index among youth.

Status: Under review by Pediatric Obesity.

Authors: Nour Hammami, MSc ; Ashok Chaurasia, PhD ; Philip Bigelow, PhD ; Scott T. Leatherdale PhD.

School of Public Health and Health Systems, University of Waterloo, Waterloo, ON, Canada

Overview

Purpose: A gender-stratified analysis assessed the extent to which latent classes of chronic disease risk behaviours are informative about Body Mass Index (BMI) and weight status at follow-up.

Methods: Longitudinal data from 4510 grades 9 to 12 students, tracked from (2013-2015) of the COMPASS study (Canada), were used to assess gender differences in the lagged association between previously determined latent classes with continuous BMI and binary BMI (classified as weight status categories: overweight/obese vs. normal) using multilevel mixed-effects models.

Results: With two latent classes – active experimenters and inactive clean youth– models for BMI when stratified by gender, showed that male inactive clean youth were associated with a 0.29 kg/m² higher (continuous) BMI (95% C.I.=0.057, 0.53) and higher odds of overweight/obesity by 72% (OR=1.72, 95% C.I.=1.2, 2.4) for binary BMI at follow-up, relative to active experimenters. No significant associations were detected among females.

Conclusions: Gender stratification is important since females and males have different contributing factors to BMI over time. Specifically, males who were inactive and non-substance users were associated with a 0.29 kg/m² higher BMI and higher odds of overweight/obesity by 72% at follow-up.

Keywords: chronic disease risk behaviours, substance use, gender, longitudinal model, Body Mass Index, obesity.

6.1 Introduction

Overweight and obesity are escalating problems among youth. Among children in Canada, 27% were found to be classified as overweight or obese in 2013 (Rodd & Sharma, 2016). Childhood obesity tracks into adulthood, increasing the risk of adult type 2 diabetes, hypertension and coronary heart disease (L. J. Lloyd, Langley-Evans, & McMullen, 2012). There is evidence that Body Mass Index (BMI) decreases among youth (more among males than females); however not among adults, (Devis-Devis et al., 2017; Malhotra et al., 2013; Rodd & Sharma, 2016) highlighting the importance of prevention efforts directed at youth specifically.

Despite public health prevention and intervention efforts, BMI among youth is also increasing (Laxer et al., 2018; Malhotra et al., 2013). Overweight/obesity have many determining factors, of which chronic disease risk behaviours (CDRB; e.g., physical inactivity, binge drinking) are major contributors (Spring, Moller, & Coons, 2012). Previous research by Laxer et al. (2018) using longitudinal data (2012-2014) from the COMPASS Study assessed the effect of 15 CDRB⁴ at baseline (via latent classes) on BMI at concurrent years, while controlling for gender. The authors found that (continuous) BMI increased by 0.61 kg/m² per year (on average); however, they were unable to identify a certain latent class that had higher risk of increasing BMI. Other studies that have used CDRB latent classes⁵, did not find them to be associated with obesity (Devis-Devis et al., 2017; Jackson & Cunningham, 2017); and hence suggested further investigation of the association between CDRB and obesity (Devis-Devis et al., 2017).

A notable shortcoming of previous research is the lack of assessing the role of gender (Jackson & Cunningham, 2017; Laxer et al., 2017, 2018; Pasch et al., 2012). For instance, Laxer et al. (2018) reported that males and older youth were associated with a higher increase in BMI, but gender-specific models were not performed. Considering that existing literature has shown gender differences in BMI (Arbour-Nicitopoulos et al.,

⁴ Including: PA behaviours, dietary behaviours, sedentary behaviour, substance use behaviours.

⁵ Included the CDRB: PA, sedentary behaviour and diet. Devis-Devis et al., 2017 only included PA and sedentary behaviours.

2010; Hammami, Chaurasia, Bigelow, & Leatherdale, 2019a), as well as engagement in CDRB – including physical activity (PA) and substance use (Hammami et al., 2019a; Harvey et al., 2017) – suggests that gender-specific models are warranted. Furthermore, previous literature finds that substance use plays a role in overweight and obesity among youth (Hammami et al., 2019a; Huang, Lanza, & Anglin, 2013; Laxer et al., 2017; Pasch et al., 2012) – emphasizing the importance of incorporating substance use, as well as gender-stratified analyses, in obesity research among youth.

With the previous notable gaps in obesity literature, Hammami et al., (2019) identified latent classes of CDRB (PA, current binge drinking, current marijuana use and current smoking) across 2013-2015 and regressed BMI onto these classes (in repeated cross-sectional analyses) among youth in Ontario using the COMPASS Study. The authors found that latent classes with inactivity and substance use among females, and activity and experimenting with substance use among males, were associated with higher odds of having overweight/obesity, relative to their active and non-substance using counterparts, and inactive non-substance using peers, respectively (Hammami et al., 2019a).

However, these findings do not inform whether these latent classes had higher BMIs relative to their counterparts, across the genders, at follow-up. This information is crucial for obesity and substance use prevention programs since CDRB are modifiable and addressing them while youth are at school will help mitigate the impact of factors associated with high/increasing BMI. As such, the aim of this study was to investigate the association of (lagged) CDRB latent classes (which include PA, binge drinking, marijuana use and smoking) with (longitudinal) BMI (across 2013-2015), while accounting for gender via stratification among youth who participated in the COMPASS study in Ontario, Canada.

6.2 Methods

COMPASS is a large longitudinal study (2012-2021) collecting behaviour and outcome data from secondary school students in Canada. Additional details on COMPASS are available in print (Leatherdale, Brown, et al., 2014) and online

(http://www.compass.uwaterloo.ca).

This study used three waves of COMPASS data from Ontario, Canada, collected in the following school years: Wave 1 (2013-2014), Wave 2 (2014-2015), and Wave 3 (2015-2016). Consistent with previous research (Hammami et al., 2019a; Laxer et al., 2018), we chose to focus our attention on Ontario since these data constitute most of the observations for these waves from COMPASS (92%).

6.2.1 Participants

Youth who participated in the student questionnaire (Cq) and were in grades 9, 10, 11 or 12 consisted of 41734 students from Wave 1, 39013 from Wave 2 and 37106 from Wave 3. Most students who did not participate in the questionnaire (Wave 1=20.9%, Wave 2=21.6%, Wave 3=20.1%) were absent from school that day. Students were recruited from schools that permit active-information, passive consent protocols (Wave 1=79 schools, Wave 2=78, Wave 3=72). In addition to the approval of schools and school boards, the University of Waterloo Office of Research Ethics approved all procedures. Informed consent was obtained from all individual participants included in the study.

Schools that participated in at least two of the three waves were included in this study (Wave 1=70 schools, Wave 2=70, Wave 3=70). As for youth, their participation was linked across the three waves and youth who participated in the Cq more than once were included (n=6594).

6.2.2 Measures

6.2.2.1 Body Mass Index (outcome variable)

Weight status was determined via Body Mass Index (BMI), from the Cq's self-reported height and weight measures $\left(BMI = \frac{weight\ (kg)}{[height\ (m)]^2}\right)$. We used the World Health Organization's (WHO) BMI-for-age cut-off values corresponding to our sample's youth (ages 13-18 years old) (World Health Organization, 2007). These cut-off points are specific to the individual's age and sex. For example, 13 year old females had the following categorization: *normal BMI*= 14.9-21.7 kg/m², *overweight*= 21.8-26.1 kg/m²,

obese= greater than 26.2 kg/m²; and 13 year old males had the following ranges: *normal BMI*= 14.9-20.7 kg/m², *overweight*= 20.8-24.7 kg/m², *obese*= greater than 24.8 kg/m² (World Health Organization, 2007). The measures used to determine BMI in COMPASS have previously been validated (ICC= 0.84) (Leatherdale & Laxer, 2013).

BMI was calculated at each time-point and ranged from 10.0 to 49.9 kg/m². Compared with the WHO cut-off values mentioned previously, this suggests the presence of outliers. As such, we removed outliers at the 1% and 99% resulting in a BMI range of 15.5 to 35.9 kg/m². In this paper, BMI was used as a (i) continuous outcome, as well as a (ii) binary outcome for comparative purposes. A binary measure of weight status based on BMI cutoffs (*overweight /obese* versus *normal*) was considered because existing literature has shown that youth classified as *overweight* or *obese* have similar future risks of chronic diseases (Peirson et al., 2015) and is consistent with previous literature (Carson, Faulkner, Sabiston, Tremblay, & Leatherdale, 2015; Hammami et al., 2019a; Laxer et al., 2017).

6.2.2.2 Chronic disease risk behaviour (CDRB) latent classes

Multilevel latent class analysis (MLCA) using gender-specific models were previously conducted for Waves 1-3 of the data in this study to independently assess the consistency of the CDRB profiles identified over time (Hammami et al., 2019a). Their findings suggested either two latent classes [active experimenters (ACE) and inactive clean youth (INC)] or three latent classes [ACE, INC and inactive substance users (INSU)].

To ensure that the classes being studied over time (in terms of their association with BMI) are comparable, an assumption that the classes are fixed and are same (in number and type) over time can be made (Tomczyk, Pedersen, et al., 2016). Since all years in our study had at least two-latent classes, we performed our longitudinal analyses with a parsimonious model of two-student latent classes; additionally, this parsimony makes for easier interpretation and communication of findings.

6.2.3 Statistical analyses

For variable descriptive statistics, frequencies and percentages were calculated for

categorical variables of interest, while means and standard deviations were reported for continuous variables. These findings are stratified by gender. All analyses in this study used SAS 9.4 with a significance level of 5%.

Bivariate exploratory analysis was also conducted to assess the degree to which youth changed binary BMI categories (i.e., BMI transitions) and latent classes (i.e., latent class transitions) across consecutive waves via McNemar's test.

Gender-stratified mixed-effects regression models assessed the longitudinal association between (lagged) CDRB latent classes and BMI (at follow-up). These models considered the outcome BMI in two ways: (i) continuous BMI, and (ii) binary BMI (overweight/obese versus normal). All mixed-models adjusted for the following predictors: BMI (at the previous wave), ethnicity (at baseline), grade (at current wave) and year, while accounting for the three-level hierarchical structure of the data: schools (level 3) enrolled students (level 2) over the three waves of the study (level 1). In terms of missing data, all mixed-effects regression models restricted analysis to monotone patterns of missingness in the outcome variable via Maximum Likelihood under the assumption that the data is missing at random (Hedeker & Gibbons, 2006). Youth who participated in at least two Cqs from the three waves (with a monotone pattern of missing BMI) were 4510; as such, the analyses were conducted on these youth.

6.3 Results

6.3.1 Study participants

Table 6.1 shows that female participation was slightly higher than male youth (Females: Wave 1=51.1%, Wave 2=51.1%, Wave 3=51.1%; Males: Wave 1=48.9%, Wave 2=48.9%, Wave 3=48.9%). The mean BMI was 21.0 kg/m² among females and 21.6 kg/m² among males (classified as *normal*) at Wave 1 with similar estimates from Waves 2 (Females: 21.6 kg/m², Males: 22.4 kg/m²) and 3 (Females: 21.9 kg/m², Males: 22.9 kg/m²).

Table 6.1 also displays that more than half of female youth reported a normal BMI (Wave 1=55.2%, Wave 2=55.0%, Wave 3=55.2%), while relatively less males reported a normal BMI (Wave 1=44.8%, Wave 2=45.0%, Wave 3=44.8%). In tandem,

males reported higher overweight/obesity rates (Wave 1=61.7%, Wave 2=61.1%, Wave 3=61.5%) relative to their female counterparts (Wave 1=38.3%, Wave 2=39.9%, Wave 3=38.5%).

In terms of latent classes and gender, Table 6.1 shows that slightly more females were in the INC latent class across the three waves (Wave 1=50.8%, Wave 2=51.3%, Wave 3=52.2%) relative to males. Females and males did not have an overarching pattern regarding their participation in ACE.

Table 6.1 Summary statistics for longitudinal outcomes and covariates among youth participating in COMPASS (Ontario, Canada) by gender in Waves 1, 2 and 3. Percentages and sample size are reported for categorical variables, mean and standard deviation are reported for continuous variables.

	Wave 1		Wave 2		Wave 3	
	Females	Males	Females	Males	Females	Males
Gender	51.1 (2307)	48.9 (2203)	51.1 (2307)	48.9 (2203)	51.1 (2307)	48.9 (2307)
Ethnicity						
White	51.5 (1826)	48.5 (1721)	_	_	_	_
Non-White	50.2 (474)	49.8 (470)	_	_	_	_
Grade						
Grade 9	50.7 (1551)	49.3 (1505)	_	_	_	_
Grade 10	53.0 (724)	47.0 (643)	50.7 (1541)	49.3 (1500)	_	_
Grade 11	36.8 (32)	63.2 (55)	53.1 (728)	46.9 (643)	50.7 (1532)	49.3 (1488)
Grade 12	_	_	37.4 (31)	62.6 (52)	52.3 (747)	47.7 (682)
Weight status (bina	ry body mass in	ndex)				
Normal	55.2 (1896)	44.8 (1541)	55.0 (1782)	45.0 (1457)	55.2 (1642)	44.8 (1334)
Overweight/ obese	38.3 (411)	61.7 (662)	39.9 (413)	61.1 (648)	38.5 (362)	61.5 (578)
BMI (continuous)	21.0 ± 3.1	21.6 ± 3.4	21.6 ± 3.2	22.4 ± 3.5	21.9 ± 3.2	22.9 ± 3.5
Latent classes						
Active experimenters	59.0 (128)	41.0 (89)	49.9 (253)	50.1 (254)	46.0 (354)	54.0 (415)
Inactive clean youth	50.8 (2179)	49.2 (2114)	51.3 (2054)	48.7 (1949)	52.2 (1953)	47.8 (1788)

6.3.2 BMI category transitions

Table 6.2 displays the transition of youth by their (binary) BMI categories across consecutive waves (Wave 1 to 2 and Wave 2 to 3). Most females and males who were classified with a normal BMI in Wave 1 remained in this category at Wave 2 (Females=92.8%, Males=75.1%), with similar results from Waves 2 to 3 (Females=89.5%, Males=78.4%). The table also shows that youth with

overweight/obesity, tended to remain in this category across consecutive waves (Wave 1 to 2: Females=75.1%, Males=78.4%) and Wave 2 to 3: Females=78.4%, Males=77.7%). In terms of transitions, fewer females transitioned from having a normal BMI at Wave 1 to an overweight/obese BMI at Wave 2 than males (Females=7.2%, Males=10.5%), with similar findings for transitions in Waves 2-3 (Females=5.0%, Males=9.7%).

Consequently, more female youth transitioned from an overweight/obese BMI at Wave 1 to a normal BMI at Wave 2, (Females=24.9%, Males=21.6%), with similar transitions from Waves 2 to 3 (Females=21.6%, Males=22.3%). These transitions were found to be significant only among females for Waves 1 to 2 via McNemar's test.

Table 6.2 Transitions in weight status (binary body mass index) [%(n)] across consecutives waves (Waves 1 to 2 and Waves 2 to 3) and by gender among youth participating in COMPASS (Ontario, Canada).

		NANT 1		
	-	Normal %(n)	Overweight/ Obese %(n)	McNemar's Chi-square
]	Females	
	Normal	92.8 (1688)	7.2 (130)	5 70*
	Overweight/ Obese	24.9 (94)	75.1 (283)	5.78*
Wave				
\geqslant	Normal	89.5 (1321)	10.5 (155)	1.24
	Overweight/ Obese	21.6 (136)	78.4 (493)	1.24
	<u>-</u>		McNemar's	
		Normal	Overweight/ Obese	Chi-square
		%(n)	%(n)	
		I	Females	
	Normal	95.0 (1565)	5.0 (82)	0.16
2	Overweight/ Obese	21.6 (77)	78.4 (280)	0.10
Wave 2				
\bowtie	Normal	90.3 (1205)	9.7 (129)	0
	Overweight/ Obese	22.3 (129)	77.7 (449)	<u> </u>
_* p	< 0.05.			

6.3.3 Latent class transitions

Table 6.3 Transitions in latent classes [%(n)] across gender in Waves 1 and 2 and Waves 2 and 3 among youth participating in COMPASS (Ontario, Canada).

	8.		` ,	,
		Wa	ve 2	
		Active	Inactive clean	McNemar's
		experimenters	youth	Chi-square
		%(n)	%(n)	-
		Fen	nales	
	Active experimenters	71.9 (92)	28.1 (36)	70.2***
$\overline{\Box}$	Inactive clean youth	7.4 (161)	92.6 (2018)	79.3***
Wave		Ma	ales	
\geqslant	Active experimenters	71.9 (64)	28.1 (25)	106 6444
	Inactive clean youth	9.0 (190)	91.0 (1924)	126.6***
		Wa	ve 3	
		Active	Inactive clean	McNemar's
		experimenters	youth	Chi-square
		%(n)	%(n)	
		Fer	males	
	Active experimenters	70.7 (179)	29.3 (74)	41 0***
7	Inactive clean youth	8.5 (175)	91.5 (1879)	41.0***
Wave 2	Males			
\geqslant	Active experimenters	70.9 (180)	29.1 (74)	02.0***
	Inactive clean youth	12.1 (235)	87.9 (1714)	83.9***
***	*p<0.0001.			

Table 6.3 shows transitions in the latent classes across consecutive waves (Waves 1 to 2, and Waves 2 to 3) among female and male youth participating in COMPASS. Table 6.3 suggests that female and male youth who were ACE at Wave 1 largely remained ACE at Wave 2 (Females=71.9%; Males=71.9%), with similar findings from Waves 2 to 3 (Females=70.7%; Males=70.9%). Similarly, female and male youth who were INC at Wave 1 largely remained INC at Wave 2 with higher rates than ACE (Females=92.6%; Males=91.0%), findings were similar for Waves 2 to 3 (Females=91.5%; Males=87.9%). As for transitions in latent classes, Table 3 shows that youth transitioned from ACE to INC youth at higher rates than transitioning from INC to ACE. Specifically, among females who were ACE in Wave 1, 28.1% transitioned to INC

at Wave 2, with the similar transition rates for males (28.1%), and similar estimates for Waves 2-3 (Females=29.3%; Males=29.1%). As for females who were INC at Wave 1, 7.4% transitioned to ACE at Wave 2, with slightly more males making this transition (9.0%), and similar estimates for Waves 2-3 (Females=8.5%; Males=12.1%). Although most youth remained in their latent class, a significant McNemar chi-square test statistic (p<0.0001); suggests that there are statistically significant transitions in youth's CDRB latent classes across a one-year period.

6.3.4 Longitudinal regression analyses

Table 6.4 Adjusted regression estimates (and 95% confidence intervals) from the regression models where Body Mass Index (BMI; as a binary and continuous measure) is regressed onto latent class at the previous wave, among female and males, participating in COMPASS across Waves 1, 2 and 3 in Ontario, Canada.

	β coefficients from the linear regression, with continuous BMI as an outcome $^{\rm a}$	Odds ratios from the logistic regression, with binary BMI as an outcome ^b
	Femal	es
Latent class at previous wave	Model 1	Model 2
Active experimenter (ref.)		
Inactive clean youth	-0.0087 (-0.20, 0.19)	0.85 (0.55, 1.32)
	Male	S
	Model 3	Model 4
Active experimenter (ref.)		
Inactive clean youth	0.29* (0.057, 0.53)	1.72** (1.2, 2.4)

^a β (95% C.I.) = Regression coefficient (95% Confidence Intervals).

All models adjusted for: BMI (at the previous wave), ethnicity (at follow-up), grade (at follow-up) and year.

Table 6.4 shows results from the mixed-effects models that regressed BMI onto lagged CDRB latent classes stratifying by gender and adjusting for variables mentioned in Section Statistical Analyses. These results suggest that males who were inactive and did not use substances (INC) at the previous wave were associated with an increase of

^b OR (95% C.I.) = Odds Ratio (95% Confidence Intervals) with *normal* weight as the reference category for binary BMI.

^{*}p<0.05; ** p<0.01; ***p<0.0001.

0.29 kg/m² (on average) in (continuous) BMI at follow-up, relative to their active experimenter (ACE) counterparts (95% C.I.= 0.057, 0.53) (see results of Model 3 in Table 6.4). Furthermore, the results from the general linear mixed models for binary BMI (see Model 4 in Table 6.4) identified that INC males were associated with 72% higher odds of overweight/obesity relative to their ACE counterparts (OR=1.72, 95% C.I.=1.2, 2.4). No significant associations were identified among females (see Model 1 and Model 2 in Table 6.4, respectively).

6.4 Discussion

Building on previous research (Hammami et al., 2019a), we conducted a longitudinal analysis assessing for gender differences in CDRB's association with BMI at follow-up. Our assessment suggests that even with annual increases in BMI and changes in CDRB latent classes over time, the association between CDRB latent classes and BMI differ by gender. Specifically, BMI was higher at follow-up (by 0.29 kg/m²) among males who were inactive and did not engage in substance use (i.e., INC), compared with male active experimenters, with no such significant association observed among females. Additionally, our findings suggest that inactive males who do not engage in substance use are associated with higher odds of overweight/obesity (by 72%) relative to their more active counterparts who experiment with substances. It is important to note that the odds of a lower BMI among ACE cannot be attributed to substance use since there is evidence that substance use is associated with higher prevalence and incidence of obesity among youth (Boone-Heinonen et al., 2008; Delk et al., 2018; Huang, Lanza, & Anglin, 2013; Pasch et al., 2012). Rather, our findings can be partially explained by the difference in PA across the two classes. Activity was found to be protective against obesity among male students in Michigan (U.S.A.) however not among female youth (Govindan et al., 2013).

Given our findings, PA is not the sole culprit behaviour – the scientific literature suggests that the collective unhealthy CDRB profile is a contributing factor to the increasing BMI levels among youth. Low PA does not occur in isolation, it is associated with poor dietary intake (e.g., poor vegetable and milk intake, high soft-drink and junk food intake) as well as sedentary behaviour (Cureau, Sparrenberger, Bloch, Ekelund, &

Schaan, 2018; Gwozdz et al., 2019; Larson et al., 2007; Wilson et al., 2005). As explained by the Problem Behaviour Theory, Jessor and Jessor (1977) suggest that youth who engaged in one problem behaviour are at a higher risk of being involved in other problem behaviours, due to the shared meanings and functions of these behaviours, as well as the social influences surrounding them. Peer effects reportedly have an effect on BMI (Gwozdz et al., 2019). Thus, ACE youth are likely to have friends who are also ACE, and also tend to engage in PA in their free time. Similarly, INC youth are likely to have INC friends, and their passing time consists of sedentary activities such as TV viewing or video games, also supported by recent findings from Europe (Gwozdz et al., 2019).

Our exploratory analyses suggest that there are annual increases in BMI, across both genders, also consistent with previous research (Laxer et al., 2018; Malhotra et al., 2013). However, the predictors of the annual increase are different across the genders as indicated by our results: PA and substance use are not likely predictors of increasing BMI among females. Previous literature reports other differences in CDRB where females have healthier dietary patterns than their male counterparts (Chambers & Swanson, 2010). A study among adults in Scotland, England and Northern Ireland report that variance in BMI was explained by PA (by 10.3%), dieting behaviours (by 10.3%), amount eaten (by 7.2%), meanwhile healthy eating explained only 1.6% of the variation in BMI (Chambers & Swanson, 2010). This suggests that physical activity and dieting behaviours are important predictors of BMI since they each explained the variance in BMI ten times more than healthy eating (Chambers & Swanson, 2010).

As such, dieting and unhealthy weight control behaviours should be at the center of BMI research among female youth. Dieting and unhealthy weight control behaviours predicted greater increases in BMI 10 years later compared with non-dieting adults in Minnesota (U.S.) (Neumark-Sztainer, Wall, Story, & Standish, 2012). Similar findings are seen among female youth in Ontario, Canada (Raffoul, Leatherdale, & Kirkpatrick, 2018). Raffoul et al. (2018) found that female youth in COMPASS who dieted had higher rates of overweight/obesity, smoking and binge drinking two years later. Such findings, from our and other aforementioned studies, indicate that diet should be incorporated as a

risk factor for obesity, as well as other CDRB among female adolescents. Our findings reiterate that BMI increases in youth; however, females and males engage in CDRB differently, report BMI differently, have different BMIs trajectories, and likely have different CDRB determinants of BMI.

Despite the increases in BMI reported among females and males, we found a reassuring finding that some female and male youth transition to 'healthier' BMI categories. With categorized BMI, we found that 28.1% of youth classified as overweight in Wave 1 transitioned to having a normal BMI in Wave 2 with similar findings from Waves 2-3 (27.3%); similar to findings from youth in Spain where 26% of youth classified as obese transitioned to having an overweight BMI (Devis-Devis et al., 2017). This is an important finding as over a quarter of youth are transitioning to the 'healthier' BMI categories. Future research should investigate attitudes, behaviours, peer and school effects among these youth specifically; this will provide valuable lessons as to how youth successfully achieve 'healthier' body categorizations.

Similar to youth, BMI also increases among adults; however, there are fewer reported decreases in BMI than among youth. Findings from adults in the U.S.A. report that over 18 years, BMI increased by 13% (3.1 kg/m²), with only 1.9% of females and 0.5% of males following a trajectory that resulted in a one unit (kg/m²) decrease in BMI (Malhotra et al., 2013). Our findings, along with others (Devis-Devis et al., 2017), show that youth who have overweight/obesity move to having 'healthier' BMI categories – emphasizing the importance of healthy weight loss and maintenance interventions during adolescence since decreases in BMI are seen – while reportedly few adults have decreases in BMI.

From the standing of obesity (and chronic disease) prevention, school-based interventions are warranted for youth. A recent review reported that school-based interventions that focused on PA found that students reported a decrease in subsequent substance use (Simonton, Young, & Johnson, 2018). Another body of systematic reviews found that successful interventions among youth have been school-based, where their students reported lower binge drinking, marijuana use and smoking behaviours (Das, Salam, Arshad, Finkelstein, & Bhutta, 2016).

A school-based intervention approach that is gaining popularity due to its success is the participatory approach. Participatory approaches encourage youth to participate in the school-based programs and has seen success with retaining students in the programs (Bogart et al., 2014), as well as reported decreases in BMI in the U.S.A. (Moonseong Heo et al., 2018). Participatory school environment changes have also seen concurrent behaviour changes when promoting healthy eating and increasing availability of healthy options at the school-level (Bogart et al., 2014).

Tailored prevention and intervention programs are reportedly more effective (Simen-Kapeu & Veugelers, 2010). Our findings are important because they highlight that female and male youth have different, gender-specific longitudinal (transitional) predictors of BMI; warranting gender-specific prevention and intervention efforts. We recommend interventions for inactivity and substance use among female and male youth – while promoting healthy food intake among males and addressing unhealthy dieting behaviours among females.

6.4.1 Strengths and limitations

Our study contributes to the discussion that chronic disease risk factors are associated with female and male youth health differently over time. We present a unique evaluation of gender differences in the association between lagged latent classes (of PA and substance use) with BMI, longitudinally, among a large sample of youth. Another strength to our study is that we adopted a novel approach by taking into consideration the dependence of students in schools in both the gender-specific multilevel latent class analyses and the gender-specific multilevel longitudinal regression analyses. Our findings suggest that increases in BMI at follow-up were significantly associated with the latent class INC among males; while no such associations found among females. Similar studies that only adjusted for gender might have not found any association because they did not stratify by gender (Laxer et al., 2018). Additionally, we accounted for monotone type missingness in BMI (the outcome variable) in our longitudinal regression models by using Maximum Likelihood models, under the assumption that data is missing at random – these models are preferred over models based on complete case analysis since the latter assumes the outcome is missing completely at random (Hedeker & Gibbons, 2006).

This study is not without limitations. The Cq is completed by youth therefore, the CDRB, weight and height measures were self-reported. Although self-reported, previous analyses showed that there are no significant differences in the prevalence of BMI among COMPASS self-reported BMI and those measured by a trained professional across a national sample of youth in Canada (Hammami et al., 2019a). COMPASS participants' self-reported BMI have a high validity when compared with measurements conducted by a trained professional (ICC=0.84) (Leatherdale & Laxer, 2013). Additionally, the Cq used passive consent since active consent procedures are discouraged when measuring substance use; it limits the participation of youth who are most likely to benefit from these programs (i.e., substance users) (Thompson-Haile et al., 2013). Lastly, COMPASS is not generalizable since it uses purposeful sampling. However, the prevalence of substance use and of BMI was comparable to those found in a nationally representative sample (Leatherdale & Rynard, 2013).

6.4.2 Conclusion

In this study, positive increases in BMI (kg/m²) are evident among female and male youth. Our findings indicate that among youth, inactive clean males are at 72% higher odds of overweight/obesity during secondary school compared with their active peers who experiment with substance use. No longitudinal predictors of BMI increase were identified among females when considering latent classes of PA and current substance use. We recommend stratified analyses and interventions in CDRB and obesity research, as well as participatory programs targeting PA and substance use. We also recommend future studies to explore dieting behaviours and other CDRB predictors and their association with longitudinal BMI among females.

Chapter 7 Exploring gender differences in the longitudinal association between bullying and chronic disease risk behaviours with Body Mass Index among a sample of youth in Canada.

Status: Intended for the International Journal of Obesity.

Authors: Nour Hammami, MSc; Ashok Chaurasia, PhD; Philip Bigelow, PhD; Scott T. Leatherdale PhD.

School of Public Health and Health Systems, University of Waterloo, Waterloo, ON, Canada

Overview

Purpose: To identify the role that bullying status [victims of bullying (VoB) versus not victims of bullying (NVoB)] plays in the gender-stratified assessment of longitudinal association between chronic disease risk behaviours and Body Mass Index (BMI).

Methods: Longitudinal data from 4510 youth were used to model BMI at follow-up with consecutive bullying status, adjusting for previously identified gender-specific chronic disease risk behaviour latent classes at the previous wave. To assess for gender differences, these mixed-effects models were stratified by gender.

Results: Youth who were VoB were more active, engaged in more substance use and reported higher BMI than their NVoB peers. Additionally, among VoB, 42.8% experienced repeated bullying over consecutive years. The gender-specific mixed models were consistent in showing that there are gender differences in the association between bullying and BMI. Among female youth, repeated bullying was associated with an increase in odds of having overweight/obese [by 51% (95% C.I.=1.03, 2.23)] at follow-up. Among male youth, being a VoB at the previous wave only, was associated with an increase in odds of having overweight/obese [by 60% (95% C.I.=1.11, 2.29)].

Conclusions: Our study found that VoB are more active, use more substances and report higher BMI than their peers. As for associations with BMI, being a VoB in the previous year was associated with increases in the odds of overweight/obesity among male youth at follow-up. Among females, repeated bullying was associated with increases in BMI as well as in the odds of overweight/obesity. Additionally, gender-stratification is warranted since results from gender adjusted models would misinform prevention programs by downplaying the effect/role of bullying. Bullying prevention programs should be implemented among all youth, with emphasis on physical activity and team sports to build social skills and comradery among youth.

Keywords: chronic disease risk behaviours, gender, bully, victimization, youth, longitudinal analysis, substance use, Body Mass Index, obesity, COMPASS, Canada.

7.1 Introduction

Youth who are victims of bullying (VoB) have poorer mental health (e.g., depression, anxiety and psychotic symptoms) and poorer health behaviours (e.g., alcohol use, prospective tobacco use and illicit drug use) than their non-victims of bullying (NVoB) peers during adolescence (Louise Arseneault, 2018; S. E. Moore et al., 2017). It has also been found that youth who were VoB have poor physical and mental health in adulthood (Louise Arseneault, 2018; Mamun et al., 2013). One of the physical health outcomes associated with being a VoB is a higher Body Mass Index (BMI) and a higher risk of having obesity in early adulthood (Mamun et al., 2013). However, the conclusions from various longitudinal studies have been mixed in terms of association between bullying status and BMI during adolescence.

A study by Lee and Vaillancourt (2018a) of a sample of youth aged 10-11 years old in Ontario, Canada, reported that VoB had a higher BMI two years later. Another study by Adams and Bukowski (2008) found that among a representative sample of 12-13 years olds in Canada, BMI increased only among VoB females with obesity four years later, while a decrease in BMI was witnessed among VoB males with no significant results for normal BMI. A recent review by Lee and Vaillancourt (2018b) found that victimization was associated with risk behaviours and that these differed by gender.

Gender differences are well reported in chronic disease risk behaviours (CDRB) and BMI research among youth (Arbour-Nicitopoulos et al., 2010; Hammami et al., 2019a; Hammami, Chaurasia, Bigelow, & Leatherdale, 2019b; Harvey et al., 2017). Gender-specific, latent classes of CDRB were previously identified by Hammami et al. (2019a) for: physical activity (PA), binge drinking, marijuana use and smoking, across three waves of data, from the COMPASS study, via multilevel latent class analysis (MLCA). In their longitudinal analyses, Hammami et al. (2019b) found that youth in the latent class with inactivity and no substance use were associated with increases in BMI at follow-up among male youth in Ontario, Canada, while no associations were identified among females – emphasizing that female and male youth have different associations between CDRB (PA and substance use) and BMI over time.

Additionally, other research reports that substance use was associated with being

a VoB and that the associations differ across gender (Janssen et al., 2004; Priesman et al., 2018). These observations are supported by the general strain theory (Gaete et al., 2017) which explains that youth who have undergone strain (e.g., VoB) are more likely to engage in substance use as a coping mechanism (Gaete et al., 2017).

Given the evidence of the co-occurrence of bullying and substance use, we wanted to explore in gender-stratified analyses: whether being a VoB affects youths' engagement in CDRB (binge drinking, marijuana use, cigarette smoking and physical activity) and whether being a VoB is associated with BMI at follow-up. A limitation with previous research is that they studied the effect bullying had on BMI at later years; while shorter duration of *exposure to outcome* have not been assessed and are valuable to inform obesity and substance use intervention efforts, especially in youth. As such, we reported a series of gender-stratified transitional regression models to assess the association of bullying with BMI at follow-up among youth participating in the COMPASS study in Ontario, Canada.

7.2 Methods

7.2.1 Design

COMPASS is prospective study (2012-2021) that collects data on youth health behaviours among secondary schools in 4 Canadian provinces (Ontario, Alberta, Québec, British Columbia) that permit active-information, passive consent protocols. Schools and school boards approved the study's procedures, as did the University of Waterloo's Office of Research Ethics. Additional details on COMPASS are available in print (Leatherdale, Brown, et al., 2014) and online (http://www.compass.uwaterloo.ca).

This study utilized three years of data from youth in grades 9, 10, 11 and 12 in Ontario, Canada collected via COMPASS's student questionnaire (Cq): Wave 1 (2013-2014), Wave 2 (2014-2015), and Wave 3 (2015-2016). The sample from Ontario was selected since these data constitute most of the observations from waves 1-3 in COMPASS (92%); these amounted to 79 participating schools in Wave 1, 78 in Wave 2 and 72 in Wave 3.

7.2.2 Participants and procedures

Schools that participated in two or more waves of data were included in this study (Wave 1=70 schools, Wave 2=70, Wave 3=70). Youth enrolled in these schools, who participated in the Cq and were in grades 9-12 were: 41734 in Wave 1, 39013 in Wave 2, and 37106 in Wave 3. Youth who did not participate in the Cq (Wave 1=20.9%, Wave 2=21.6%, Wave 3=20.1%) were absent from school that day. For the longitudinal analysis, the three waves of data were linked (Qian et al., 2015) and youth with two or more Cqs were included with monotone type missingness in the outcome (n=4510) (Hedeker & Gibbons, 2006).

7.2.3 Measures

7.2.3.1 Body Mass Index (outcome variable)

Body Mass Index (BMI) was used as a continuous and binary measure as calculated from youth's self-reported weight and height via the formula $\left(BMI = \frac{weight\ (kg)}{[height\ (m)]^2}\right)$. The World Health Organization's (WHO) age- and sex-specific cut-off points (ages 13–18 years old) were used to classify BMI as weight status (World Health Organization, 2007). The categories *overweight* and *obese* were combined since youth with overweight/obesity are seen to have similar future risks of chronic diseases (Peirson et al., 2015) and this is consistent with previous research (Hammami et al., 2019a, 2019b; Laxer et al., 2018). Outliers were removed at the 1% and 99% resulting in a BMI range of 15.7 to 37.2 rather than the original range of 10.9 to 49.9. The COMPASS BMI measure was validated in a sample of grade 9 students from Ontario, Canada, and was found to have substantial 1-week test-retest reliability [intraclass correlation (ICC) = 0.95] and concurrent validity with measured height and weight (ICC = 0.84) (Leatherdale & Laxer, 2013).

7.2.3.2 Bullying behaviour (variable of interest)

Our main independent variable of interest was whether youth were victims of bullying (VoB) by peers in the past 30 days. Youth replied to the question "In the last 30 days, how often have you been bullied by other students?" using the following selections:

"I have not been bullied by other students in the last 30 days" or "less than once a week" or "about once a week" or "2 or 3 times a week" or "daily or almost daily". To be considered not a victim of bullying (NVoB), the answer: "I have not been bullied by other students in the last 30 days" had to be selected, otherwise youth were classified as VoB.

Furthermore, we conducted an interaction term between bullying status at consecutive waves (i.e., VoB/VoB, VoB/NVoB, NVoB/VoB, NVoB/NVoB). This variable was used in the regression model as it provides evidence as to whether repeated bullying (i.e., VoB/VoB), or changes in bullying status (i.e., VoB/NVoB or NVoB/VoB) were associated with changes in BMI.

7.2.3.3 Chronic disease risk behaviours (CDRB)

In line with previous research (Hammami et al., 2019b, 2019a), four CDRB acted as control variables in this study via latent classes: PA, current binge drinking, current marijuana use and current smoking. These CDRB were used as binary variables: youth met the respective guideline or standard, or they did not. Public health guidelines were used for PA since they are in place (Tremblay et al., 2016); however, for substance use there are no public health guidelines since no use is recommended among this age group. In this case, we used standards that have been used in previous literature on youth (Leatherdale, 2015; Leatherdale & Burkhalter, 2012; Wong et al., 2012). A detailed description of the measures have been previously described (Hammami et al., 2019a).

7.2.4 Statistical analyses

7.2.4.1 Cross-sectional analyses

Frequencies were reported for categorical variables of interest, while means and standard deviations were reported for continuous variables of interest among VoB and NVoB across the three waves of data. SAS 9.4 (SAS Institute Inc., 2013) was used for all analyses with significance level of 5%.

In their previous analyses, Hammami et al., (2019a) describe the composition of the latent classes, as well as their consistent finding that either two student latent classes [active experimenters (ACE) and inactive clean youth (INC)] or three latent classes [ACE, INC and inactive substance users (INSU)] best identified youths' CDRB classes. For the purpose of our analysis, we fixed the latent classes to two-student latent classes to ensure the associations being studied are comparable over time, as previously reported (Hammami et al., 2019b; Tomczyk, Pedersen, et al., 2016). The two-student class model was chosen since all MLCA models had at least two classes, and since the two classes model is more parsimonious, and thus making for easier interpretation of findings (if any).

7.2.4.2 Longitudinal analyses

Since this study uses linked waves of data, we can track and observe transitions in youths' bullying status, weight status and latent class categories across the three consecutive waves. Therefore, we used the McNemar test to explore the stability (i.e., the extent to which youth remained in the same category) and transitions (i.e., the extent to which youth changed categories) for bullying status, weight status, and latent classes, across the three waves.

For our transitional models, we fit two sets of gender-stratified, multilevel, mixed-effects models using the outcome variable BMI as a (i) continuous and (ii) binary [binary BMI will be referred to as weight status (overweight/obese versus normal)]. These models were also fit using the variable of interest (i.e., bullying status) in two different ways: (i) bullying as a main effect (as bullying status at the previous year) and (ii) as an interaction term (between bullying status at the previous wave and bullying status at current wave). All models adjusted for: CDRB latent class (at the previous wave), and BMI (at the previous wave), as well as ethnicity (at baseline), grade (current wave), and year. Our models adjusted for the clustered nature of the data as follows: schools (level 3) enrolled students (level 2) who had repeated measures (level 1) (Snijders & Bosker, 2012). We also restricted the analysis to include monotone patterns of missingness in BMI via Maximum Likelihood (Hedeker & Gibbons, 2006) under the assumption that the data is missing at random (Rubin, 1976).

7.3 Results

7.3.1 Participant characteristics

Table 7.1 shows summary statistics for longitudinal outcomes and covariates among youth across waves 1, 2 and 3, for VoB and NVoB youth. Youth who were VoB constituted 17.5% of youth in Wave 1, 16.2% in Wave 2 and 14.4% in Wave 3. For continuous BMI (kg/m²), youth who were VoB and NVoB had similar mean BMI across the waves (Wave 1: VoB=22.3 kg/m², NVoB=21.3 kg/m²; Wave 2: VoB=21.9 kg/m², NVoB=22.0 kg/m²; Wave 3: VoB=22.5 kg/m², NVoB=22.4 kg/m²). This also held true for weight status (i.e., binary BMI): weight status did not significantly differ across VoB and NVoB, at any of the three waves, via chi-square tests. VoB who were categorized with overweight/obesity were 17.4% in Wave 1, 15.9% in Wave 2 and 14.2% in Wave 3.

Table 7.1 Summary statistics for longitudinal outcomes and covariates among youth participating in COMPASS by bullying status in Waves 1, 2 and 3. Percentages and sample size are reported for categorical variables, mean and standard deviation are reported for continuous variables

	Wa	ive 1	Wa	ive 2	Wa	ive 3
	Victims of	Not victims	Victims of	Not victims	Victims of	Not victims
	bullying	of bullying	bullying	of bullying	bullying	of bullying
Bullying status	17.5 (774)	82.5 (3647)	16.2 (720)	83.8 (3714)	14.4 (630)	85.6 (3758)
Gender						
Female	21.0 (478)	79.0 (1797)	18.8 (429)	81.1 (1849)	16.0 (363)	84.0 (1902)
Male	13.8 (296)	86.2 (1864)	13.5 (291)	86.5 (1865)	12.6 (267)	87.4 (1856)
Ethnicity						
White	18.0 (626)	82.0 (2847)	16.9 (590)	83.1 (2904)	15.0 (519)	85.0 (2936)
Non-White	15.5 (144)	84.5 (786)	13.8 (127)	86.2 (794)	12.0 (110)	88.0 (804)
Grade						
Grade 9	17.7 (530)	82.3 (2464)	_	_	_	_
Grade 10	17.3 (233)	82.7 (1110)	17.0 (510)	83.0 (2496)	_	_
Grade 11	13.1 (11)	86.9 (73)	15.0 (202)	85.0 (1146)	14.2 (424)	85.8 (2554)
Grade 12	_	_	10.0 (8)	90.0 (72)	14.6 (204)	85.4 (1196)
Weight status (i.e., b	inary body ma	ss index)				
Normal	17.5 (590)	82.5 (2776)	16.1 (515)	83.9 (2688)	14.0 (413)	86.0 (2530)
Overweight/ obese	17.4 (184)	82.5 (871)	15.9 (166)	84.1 (879)	14.2 (131)	85.8 (791)
Body Mass Index (continuous)	21.3 ± 3.4	21.3 ± 3.3	21.9 ± 3.4	22.0 ± 3.4	22.5 ± 3.6	22.4 ± 3.4
Latent class						
Active experimenter	32.7 (70)	67.3 (144)	25.0 (124)	75.0 (371)	21.3 (159)	78.7 (587)
Inactive clean	16.7 (704)	83.3 (3503)	15.1 (596)	84.9 (3343)	12.9 (471)	87.1 (3171)

Table 7.1 also shows that more females reported to be VoB relative to males, and this is statistically significant (Wave 1: Females=21.0%, Males=13.8%, Chisquare=39.8, P<0.0001; Wave 2: Females=18.8%, Males=13.5%, Chi-square=23.2, P<0.0001; Wave 3: Females=16.0%, Males=12.6%, Chi-square=10.6, P=0.001). Additionally, there were differences in the latent classes of youth who were VoB and those who were not. VoB had a significantly higher prevalence in the active experimenters (ACE) latent class relative to inactive clean youth (INC) (VoB in Wave 1: ACE=32.7%, INC=16.7%, Chi-square=36.0, P<0.0001; VoB in Wave 2: ACE=25.0%, INC=15.1%, Chi-square=31.8, P<0.0001; VoB in Wave 3 ACE=21.3%, INC=12.9%, Chi-square=35.4, P<0.0001).

7.3.2 Differences in chronic disease risk behaviours by bullying status

Figure 7.1 shows youth's engagement in chronic disease risk behaviours by bullying status across the three waves. Youth who are VoB were slightly more physically active; however, they also reported more substance use behaviours (binge drinking, marijuana use and cigarette smoking) and higher rates of overweight/obesity and relative to their NVoB peers. All these differences were significant at p<0.01 and p<0.0001 as indicated in Figure 7.1.

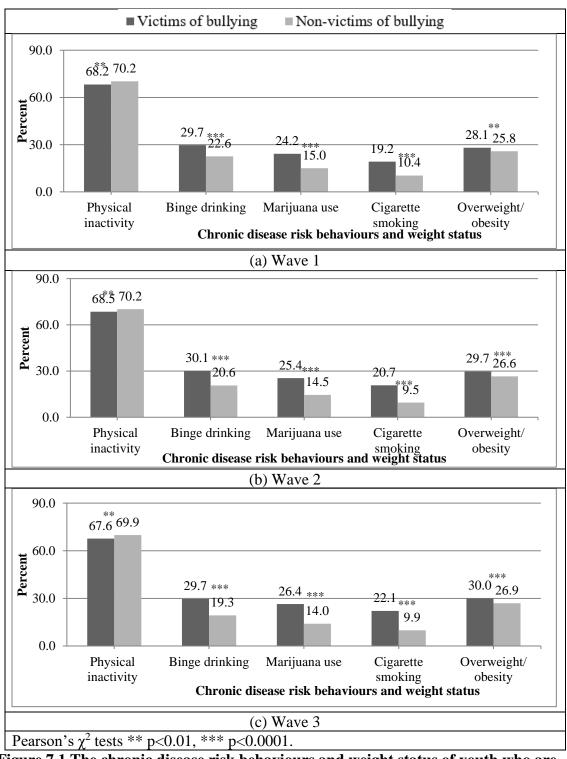


Figure 7.1 The chronic disease risk behaviours and weight status of youth who are victims of bullying and non-victims of bullying (in percentages) who participated in COMPASS across Waves 1, 2 and 3 in Ontario, Canada.

7.3.3 Longitudinal analyses

Table 7.2 Transitions in bullying status [%(n)] across consecutives waves (Waves 1 to 2 and Waves 2 to 3) among youth participating in COMPASS in Ontario, Canada.

	Victims of bullying % (n)	Not victims of bullying % (n)	McNemar's Chi-square	
0		Wave 2		
Victims of bullying Not victims of bullying	46.5 (353)	53.5 (407)	2.7	
Not victims of bullying	10.1 (361)	89.9 (3229)	2.7	
e 7		Wave 3		
Victims of bullying	39.2 (274)	60.8 (425)	7 7**	
Not victims of bullying	9.6 (348)	90.4 (3274)	7.7***	
*p<0.05; ** p<0.01; ***p<0.001.				

Table 7.2 displays the transitions in bullying status that youth engaged in across Waves 1 to 2 and 2 to 3. Among those who were VoB at Wave 1, 46.5% were still VoB at Wave 2, with a slightly lower proportions for Waves 2 to 3 (39.2%; average of repeated bullying across the waves= 42.8%). Most youth were NVoB and remained NVoB at follow-up (Waves 1-2= 89.9%; Waves 2-3= 90.4%). As for transitions in bullying status, most youth who were VoB at the previous wave became NVoB at follow-up (Waves 1-2= 53.5%; Waves 2-3=60.8%). Approximately 10% of youth were NVoB at the previous wave, but became VoB at follow-up (Waves 1-2=10.1%; Waves 2-3=9.6%). These transitions were found to be significant only for Waves 2 to 3 via McNemar's test.

Table 7.3 shows transitions in youth's weight status across consecutive waves by bullying status. Most VoB who had a normal BMI remained in this category at follow-up (Wave 1-2=89.5%, Wave 2-3=94.2%) as did VoB in the overweight/obese category (Wave 1-2=73.8%, Wave 2-3=75.0%). Similar findings are reported from NVoB youth maintaining a normal BMI (Wave 1-2=91.7%, Wave 2-3=92.8%) and an overweight/obese BMI (Wave 1-2=77.7%, Wave 2-3=78.5%). As for transitions in BMI, slightly more youth who are VoB moved from an overweight/obese BMI to a normal

BMI compared with their NVoB peers (Wave 1-2: VoB=26.2%, NVoB=22.3%; Wave 2-3: VoB=25.0%, NVoB=21.4%) as seen in Table 3. BMI transitions were not found to be statistically different (p>0.05) across the waves and across VoB and NVoB.

Table 7.3 Transitions in weight status (binary BMI) [%(n)] across consecutives waves (Waves 1 to 2 and Waves 2 to 3) and by bullying status among youth participating in COMPASS in Ontario, Canada.

-		Normal	Overweight/ Obese	McNemar's		
		% (n)	% (n)	Chi-square		
			Victims of bullying			
_,	Normal	89.5 (476) 10.5 (56)		2.0		
ve	Overweight/ Obese	26.2 (39)	73.8 (110)	3.0		
Wave			Not victims of bullying			
	Normal	91.7 (2500)	8.3 (225)	2.2		
	Overweight/ Obese	22.3 (188)	77.7 (654)	3.3		
	Wave 3					
		W	Vave 3			
_		Normal W	Vave 3 Overweight/ Obese	McNemar ³		
-						
-		Normal	Overweight/ Obese			
-	Normal	Normal	Overweight/ Obese % (n)	Chi-square		
ve <u>7</u>	Normal Overweight/ Obese	Normal % (n)	Overweight/ Obese % (n) Victims of bullying			
Wave 2		Normal % (n) 94.2 (377)	Overweight/ Obese % (n) Victims of bullying 5.7 (23)	McNemar' Chi-square		
Wave 2		Normal % (n) 94.2 (377)	Overweight/ Obese % (n) Victims of bullying 5.7 (23) 75.0 (108)	Chi-square		

Table 7.4 displays the transitions in youth's latent classes across consecutive waves by bullying status. Youth who were VoB tended to remain in the ACE latent class at follow-up more than their NVoB peers (Wave 1 to 2: VoB=82.3%, NVoB=69.9%; Wave 2 to 3: VoB=74.8%, NVoB=70.9%). On the other hand, NVoB youth tended to remain in the INC latent class at follow-up more than their ACE counterparts (Wave 1 to 2: NVoB=92.3%, VoB=87.7; Wave 2 to 3: NVoB=90.7%, VoB=84.4%).

As for transitions in the latent classes, Table 7.4 shows that more youth who were VoB moved from INC to ACE at follow-up than their NVoB peers (Wave 1 to 2:

VoB=12.3%, NVoB=7.4%; Wave 2 to 3: VoB=15.5%, NVoB=9.3%), and more youth who were NVoB moved from ACE to INC at follow-up than their VoB peers (Wave 1 to 2: NVoB=30.1%, VoB=17.6; Wave 2 to 3: NVoB=29.1%, VoB=25.2%).

Table 7.4 Transitions in latent classes [%(n)] across consecutives waves (Waves 1 to 2 and Waves 2 to 3) and by bullying status among youth participating in COMPASS in Ontario, Canada.

		Active experimenters % (n)	Inactive clean youth % (n)	McNemar's Chi-square		
			Victims of bullying			
<u>ve 1</u>	Active experimenters Inactive clean youth	82.3 (42) 12.3 (82)	17.6 (9) 87.7 (587)	58.5***		
Wave			Not victims of bullying			
·	Active experimenters Inactive clean youth	69.9 (109) 7.4 (262)	30.1 (47) 92.6 (3296)	149.6***		
		Wave 3				
		Active experimenters % (n)	Inactive clean youth % (n)	McNemar's Chi-square		
			Victims of bullying			
/e 2	Active experimenters Inactive clean youth	74.8 (77) 15.5 (82)	25.2 (26) 84.4 (445)	29.0***		
Wave 2	•		Not victims of bullying			
	Active experimenters Inactive clean youth	70.9 (273) 9.3 (314)	29.1 (112) 90.7 (3059)	95.8***		

7.3.3.1 Regression findings

Table 7.5 displays the results of the regression models that used *bullying status at the previous wave* as a main effect. These models were reported for females (Models 1 and 2) and males (Models 3 and 4) separately, and for BMI as a continuous outcome variable (Models 1 and 3) and as weight status (BMI as a binary outcome variable; Models 2 and 4) while adjusting for: CDRB latent class (at the previous wave), and BMI

(at the previous wave), as well as ethnicity (at baseline), grade (current wave), and year.

The results in Table 7.5 indicate that among males, being a victim of bullying at the previous wave was associated with higher odds of overweight/obesity by 38% (O.R.= 1.38, 95% C.I.=1.04, 1.83; results of Model 4). No significant associations were detected among males in the model that assessed for associations in continuous BMI (Model 3) nor in the female-specific models (Models 1 and 2).

Table 7.5 Adjusted regression estimates (and 95% confidence intervals) from the regression models where Body Mass Index (BMI; as a binary and continuous measure) is regressed onto bullying status at the previous wave, among female and males, participating in COMPASS across Waves 1, 2 and 3 in Ontario, Canada.

	β coefficients from the linear regression, with continuous BMI as an outcome $^{\rm a}$	Odds ratios (OR) from the logistic regression, with weight status (binary BMI) as an outcome b
	Fem	ales
	Model 1	Model 2
Bullying status at the previous wave NVoB (ref.)		
VoB	0.10 (-0.03, 0.24)	1.26 (0.95, 1.70)
	Ma	ıles
	Model 3	Model 4
NVoB (ref.)		
VoB	0.062 (-0.12, 0.24)	1.38* (1.04, 1.83)

^a β (95% C.I.) = Regression coefficient (95% Confidence Intervals).

Furthermore, we assessed whether consecutive bullying status has an association with BMI; Table 7.6 displays results from the regression models that used bullying status as an interaction effect (between bullying status at the previous wave and bullying status at the current wave). Similar to the models in Table 7.5, the models in Table 7.6 were gender-specific and regressed BMI [as a continuous outcome (Models 1 and 3), and a

^b OR (95% C.I.) = Odds Ratio (95% Confidence Intervals).

^c NVoB: Not a victim of bullying at the previous wave.

^d VoB: Victim of bullying at the previous wave.

All models adjusted for: BMI (at the previous wave), latent class (at the previous wave),

ethnicity (at baseline), grade (at current wave) and year. p<0.05.

binary outcome (i.e., weight status; Models 2 and 4)] onto bullying status' interaction term while adjusting for: CDRB latent class (at the previous wave), and BMI (at the previous wave), as well as ethnicity (at baseline), grade (current wave), and year. Models 1 and 2 display the results from the regression models for females with the outcome continuous BMI (Model 1) and with the outcome binary BMI (Model 2). Models 3 and 4 display the results for males: with the outcome continuous BMI (Model 3) and with the outcome binary BMI (Model 4).

Table 7.6 Adjusted regression estimates (and 95% confidence intervals) from the regression models where Body Mass Index (BMI; as a binary and continuous measure) is regressed onto consecutive bullying status, among female and males, participating in COMPASS across Waves 1, 2 and 3 in Ontario, Canada.

Recoefficients from the linear

	regression, with continuous BMI as an outcome a	logistic regression, with weight status (binary BMI) as an outcome b
	Females	
	Model 1	Model 2
Consecutive bullying status NVoB/NVoB ^c (ref.)		
VoB/VoB d	0.14 (-0.06, 0.33)	1.51* (1.03, 2.23)
VoB/NVoB e	0.087 (-0.086, 0.26)	1.11 (0.77, 1.60)
NVoB/VoB f	-0.043 (-0.24, 0.15)	1.06 (0.61, 1.46)
	Males	
	Model 3	Model 4
NVoB/NVoB c (ref.)		
VoB/VoB d	-0.035 (-0.30, 0.23)	1.03 (0.66, 1.59)
VoB/NVoB e	0.11 (-0.12, 0.35)	1.60* (1.11, 2.29)
NVoB/VoB f	0.13 (-0.11, 0.37)	1.13 (0.78, 1.63)

Odds ratios (OR) from the

All models adjusted for: BMI (at the previous wave), latent class (at the previous wave), ethnicity (at baseline), grade (at current wave) and year.

Using consecutive bullying status (via the interaction term) provides a further

 $^{^{}a}$ β (95% C.I.) = Regression coefficient (95% Confidence Intervals).

^b OR (95% C.I.) = Odds Ratio (95% Confidence Intervals).

^c NVoB/NVoB : Not a victim of bullying (NVoB) at previous wave and NVoB at follow-up

^d VoB/VoB: Victim of bullying (VoB) at previous wave and VoB at follow-up

^e VoB/NVoB: VoB at previous wave and NVoB at follow-up

f NVoB/VoB: NVoB at previous wave and VoB at follow-up

^{*}p<0.05.

understanding with regards to the association between changes in bullying status and BMI. Table 7.6 shows that male youth were VoB at the previous wave only (i.e., VoB/NVoB), were associated with 60% higher odds of overweight/obesity (O.R.=1.60, 95% C.I.=1.11, 2.29). Furthermore, using consecutive bullying status elucidated a relationship between bullying status and BMI among females. Among females, being a VoB at consecutive waves (VoB/VoB; repeated bullying) was associated with 51% higher odds of overweight/obesity (Model 2; O.R.=1.51, 95% C.I.=1.03, 2.23). No significant associations were detected among females nor among males using continuous BMI (Models 1 and 3, respectively).

7.4 Discussion

Our study assessed whether youth who are victims of bullying (VoB) engage in chronic disease risk behaviours differently compared with their non-VoB (NVoB) peers and whether being a VoB is associated with BMI over time in a sample of secondary school students in Canada. We found that youth who were VoB engaged in more PA, substance use and reported higher BMI than their NVoB peers. As for bullying's association with BMI, there were gender differences among youth. Among males, bullying at the previous wave, even though the bullying did not continue to follow-up (i.e., VoB/NVoB), was associated with a higher risk of overweight/obesity relative to their repeatedly NVoB peers (i.e., NVoB/NVoB). As for females, repeated bullying (i.e., being a VoB at the previous wave and at follow-up, VoB/VoB) was associated with higher odds of having an overweight/obese BMI at follow-up relative to their repeatedly NVoB peers (i.e., NVoB/NVoB). This means that VoB youth have a higher association with overweight/obesity, this differs across gender and is apparent within short *exposure* to *outcome* durations (relative to the scientific literature).

Our findings are in line with previous literature that evaluated the same relationship over a longer period. Mamun et al. (2013) found that youth who were victims of bullying (at age 14) had a higher BMI by young adulthood (at age 21), with a stronger effect seen among females than males in Brisbane, Australia. Similarly, Lee and Vaillancourt (2018b) suggest that bullied female youth who engaged in dieting behaviours or suffered from eating disorders, on average have higher BMI. The authors

suggested the following: being victimized has an internalizing effect, by integrating other people's attitudes into one's own self-image (Lee & Vaillancourt, 2018b). When bullied, youth tend to blame themselves and in turn this affects how they see their bodies, causing a lower self-esteem and body-esteem (Lee & Vaillancourt, 2018b). Body dissatisfaction is a well-established risk factor for problematic eating behaviour (Lee & Vaillancourt, 2018b). Therefore, bullying is an influential factor for problematic eating behaviour mediated via psychological functioning (e.g., body dissatisfaction). Furthermore, BMI is associated with these factors, and other research also supports the notion that bullying affects changes in BMI via reduced body esteem among obese youth (Adams & Bukowski, 2008).

Our results indicate that VoB used more substances and reported higher rates of overweight/obesity, than their NVoB peers. Although they were slightly more physically active than their NVoB peers; still, most VoB did not meet PA guidelines. These findings are similar to previous literature (Gaete et al., 2017; Kritsotakis, Papanikolaou, Androulakis, & Philalithis, 2017), as well as a national study in the U.S. that found that VoB reported substance use (alcohol, illicit drugs and smoking) and low PA engagement (Hertz et al., 2015).

This relationship (being a VoB and engaging in substance use) is reported among both females and males (Moore et al., 2017), but it is also different across the genders where it is more prominent among males. Kritsotakis et al., (2017) found that among males, VoB had two times higher odds for past month drunkenness, while this association was not reported among females. Additionally, another study found that the association between substance use and bullying was reportedly mediated by depression among female youth in the U.S.A; however, it was found to be direct among males (Luk, Wang, & Simons-Morton, 2010).

Even after controlling for substance use (via adjusting for latent classes), longitudinal associations were detected between bullying status and BMI. Other research indicates that there are a plethora of additional factors to consider when studying longitudinal associations with bullying; for example, attitudes towards school or academic achievement, social behaviours and peer pressure (Hong & Espelage, 2012).

Although our study did not look at the aforementioned factors, our analyses took into consideration that bullying status, CDRB and BMI may change over time; similarly, we recommend that longitudinal studies also take into consideration the dynamic (longitudinal) nature of youth's behaviours and health outcomes (e.g., BMI) for a deeper understanding of these associations.

7.4.1 Recommendations

Victimized youth tend to be bullied by perpetrators (i.e., bullies) who perceive the victim as someone who is not likely to confront back (Cook, Williams, Guerra, Kim, & Sadek, 2010). Therefore, we recommend that school-based prevention and intervention programs emphasize building social problem-solving skills and conflict resolution skills among all students (Cook et al., 2010; Hemphill & Heerde, 2014). The programs should instill consequences for perpetrators (Smith, 2016) and encourage bystanders to speak up, as such programs have seen lower bullying rates (Espelage & De La Rue, 2012). Programs should also promote positive/uplifting coping mechanisms so that youth refrain from engaging/initiating into unhealthy and harmful habits.

Engagement in PA and team sports are seen to have a protective effect against bullying (Merrill & Hanson, 2016). PA imparts youth with a sense of achievement, and team sports can be an empowering experience for youth as team sports foster comradery and peer engagement. Encouraging PA may also address VoB's reported loneliness and social isolation (Katapally, Thorisdottir, Laxer, Qian, & Leatherdale, 2018; Kim, Okumu, Small, Nikolova, & Mengo, 2018). In addition to PA programs directed at all youth, programs should have a gender-specific sports and address barriers to sports (Martins, Marques, Sarmento, & Carreiro Da Costa, 2014).

Our results also highlight the importance of gender-stratification in BMI, bullying and CDRB research. Our gender-stratified models identify that bullying is associated with BMI only among females who were repeatedly bullied. The male-specific models show that being a VoB at the previous wave, but not at follow-up is associated with higher odds of overweight/obesity. Future research can build upon our findings by investigating the types of bullying (e.g., physical, cyber-bullying, verbal or incidents of

theft) and their associations with BMI longitudinally and whether these differ across gender. Gender-stratified results, such as ours, inform programs and policies that will be tailored to youth's needs and behaviours.

7.4.2 Strengths and limitations

Our findings are unique to the literature on youth bullying and BMI as we assess a shorter *exposure to outcome* duration, relative to the existing literature and by using a large sample of youth (n=4510) in multilevel, longitudinal analyses. This study takes a novel approach in its gender-specific multilevel latent class analyses and gender-specific multilevel longitudinal regression models to account for gender differences and the dependence of students in schools. Our use of mixed-effects models use maximum likelihood estimation that make the assumption that missingness in the outcome (BMI) is missing at random – which is favored, in comparison with complete case analysis which is appropriate only for outcomes with information that is missing completely at random (Hedeker & Gibbons, 2006). We also controlled for substance use, a well-established internalizing behaviour among VoB.

However, this study is not without limitations; our study did not control for all internalizing behaviours reported in the literature (i.e., problematic eating behaviours, depression, and anxiety) nor other externalizing behaviours (e.g., aggression and violence towards others). This study's models, which assessed the impact of bullying status over consecutive years, are based on sparse data (note the small cell count in Table 7.4); this sparsity may bias the regression coefficients away from the null hypothesis of *no association*, thereby leading to false positive findings (Greenland, Mansournia, & Altman, 2016). To clarify, Table 7.4 displays changes in latent classes stratified by bullying status. In this assessment for association of consecutive bullying status, the latent classes were only used as a control variable where the presence of sparse data is not apparent from Tables 7.2 (bullying status) and 7.3 (weight status), our main variables of interest. Another limitation is that our results are not generalizable since COMPASS uses purposeful sampling; however, our study provides a further understanding of bullying behaviour, CDRB and BMI among youth (and their gender differences) that will inform future research.

7.4.3 Conclusion

Our study found that VoB engage in more substance use and report higher BMI than their NVoB peers, and that 42.8% of youth who are victims of bullying experience repeated bullying (i.e., continued to be bullied at follow-up). In the model that assessed for the association between bullying at the previous wave (as a main effect) and overweight/obesity, male youth had higher odds of overweight/obesity by 38% at follow-up relative to their NVoB peers, with no significant findings among females. As for the models which used consecutive bullying status (i.e., bullying status as an interaction term), females who were repeated victims of bullying were associated with increases in the odds of overweight/obesity at follow-up (by 51%). Using consecutive bullying status also elucidated that among males, being bullied at the previous wave only is associated with higher odds of overweight/obesity (by 60%) even when the bullying did not continue to the follow-up wave. We recommend that schools initiate social skills and conflict resolution prevention and intervention programs, as well as promote PA and team sports to all youth as a means of empowerment, bonding and promoting social engagement.

Chapter 8 General Discussion

8.1 Overview

Obesity is recognized as a disease by the Canadian Medical Association and it also increases a person's risk for chronic diseases (Canadian Medical Association, 2015). An overweight/obese BMI increases youths' risk of detrimental health (e.g., metabolic and cardiovascular diseases) and psychosocial (e.g., poor self-esteem, emotional and behavioural disorders and depression) outcomes during adolescence (Maggio et al., 2014; Public Health England, n.d.; Rankin et al., 2016). BMI also tracks into adulthood and places the individual at a higher risk of chronic diseases in adulthood (e.g., cancer, type 2 diabetes and heart diseases) (Statistics Canada, 2015).

Obesity has many determining factors that include: the wide-spread availability of energy-dense, nutrient-poor food, mechanized transportation, socio-economic and hereditary factors, and others (Hruby & Hu, 2015). Obesity's determinants are numerous; therefore, this dissertation focused on the effect of modifiable risk behaviours (i.e., CDRB) which play a dominant role in overweight/obesity (Hruby & Hu, 2015). Youth are not meeting the public health guidelines for CDRB which are intended to improve health (Conry et al., 2011; Deliens et al., 2013; Delk et al., 2018; Leatherdale & Rynard, 2013; Minaker & Hammond, 2016; Sisson et al., 2016).

This dissertation specifically addressed the CDRB: PA, binge drinking, marijuana use and cigarette smoking. These specific CDRB (i.e., PA and substance use) were examined because PA is reportedly inversely associated with substance use behaviours. Previous literature reported that among youth, increases in PA participation were associated with decreases in tobacco use over time (DeRuiter et al., 2014). These findings warrant including PA in substance use and obesity research – as a better understanding of PA in the substance use and obesity discussion may present novel findings, prevention and intervention avenues.

Since these CDRB co-occur among youth, multilevel latent class analyses were used to identify latent classes of the chronic disease risk behaviours – to observe how the behaviours co-occur naturally and the youth's behavioural profiles. Multi-component

interventions will benefit from this approach as such approaches elucidate which behaviours should be addressed together, for targeted, more effective interventions (DeRuiter et al., 2014; Leech et al., 2014).

Furthermore, youth's engagement in CDRB and rates of overweight/obesity differ across the genders as reported in previous literature. More males were found to have overweight/obesity than female youth in objective measures of BMI (Roberts et al., 2012). In subjective measures of BMI, female and male youth were found to report BMI differently (Statistics Canada, 2015). As for the CDRB, females have been frequently found to engage in less PA than male youth, and male youth have been found to also engage in more substance use relative to their female counterparts in a national study in Canada (Leatherdale & Rynard, 2013). Therefore, investigations in CDRB and BMI among youth should be gender-specific.

The broad aim of this dissertation was to investigate gender differences in latent classes of chronic disease risk behaviours and their association with BMI among youth. This was achieved through the following objectives: by assessing (i) gender-specific multilevel latent classes of chronic disease risk behaviours and the association of the latent classes with BMI at the same time point for female and male youth; (ii) the association of the CDRB latent classes with BMI over time among female and male youth; and (iii) by evaluating (via gender-specific analyses) whether youth who are victims of bullying have the same association with BMI as non-victims of bullying.

This dissertation takes the recent approach of assessing CDRB collectively as youth engage in them, rather evaluating CDRB individually. This approach is in line with the Problem Behaviour Theory that stipulates that certain behaviours have similar psychosocial and social-cognitive influences which is why they are likely to co-occur (Jessor & Jessor, 1977).

8.2 Summary of key findings

This section will summarize the findings from this dissertation for each of the three studies. This will be supplemented with overarching themes from each of the three chapters. Lastly, this section will include a summary of the strengths and limitations of

this dissertation along with implications for public health and school programs, and then the section will end with overall concluding remarks.

8.2.1 Findings and discussion for each of the three studies

The first manuscript of this dissertation (chapter 5) sought to identify multilevel latent classes of CDRB (PA, binge drinking, marijuana use and cigarette smoking), then regress BMI onto the resulting classes, with the aim of assessing gender differences via stratification.

Results from this manuscript indicated that female and male youth engaged in CDRB differently and had different BMI statuses. Most youth in this study did not meet PA guidelines, with more females not meeting the guidelines compared with males. Females also had less engagement in substance use behaviours and tended to have a lower BMI compared with males consistently across three waves (2013, 2014 and 2015). Multilevel latent class analyses, stratified by gender, were conducted for each of the three waves, independently. Across the three waves, and across both analyses, the 'best' fitted models were either with a two-student or three-student class model. The composition of the two-student class models consisted of: active experimenters (ACE) and inactive clean youth (INC), while the three-student class model identified an additional class of inactive substance users (INSU) to the classes ACE and INC.

The regression analyses from this study showed that among females and males, latent classes with substance use had higher risks of having overweight/obesity. Among females, the latent classes characterized with inactivity and substance use (INSU) had 20% higher odds of overweight/obesity among females relative to their ACE counterparts (2015: C.I.= 1.1, 1.4) and were found to be associated with a 0.25 kg/m² (CI= 0.04, 0.45) higher BMI than their ACE peers. As for males, latent classes with no substance use (INC) were associated with a 15% lower odds of overweight/obesity (OR=0.85, CI=0.78, 0.93) and lower BMI by 0.50 kg/m² (CI= -0.68, -0.35) compared with their active experimenting peers (ACE).

There are similarities across the genders as the latent class with the highest substance use (INSU and ACE) were associated with higher odds of overweight/obesity. However,

there are gender differences as classes with physical inactivity and substance use (INSU) were associated with higher odds of overweight/obesity among females and classes with activity and substance use (ACE) were associated with higher odds of overweight/obesity among males. This finding is in line with conclusions of two other studies where CDRB classes with inactivity were associated with higher odds of overweight/obesity among female youth (Carson et al., 2015; Te Velde et al., 2007). However, these two studies did not include substance use and did not identify associations between the latent classes and overweight/obesity among males. In other research that have assessed for such associations (Delk et al., 2018; Larson et al., 2007; Laxer et al., 2018), found that substance use was positively associated with overweight/obesity among youth. Youth who engaged in substance-use were more likely to engage in other risky behaviours such as poor dietary intake and physical inactivity. Therefore, the collective profile of youth who use substances places them at a higher risk of overweight/obesity.

With regards to the gender differences, the existing body of literature reports that males engage in more substance use than their female counterparts (Harvey et al., 2017; Schilling et al., 2017). Findings from this dissertation show that male youth in the ACE (Active [substance] experimenter) latent class were associated with a higher BMI and weight status compared with INC males. As the class names suggests, ACE males are more likely to meet PA guidelines compared with INC; however, they engage in substance use, mainly, binge drinking behaviour. This is not a new observation, as previous literature observed that boys in sports teams had the highest odds of extreme binge drinking (over 10 drinks in the past month) (Veliz, McCabe, & Boyd, 2016). A recent study assessing extra calories from binge drinking among youth found that youth who engage in binge drinking twice a week consume the equivalent of 14.8 kilograms of fat a year (Battista & Leatherdale, 2017). Reports from youth with high PA and binge drinking habits show that the active youth exercise to compensate for calories in alcohol, enhancement motives (i.e., drinking to feel better) and for the enjoyment of PA (Abrantes, Scalco, O'Donnell, Minami, & Read, 2017).

The gender differences also stem from how each group perceives and values body image/shape. Specifically, male youth value building muscles (Eik-Nes, Austin, Blashill,

Murray, & Calzo, 2018); this is especially relevant since the witnessed higher weight status (among ACE) is likely due to a higher proportion of lean body mass (i.e., muscle mass). Lean mass weighs more than fat mass and adolescent athletes have been reported to be classified in a high BMI category, even though their body composition indicated them to not be obese (Etchison et al., 2011). The reported increase in overweight/obesity (among ACE males) may be an increase in muscle mass rather than fat mass, as this is one of the limitations of using BMI in population-level studies; however, this misclassification is found to be rare (Must & Anderson, 2006). The co-occurrence of PA and binge drinking habits enforce the importance of investigating how CDRB co-occur and are associated with health outcomes.

The second manuscript of this dissertation (chapter 6) assessed whether there are significant changes in youth's weight status from one year to the next, and evaluated the extent to which the latent classes of CDRB (that were identified in chapter 5) are associated with BMI (in the following year) across the gender groups.

My findings suggest that most female and male youth remained in the same BMI category at the previous wave and at follow-up. As for transitions, females were less likely to transition from a normal BMI to having an overweight/obese BMI at follow-up, relative to males. Yet, an encouraging finding was that a considerable number of youths transitioned from having an overweight/obese BMI to a healthier BMI category. Slightly more females transitioned from having overweight/obesity to a normal BMI in Waves 1 to 2 (Females=24.9%, Males=21.6%). These reports are similar to findings from youth in Spain (Devis-Devis et al., 2017).

As for transitions in latent classes, most youth also tended to remain in their respective latent class at the previous wave and at follow-up, but the transitions were enough to be statistically significant (p<0.0001). This suggests that youth change latent classes at a faster rate than they change weight status; likely since changing weight status takes time and cannot happen at the same pace that behaviour changes can occur. For example, youth may choose to start (or stop) engaging in behaviours overnight and seek assistance to maintain these behaviours (i.e., enroll in organized school sports or in a smoking cessation program, etc.); the same cannot be said about weight status change.

A transition that is worth mentioning in the latent classes is that approximately one-third of youth in the ACE latent class transitioned to the INC latent class at follow-up. This indicates that active youth who experiment with substance use are becoming inactive, non-substance users. Although their transition to non-substance users is reassuring, their transition from active to inactive is worrisome and should be further investigated in future research.

The gender-specific multilevel mixed-effects models showed that one latent class was significantly associated with a change in BMI in the following year. Specifically, male youth who were inactive, non-substance users (INC) had an increase of 0.29 BMI units (kg/m²), on average, (95% C.I.= 0.057, 0.53) and 72% higher odds of overweight/obesity (C.I.=1.2, 2.4) in the follow-up year, relative to their peers who were more active and experimented with substance use (ACE). The lower BMI among ACE cannot be attributed to substance use, as previous research demonstrates that substance use is associated with increases in BMI (Boone-Heinonen et al., 2008; Delk et al., 2018; Huang, Lanza, & Anglin, 2013; Pasch et al., 2012). This finding is also supported by results from Michigan where male youth who are more physically active were also seen to have lower obesity rates relative to their less active peers (Govindan et al., 2013).

Furthermore, a closer look should be turned towards PA as well as the factors that cooccur among more active youth. The Problem Behaviour Theory stipulates that if youth
engage in one problem behaviour, they are more likely to engage in other problem
behaviours as well because they share functions and social influences (Jessor & Jessor,
1977). Confirmed with findings from the literature, youth with low PA also have poor
dietary habits and sedentary behaviour (Cureau et al., 2018; Gwozdz et al., 2019; Larson
et al., 2007; Wilson et al., 2005). Additionally, youth are influenced by their social
surroundings. Findings from Europe suggest that inactive youth tend to have friends who
are also inactive and they engage in non-PA activities together; likewise, active youth
have friends who are also active, and they tend to engage in physical activities together
(Gwozdz et al., 2019). Peer influences seem to be one of the drivers that explain why
INC males are associated with a higher BMI relative to their ACE counterparts.

The findings regarding latent classes' association with BMI don't extend to female

youth. The CDRB latent classes (from PA, binge drinking, marijuana use and cigarette smoking) were not associated with changes in BMI one year later among females. This indicates that other factors may be contributing to the increasing BMI rates among females. A behaviour that was not included in this analysis was dieting behaviour. Dieting behaviours have predicted increases in BMI over 10 years in the U.S. compared with non-dieting counterparts (Neumark-Sztainer et al., 2012). Additionally, female youth who dieted were found to have higher rates of having overweight/obesity as well as substance use (smoking and binge drinking) two years later (Raffoul et al., 2018). Problematic eating behaviours have been reported to be associated with increases in BMI over time among females, demonstrating that gender-specific analyses are required moving forward.

Despite the alarming observation that BMI is increasing among youth, this study found that some female and male youths are moving from higher weight status categories (overweight/obesity) to the healthy BMI category. This is a very promising finding and more future research should further investigate the experience of these youth and their success strategies as they may play a key role in informing future prevention and intervention efforts.

The third manuscript of this dissertation (chapter 7) assessed differences in CDRB across youth who are victims of bullying (VoB) and those who are not (NVoB), then investigated the association of bullying with BMI longitudinally, controlling for the latent classes, while stratifying by gender.

My findings suggest that VoB engaged in more substance use, had higher overweight/obesity and were more physically active than their NVoB peers (although most VoB remained physically inactive). These results are also commonly reported in the literature – youth who are victimized have more substance use behaviours that their counterparts (Mamun et al., 2013). The General Strain Theory explains that youth who undergo strain are more likely to engage in internalizing behaviours such as substance use (Hay et al., 2010). Findings in Chapter 7 are in line with previous literature (Gaete et al., 2017; Kritsotakis et al., 2017), as well as a national study in the U.S. that found that VoB reported an overall CDRB profile similar to youth from this study: low PA coupled

with substance use (alcohol, illicit drugs and smoking) (Hertz et al., 2015). My findings, and the literature, support that youth who are VoB resort to unhealthy and risky behaviours to deal with the strain.

The mixed-effects regression models that were reported assessed whether bullying status is associated with BMI in a longitudinal analysis while controlling for substance use (via the multilevel latent classes). The results showed that youth who were bullied had higher odds overweight/obesity. Male youth who were bullied at the previous wave, but no longer bullied at follow-up, had higher odds of having overweight/obesity, by 60% (95% C.I.=1.11, 2.29), relative to their repeated NVoB peers. As for females, repeated bullying, at the previous wave and at follow-up, was associated with higher odds of having overweight/obesity by 51% (95% C.I. = 1.03, 2.23) (on average) among females, compared with their repeated NVoB peers.

The results among females are explained by a mechanism suggested by Lee and Vaillancourt (2018b): VoB internalize bullying and it affects their self-image; low self-image is a risk factor for problematic eating and problematic eating is associated with changes in BMI. It is likely that female VoB have problematic eating behaviours which is causing an increase in their BMI and in their risk of overweight/obesity one year later. Among females, bullying influences internalized behaviours such as problematic eating and substance use (as is apparent in my findings as well as the scientific literature) (Moore et al., 2017).

Males who are VoB also resort to substance use as an internalizing behaviour. The relationship between bullying and substance use is suggested to be mediated via depression among female youth; however, it was found to be direct among males (Luk et al., 2010). Additionally, males who were VoB had two times higher odds for past month drunkenness than their peers, while this relationship was not identified among female youth (Kritsotakis et al., 2017). These findings suggest that there are gender differences in how youth react/cope with bullying, and most concerning is that they look to unhealthy and risky behaviours as coping mechanisms.

The models (discussed in chapter 7) adjusted for substance use; yet they still identified associations between bullying and BMI. Hence, future studies should

investigate the role of factors (like substance use) when assessing the association between bullying and BMI; these factors could include other internalizing behaviours (e.g., aggression, depression or anxiety), externalizing behaviours externalizing behaviours (e.g., social or other CDRB) and peer groups (Hong & Espelage, 2012). Such factors are dynamic among youth and as this analysis accounted for the dynamic nature of bullying and BMI, future research should adopt a similar approach.

8.2.2 Overall findings from the three studies

This dissertation provides evidence of the gender differences in youth's engagement in chronic disease risk behaviours, in agreement with the scientific literature. Female and male youth engage in CDRB differently – males were more likely to meet recommendations for PA; but, were also more likely to report binge drinking behaviour, marijuana use, cigarette smoking and overweight/obesity, relative to their female counterparts. Despite differences in their engagement in CDRB, latent classes of CDRB were similar across the genders; they were also similar across the three waves – when the consistency of the latent classes was evaluated. Youth were found to change latent classes over time, across genders and bullying status. These findings are reasonable since CDRB are modifiable (i.e., can change from one day to the next); a person can adopt a new behaviour or decide to stop engaging in a new behaviour at any time, this would lead to a change in their latent class.

Regarding the outcome variable BMI: across the three waves, females and males consistently had different BMI. Females were more likely to have lower BMI and a lower prevalence of overweight/obesity than their male peers at each wave. Over time, BMI was found to increase from one wave to the next among youth; nonetheless, there were transitions in weight status (i.e., binary BMI) to the healthy weight status category among youth in this dissertation which is assuring. This means that youth are successfully moving to healthier BMI categories; a further investigation of how these youth are successfully moving to healthier BMI categories will be informative to future prevention and intervention efforts that will benefit other youth.

In addition to differences in CDRB engagement and BMI, female and male youth had

different associations with BMI in both the cross-sectional and longitudinal analyses. Among females, latent classes with substance use (INSU) were associated with higher odds of overweight/obesity among females relative to their more active counterparts who experiment with substances, in cross-sectional analyses. This association was not significant over time: latent classes of substance use and physical inactivity were not associated with BMI or overweight/obesity among females at follow-up.

As mentioned, BMI increased among females over time; factors other than the ones studied in this dissertation are likely to be contributing to the increases in BMI. A study reports that variation in BMI was explained by PA (by 10.3%), dieting behaviours (by 10.3%), amount eaten (by 7.2%), meanwhile healthy eating explained only 1.6% of the variation in BMI (Chambers & Swanson, 2010). In other words, dieting behaviours may influence BMI ten times more than healthy eating and almost equally as PA.

Problematic eating behaviours should be a central component in BMI research. The scientific literature also supports that problematic eating behaviours contribute to increases in BMI (Neumark-Sztainer et al., 2012; Ritchie, 2012). A previous COMPASS study found that 57.5% of females reported dieting behaviours (Raffoul et al., 2018). Furthermore, this study reports that females with these behaviours had a higher risk of overweight/obesity as well as binge drinking and smoking two years later (Raffoul et al., 2018). In addition to their association with BMI, problematic eating behaviours are suggested to be an internalizing behaviour that female youth resort to when under strain (Hay et al., 2010). During adolescence, being a victim of bullying is considered a strain. Findings from this dissertation report that among female youth, being a repeated victim of bullying only is associated with higher odds of overweight/obesity (by 51%).

The cross-sectional findings (that indicate that youth with higher substance use are associated with higher BMI and odds of overweight/obesity) did not extend to the longitudinal analysis; the longitudinal analyses suggest that the latent class with the lowest PA (i.e., INC) was associated with (on average) 0.29 kg/m² higher BMI at follow-up among only male youth, relative to their peers who are more active but experiment with substances (i.e., ACE). The Problem Behaviour Theory explains that some behaviours have similar psychosocial influences and the engagement in the behaviours

may co-occur (Jessor & Jessor, 1977). Jessor & Jessor (1977) also explain that youth's social circles influence their behaviours. Recent findings from Europe also confirm that youth who are active tend to have active friends and they tend to engage in active activities together (e.g., ACE); similarly, inactive youth are more likely to have inactive friends and they tend to engage in inactive activities together (i.e., INC) (Gwozdz et al., 2019).

Other than peer influences, there are a myriad of factors which may cause male youth to engage in more substance use than their peers; bullying is one such factor. Youth who were VoB were found to engage in more substance use behaviours than their counterparts and this association is well reported in the scientific literature (Luk et al., 2010). This is likely mediated by VoB youth's low self-esteem (Lee & Vaillancourt, 2018b). Youth with low self-esteem will resort to other means to attract attention, one avenue is through the engagement in problem behaviours (Kaplan, 1976). Being a VoB at the previous wave was associated with increases in the odds of overweight/obesity among males, after controlling for substance use. Furthermore, assessing the association of consecutive bullying status on BMI showed that among male youth, being a victim of bullying was associated with higher odds of overweight/obesity – when the bullying behaviour did not continue to follow-up.

As previously suggested, a wide range of factors are associated with bullying (Hong & Espelage, 2012); studying the dynamic nature of youth's behaviours, social interactions and health outcomes (such as BMI) will clarify why bullying behaviour that is discontinued at follow-up is associated with increases in BMI among male youth and why repeated bullying behaviour is not associated with increases in BMI among male youth, in contrast to their female counterparts.

8.3 Overall Strengths

This dissertation provides a novel approach in evaluating gender differences among youth in their engagement in CDRB and the CDRB's association with BMI. It presents findings from (repeated) cross-sectional mixed-effects regression models and longitudinal (transitional) mixed-effects models to evaluate the association of CDRB

latent classes with BMI. This dissertation presents findings from gender-stratified, multilevel latent class analyses and gender-stratified, multilevel mixed-effects regression analyses which account for the dependency of students within schools and gender as a confounding factor. Gender is a well reported confounding factor in CDRB and BMI research among youth (Arbour-Nicitopoulos et al., 2010; Harvey et al., 2017; Milicic et al., 2017). In such analyses, female and male youth should not be complied into one category; rather, separate analyses, interpretations and prevention and intervention efforts should be considered across the genders as this dissertation reports.

Additional strengths to this dissertation are that multiple CDRB were studied at once through latent classes. Multilevel latent class analysis (MLCA) is a person-centered approach and is an advanced data-driven clustering technique that, unlike other clustering methods, does not force predefined classes on the data; it also accounts for the dependent nature of students within schools (Henry & Muthén, 2010; S. T. Lanza et al., 2007). MLCA captures the complexity of youth's patterns of CDRB as they occur in real life. Furthermore, the MLCA's results were reported over the three waves of data independently to assess the reliability of the MLCA results. The MLCA accounted for the school's effect within the student-latent classes (i.e., it accounted that schools influence the latent class composition or proportion of students in the latent classes); unlike a latent class analysis (LCA) that does not consider this effect.

Second, this dissertation used mixed-effects regression models. Mixed-effects regression models make estimations in the outcome variable via Maximum Likelihood under the assumption that the data is *missing at random* (Hedeker & Gibbons, 2006). Mixed-effects models are preferred over other models (e.g., Generalized Estimating Equations) which make the assumption that the missing data in the outcome are *missing completely at random* (Hedeker & Gibbons, 2006). Additionally, mixed-effects regression models allow interpretations to be transferable to the individual which cannot be done when the outcome is categorical or other models are used (e.g., Generalized Estimating Equations) (Hedeker & Gibbons, 2006). Using BMI as an outcome variable in two forms (continuous and as weight status/binary BMI) allowed for this dissertation's results to identify associations with unit changes in BMI over time (i.e., continuous BMI)

and make inferences at the individual level, as well as associations with increases in the odds of overweight/obesity (i.e., weight status) and make inferences at the population level (Hedeker & Gibbons, 2006).

Third, errors and biases were minimized as follows: Type II error was reduced by the use of a large sample size in each chapter (Chapter 5: n= 116,086; Chapter 6: n= 4,510; Chapter 7: n=4,510); a large sample size minimizes the chance of a false-negative finding (i.e., a Type II error) (Biau, Kernéis, & Porcher, 2008). To reduce bias, gender was considered a confounding factor through stratification throughout the dissertation.

Finally, the COMPASS system is a unique study that provides an opportunity for researchers to assess several CDRB at the same time and to track youth behaviours over time (Leatherdale, Brown, et al., 2014). The COMPASS system is hierarchical which allowed for this dissertation's regression models to take into consideration the clustered nature of the data: schools (level 3) enrolled students (level 2) who had repeated measures (level 1) (Snijders & Bosker, 2012).

8.4 Overall Limitations

Despite the many strengths mentioned, this dissertation is not without limitations. First, the results cannot be considered generalizable to youth across Canada since COMPASS used purposeful sampling; the aim of COMPASS is not to be generalizable but rather to guide and improve youth's health through research and practice. The COMPASS system uses purposeful sampling when recruiting schools to ensure that passive consent procedures are allowed. Even though not generalizable, the prevalence of substance use and of BMI was comparable to those found in a nationally representative sample (Leatherdale & Rynard, 2013).

Second, COMPASS questionnaire is self-reported by youth, retaining the possibility for recall bias (i.e., inaccurate reporting). The design of the COMPASS mitigated the possible recall bias by ensuring confidentiality by not asking for names on the questionnaire and providing sealed envelopes for the questionnaire to be placed in before submission. Additionally, the Cq uses passive consent deliberately, since active consent procedures are discouraged when measuring substance use; it limits the

participation of youth who are most likely to benefit from these programs (i.e., substance users) (Thompson-Haile et al., 2013). This also means that measures such as substance use are not validated in COMPASS due to the sensitive nature of this information and the lack of a 'gold standard' for comparison. Despite these drawbacks, the Cq has been found to be valid for measures of PA (MVPA, ICC=0.75), weight (ICC=0.95) and height (ICC=0.88) (Leatherdale & Laxer, 2013; Leatherdale, Laxer, et al., 2014).

Third, BMI was calculated via self-reported weight and height measures. As a measure, BMI does not discriminate if the 'excess weight' is muscle mass or fat mass. Since muscle weighs more than fat, theoretically, youth classified as overweight/obese may have a 'metabolically healthy' physiology with more muscle than fat; but, BMI will still classify them as overweight/obese. However, evidence suggests that this misclassification is rare, and that BMI has good correlations with direct measures of adiposity, and it is also associated with adult chronic diseases that are associated with overweight/obesity (Must & Anderson, 2006). The authors recommended and saw value in continuing to use BMI among children and youth (Must & Anderson, 2006).

Furthermore, the BMI estimates in COMPASS are similar to national prevalence rates in Canada (results of the Wilcoxon-Mann-Whitney test in Chapter 5). The rates of missing BMI were also consistent with previous research: 23% of youth in this study did not report weight, height, or both and were not included in the analyses (Sherry, Jefferds, Grummer-Strawn, et al., 2007). Additionally, the use of mixed effects models adjusted for monotone missingness in the outcome via the Maximum Likelihood function (Hedeker & Gibbons, 2006; Ibrahim & Molenberghs, 2009)

Fourth, gender was considered as a binary variable (female or male). Due to the nature of the question in the Cq (Question 3 in Appendix B), non-gender binary identities (e.g., members of the LGBTQ community) were not considered. The question in the Cq is phrased as "Are you female or male?" with the options available being "Female" or "Male"; therefore, youth identifying as a non-binary gender category either omitted answering this question or they identified as one of the binary gender identities presented.

Finally, theories such as the theory of triadic influence emphasize the importance of socio-cognitive factors in predicting future behaviour engagement such as intrapersonal

characteristics (self-efficacy), interpersonal situations (social normative beliefs) and social factors (peer and familial). Although this dissertation did not include such an approach, this dissertation provides evidence as to how CDRB cluster together and their relationship with BMI and overweight/obesity at an individual level and within their schools. This dissertation provides an understanding of individual-level associations and future research can build on these results by including a theory of triadic influence approach.

8.5 Overall Implications

This dissertation found that female and male youth have different levels of engagement in CDRB (including PA, binge drinking, marijuana use and cigarette smoking), prevalence of BMI and longitudinal associations between latent classes of CDRB and BMI as well as bullying behaviour. These findings carry important implications and directions for future research.

8.5.1 Implications for public health

This dissertation's results show the importance of gender-specific analyses. This dissertation's analyses showed results from analyses that *stratified for gender*. Past research that *only adjusted for gender* (i.e., did not stratify for gender) may have not identified associations between CDRB and BMI due to their lack of gender-stratification (Laxer et al., 2018). Future research should follow suit and stratify for gender in assessing associations of CDRB, BMI and bullying among youth.

Additionally, CDRB should continue to be identified as classes or clusters followed by assessing their association with health outcomes. The health effects of CDRB are reportedly compounded when youth engage in several CDRB at the same time (Leech et al., 2014). This dissertation used a multilevel latent class analysis to classify subjects into homogeneous classes based on their CDRB characteristics. This approach is also in line with the Problem Behaviour Theory that stipulates that certain behaviours have underlying shared meanings and functions that increase the risk of an individual being involved with other similar behaviours (e.g., substance use behaviours) (Jessor & Jessor, 1977). The latent classes identified in this analysis were found to be associated

with overweight/obesity as well as with increases in BMI and to be associated with higher odds of overweight/obesity at follow-up.

Additionally, substance use plays a role in overweight/obesity research among youth as reported in our research and others (Delk et al., 2018; Laxer et al., 2017). Continuing to integrate substance use behaviours in CDRB and BMI research is paramount. The latent classes with substance use and inactivity were associated with overweight/obesity (among both genders). Substance use is also an internalizing behaviour that youth engage in when faced with strain (e.g., being bullied). Youth who are VoB were found to have higher substance use than their NVoB peers. Among those who are VoB, PA has a protective effect on bullying (Merrill & Hanson, 2016). PA such as team sports can be a powerful means to widen youth's social circle, enhance their sense of achievement and sense of empowerment (Eime, Young, Harvey, Charity, & Payne, 2013).

PA is also a CDRB that should be emphasized as it acts on many fronts. PA has health benefits in supporting well-being, physical and mental health, disease prevention and social benefits (Eime et al., 2013; Penedo & Dahn, 2005; Saunders et al., 2014). This dissertation's findings show that male youth in latent classes with low PA (i.e., INC) have higher BMI at follow-up relative to their more active peers who experiment with substance use. Attention should be turned to PA since it influences other behaviours as well. In line with the Problem Behaviour Theory (i.e., one behaviour may influence others) DeRuiter et al. (2014) report that increases in PA and in smoking co-occur among youth and may influence binge drinking behaviour as well. Other research also found that students whose school implemented a policy or program that targeted PA reported lower screen time use in Alberta and Ontario, Canada (Katapally et al., 2018).

Prevention and intervention policies should have components for all youth and others that are gender-specific: as females report more inactivity and males report more engagement in substance use and these behaviours are associated with BMI differently. Canada recently legalized marijuana (Parliament of Canada, 2018); therefore, close monitoring of substance use is needed, as marijuana use is likely to increase among youth. Programs and policies should address polysubstance use and encourage PA among

youth.

8.5.2 Implications for school programs

Prevention and intervention programs during adolescence are imperative. Like youth, BMI is also seen to increase among adults; however, there are fewer reported decreases in BMI than among youth. Findings from adults in the U.S.A. report that over 18 years, BMI increased by 13% (3.1 kg/m²), with only 1.9% of females and 0.5% of males following a trajectory that resulted in a one unit decrease in BMI (Malhotra et al., 2013). When BMI was categorized, results from this dissertation found that about 27% of youth classified with overweight transitioned to having a normal BMI (Appendix D, Supplemental Table 7); and similar to findings from youth in Spain, 26% of youth classified as obese transitioned to having an overweight BMI (Devis-Devis et al., 2017).

Besides adolescence being a prime time for interventions, school-based interventions have been found to be successful in lowering binge drinking, marijuana use and smoking in an overview of systematic reviews (Das et al., 2016). A recent approach in interventions have a participatory nature where youth contribute to the program: they are seen to remain in the programs and have reported decreases in BMI in the U.S.A. (Bogart et al., 2014; Moonseong Heo et al., 2018). Additionally, substance use prevention efforts at the school-level are successful and can be used for obesity prevention programs (Sakuma et al., 2012; Skara & Sussman, 2003). Schools may begin with a policy/program that addresses one or a group of CDRB for all youth.

In addition to prevention programs directed at all youth, programs should have a gender-specific component that address problematic eating behaviours among females and substance use among males, ideally teaching them how to deal with strain in a healthy manner (e.g., PA and establishing healthy social networks). Differentiating that female and male youth have gender-specific longitudinal predictors of BMI changes how chronic disease prevention programs address obesity, resulting in tailored, more effective programs (Simen-Kapeu & Veugelers, 2010).

CDRB co-occur and influence each other; as such, there is great value in programs that promote PA. School-based interventions that focused on PA were seen to

decrease subsequent substance use, as reported by a recent review and other previous research (DeRuiter et al., 2014; Simonton et al., 2018). In addition to influencing other CDRB, PA also contributes to social benefits such as having a protective effect against bullying (Merrill & Hanson, 2016). When physically active, youth have a sense of achievement, and team sports foster comradery and peer engagement making it an empowering experience for youth. PA may also address VoB's reported loneliness and social isolation (Katapally, et al., 2018; Kim et al., 2018).

Prevention programs that target bullying more closely are also warranted. Such programs may include fostering skills such as social problem-solving and conflict resolution among all students (Cook et al., 2010; Hemphill & Heerde, 2014). The programs should also encourage bystanders of bullying to speak up, as such programs have seen lower bullying rates (Espelage & De La Rue, 2012).

8.6 Directions for Future Research

This dissertation provides evidence that CDRB are associated with higher odds of overweight/obesity and BMI among youth. Although males who were inactive and did not engage with substances (INC) had lower odds of overweight/obesity in the cross-sectional analyses (relative to ACE), these findings did not carry through to the longitudinal analyses. Males in latent classes with the lowest substance use and low PA (INC) were found to have an association with increases in BMI by about 0.3 kg/m² at follow-up. The overall health profile of youth in this class is the culprit. Males who are inactive are reported to also have a poor dietary intake and consume more energy-dense foods compared with their peers (Larson et al., 2007); binge drinking is also associated with increases in BMI among youth (Battista & Leatherdale, 2017; Fazzino, Fleming, Sher, Sullivan, & Befort, 2017). Further research can evaluate the association between other CDRB and BMI in cross-sectional and longitudinal analyses so that we may get a better idea of the culprit behaviours that are associated with male youth's BMI.

With regards to associations between the social environment and BMI, this dissertation found that males who were VoB at the previous wave were associated with higher odds of overweight/obesity. Furthermore, when consecutive bullying status was

evaluated, it elucidated that this relationship was only significant when bullying was discontinued at follow-up. These finding were observed even after controlling for substance use (via the latent classes), providing evidence that substance use is not likely to be a mediating factor in these results. Further research should evaluate different factors that are associated with bullying and BMI to identify why the bullying stopped among this group of youth and why being a VoB at the previous wave impacted their BMI at follow-up even though the bullying was discontinued.

As for females, over the three waves more females did not meet PA guidelines compared with their male counterparts. A deeper investigation as to why females are more inactive is warranted; as is identifying correlates of inactivity. For example, investigating barriers to PA among females would provide valuable evidence to inform prevention and intervention efforts that target increasing PA among females. Such evidence would also be valuable since this dissertation found that being a VoB was associated with increases in their BMI and in their odds of overweight/obesity at follow-up.

This dissertation provides evidence on latent classes of chronic disease risk behaviours among youth and their association with overweight/obesity considering gender differences. Future research should build upon these findings by considering contextual factors: such as the effect that provincial policies, community factors and school policies and programs play in the association between CDRB and BMI across the genders. For example, school characteristics have been seen to have an effect in how their students engage in CDRB (Allison et al., 2016). The MLCA reported in this dissertation confirms that schools play a role in the latent classes that youth belong to, as apparent by the differing prevalence rates of students within the latent classes across schools. Although this dissertation's analyses controlled for the school-effect and used data from one province, future research can be hosted using the COMPASS study (since more provinces are included in recent years) that assess for differences across provincial policies and school policies and programs across the genders.

8.7 Overall Conclusions

This dissertation finds that female and male youth engage in chronic disease risk behaviours (PA, binge drinking, marijuana use and cigarette smoking) differently and have different associations with BMI. Females and male youth also have differences in the prevalence of BMI statuses (i.e., normal versus overweight/obese categories). Latent classes of CDRB were identified, via multilevel latent class analysis, to assess whether the differences in CDRB participation across the genders would lead to different CDRB co-occurring or clustering. The MLCA found that the similar latent classes occur across females and males and they are: active experimenters (ACE), inactive clean youth (INC) and inactive substance users (INSU). Gender-stratified mixed-effects regression models found that substance use increases the risk of overweight/obesity among youth in a cross-sectional analysis.

There are unit increases in BMI seen among female and male youth over time. The transitional models clarify that there is a longitudinal association between males in the INC class with increases in BMI. Additionally, increases in BMI were associated with bullying when males were VoB at the previous wave, but not at follow-up. VoB are seen to engage in more substance use; this association is explained by the general strain theory that suggests that youth resort the internalizing behaviours (such as substance use) to deal with strains such as bullying. As for females, being a VoB was associated with an increase in the odds of overweight/obesity at follow-up possibly via problematic eating behaviours. Longitudinal associations between the gender-specific latent classes were not identified among females.

Factors associated with increases in BMI, and in the odds of overweight/obesity, are different across the genders. Moving forward, substance use prevention efforts should emphasize that substance use and inactivity are associated with higher odds of overweight/obesity among youth and increasing BMI among males one year later. School programs that include PA, problem solving and conflict resolution skills and address problematic eating behaviours among females and substance use among males, are warranted; to ameliorate bullying, substance use and overweight/obesity among youth.

References

- Abrantes, A. M., Scalco, M. D., O'Donnell, S., Minami, H., & Read, J. P. (2017).

 Drinking and exercise behaviors among college students: between and within-person associations. *Journal of Behavioral Medicine*. https://doi.org/10.1007/s10865-017-9863-x
- Adab, P., Pallan, M., & Whincup, P. H. (2018). Is BMI the best measure of obesity? *BMJ* (*Online*). https://doi.org/10.1136/bmj.k1274
- Adams, R. E., & Bukowski, W. M. (2008). Peer victimization as a predictor of depression and body mass index in obese and non-obese adolescents. *Journal of Child Psychology and Psychiatry and Allied Disciplines*. https://doi.org/10.1111/j.1469-7610.2008.01886.x
- Agudo, A. (2005). *Measuring intake of fruit and vegetables*. World Health Organization. Retrieved from
 - http://www.who.int/dietphysicalactivity/publications/f&v_intake_measurement.pdf
- Alamian, A., & Paradis, G. (2012). Individual and social determinants of multiple chronic disease behavioral risk factors among youth. *BMC Public Health*, *12*, 224. https://doi.org/10.1186/1471-2458-12-224
- Allison, K. R., Adlaf, E. M., Irving, H. M., Schoueri-Mychasiw, N., & Rehm, J. (2016).
 The search for healthy schools: A multilevel latent class analysis of schools and their students. *Preventive Medicine Reports*.
 https://doi.org/10.1016/j.pmedr.2016.06.016
- Arbour-Nicitopoulos, K. P., Faulkner, G. E., & Leatherdale, S. T. (2010). Learning from non-reported data: Interpreting missing body mass index values in young children. *Measurement in Physical Education and Exercise Science*, 14(4), 241–251. https://doi.org/10.1080/1091367X.2010.520243
- Arseneault, L., Bowes, L., & Shakoor, S. (2010). Bullying victimization in youths and

- mental health problems: Much ado about nothing? *Psychological Medicine*. https://doi.org/10.1017/S0033291709991383
- Arseneault, Louise. (2018). Annual Research Review: The persistent and pervasive impact of being bullied in childhood and adolescence: implications for policy and practice. *Journal of Child Psychology and Psychiatry and Allied Disciplines*. https://doi.org/10.1111/jcpp.12841
- Battista, K., & Leatherdale, S. T. (2017). Estimating how extra calories from alcohol consumption are likely an overlooked contributor to youth obesity. *Health Promotion and Chronic Disease Prevention in Canada*, *37*(6), 194–200. https://doi.org/10.24095/hpcdp.37.6.03
- Begg, D. J., & Gulliver, P. (2008). A longitudinal examination of the relationship between adolescent problem behaviors and traffic crash involvement during young adulthood. *Traffic Inj Prev*, 9(6), 508–514. https://doi.org/10.1080/15389580802335117
- Berkey, C. S., Rockett, H., Field, A., Gillman, M., Frazier, L., Camargo, C., & Colditz, G. (2000). Activity, Dietary Intake, and Weight Changes in a Longitudinal Study of Preadolescent and Adolescent Boys and Girls. *Pediatrics*, *105*(4), e56–e56. https://doi.org/10.1542/peds.105.4.e56
- Biau, D. J., Kernéis, S., & Porcher, R. (2008). Statistics in brief: The importance of sample size in the planning and interpretation of medical research. *Clinical Orthopaedics and Related Research*. https://doi.org/10.1007/s11999-008-0346-9
- Bogart, L. M., Cowgill, B. O., Elliott, M. N., Klein, D. J., Hawes-Dawson, J., Uyeda, K., ... Schuster, M. a. (2014). A Randomized Controlled Trial of Students for Nutrition and eXercise: A Community-Based Participatory Research Study. *The Journal of Adolescent Health: Official Publication of the Society for Adolescent Medicine*, 55(3), 1–8. https://doi.org/10.1016/j.jadohealth.2014.03.003
- Boone-Heinonen, J., Gordon-Larsen, P., & Adair, L. S. (2008). Obesogenic clusters: Multidimensional adolescent obesity-related behaviors in the U.S. *Annals of Behavioral Medicine*, *36*(3), 217–230. https://doi.org/10.1007/s12160-008-9074-3
- Bredin, C., & Leatherdale, S. T. (2013). *Methods for linking COMPASS student-level data over time*. Waterloo, Ontario. Retrieved from www.compass.uwaterloo.ca

- Busch, V., Van Stel, H. F., Schrijvers, A. J., & De Leeuw, J. R. (2013). Clustering of health-related behaviors, health outcomes and demographics in Dutch adolescents:
 A cross-sectional study. *BMC Public Health*, 13(1), 1118.
 https://doi.org/10.1186/1471-2458-13-1118
- Canadian Medical Association. (2015). CMA recognizes obesity as a disease. Retrieved December 9, 2018, from https://www.cma.ca/En/Pages/cma-recognizes-obesity-as-a-disease.aspx
- Cancer Care Ontario, & Public Health Ontario. (2012). *Taking action to prevent chronic disease: Recommendations for a healthier Ontario*. Toronto, ON. Retrieved from https://www.cancercare.on.ca/common/pages/UserFile.aspx?fileId=125697
- Carson, V., Faulkner, G., Sabiston, C., Tremblay, M., & Leatherdale, S. T. (2015).

 Patterns of movement behaviors and their association with overweight and obesity in youth. *International Journal of Public Health*, 60(5), 551–559.

 https://doi.org/10.1007/s00038-015-0685-8
- Carson, V., Pickett, W., & Janssen, I. (2011). Screen time and risk behaviors in 10- to 16-year-old Canadian youth. *Prev Med*, 52(2), 99–103. https://doi.org/10.1016/j.ypmed.2010.07.005
- Chambers, J. a, & Swanson, V. (2010). A health assessment tool for multiple risk factors for obesity: age and sex differences in the prediction of body mass index. *The British Journal of Nutrition*, 104(2), 298–307. https://doi.org/10.1017/S0007114510000607
- Chau, N., Chau, K., Mayet, A., Baumann, M., Legleye, S., & Falissard, B. (2013). Self-reporting and measurement of body mass index in adolescents: refusals and validity, and the possible role of socioeconomic and health-related factors. *BMC Public Health*, *13*, 815. https://doi.org/10.1186/1471-2458-13-815
- Chung, T., Creswell, K. G., Bachrach, R., Clark, D. B., & Martin, C. S. (2018).
 Adolescent Binge Drinking: Developmental Context and Opportunities for Prevention. *Alcohol Research: Current Reviews*.
- Collins, L. M., & Lanza, S. T. (2010). Latent Class and Latent Transation Analysis With Applications in the Social, Behavioral, and Health Sciences. New Jersey: John Wiley & Sons, Inc.

- Conry, M. C., Morgan, K., Curry, P., McGee, H., Harrington, J., Ward, M., & Shelley, E. (2011). The clustering of health behaviours in Ireland and their relationship with mental health, self-rated health and quality of life. *BMC Public Health*, *11*, 692. https://doi.org/10.1186/1471-2458-11-692
- Cook, C. R., Williams, K. R., Guerra, N. G., Kim, T. E., & Sadek, S. (2010). Predictors of bullying and victimization in childhood and adolescence: A meta-analytic investigation. *School Psychology Quarterly*. https://doi.org/10.1037/a0020149
- Costa, F., & Jessor, R. (n.d.). Problem-Behavior Theory ~ A Brief Overview. Retrieved from http://www.colorado.edu/ibs/jessor/
- Croisant, S. A. P., Laz, T. H., Rahman, M., & Berenson, A. B. (2013). Gender Differences in Risk Behaviors among High School Youth. *Global Advances in Health and Medicine*. https://doi.org/10.7453/gahmj.2013.045
- Cureau, F. V., Sparrenberger, K., Bloch, K. V., Ekelund, U., & Schaan, B. D. (2018).
 Associations of multiple unhealthy lifestyle behaviors with overweight/obesity and abdominal obesity among Brazilian adolescents: A country-wide survey. *Nutrition, Metabolism and Cardiovascular Diseases*, 28(7), 765–774.
 https://doi.org/10.1016/j.numecd.2018.04.012
- Das, J. K., Salam, R. A., Arshad, A., Finkelstein, Y., & Bhutta, Z. A. (2016).
 Interventions for Adolescent Substance Abuse: An Overview of Systematic Reviews. *Journal of Adolescent Health*.
 https://doi.org/10.1016/j.jadohealth.2016.06.021
- De Leo, J. A., & Wulfert, E. (2013). Problematic Internet use and other risky behaviors in college students: an application of problem-behavior theory. *Psychol Addict Behav*, 27(1), 133–141. https://doi.org/10.1037/a0030823
- de Winter, A. F., Visser, L., Verhulst, F. C., Vollebergh, W. A., & Reijneveld, S. A. (2016). Longitudinal patterns and predictors of multiple health risk behaviors among adolescents: The TRAILS study. *Prev Med*, *84*, 76–82. https://doi.org/10.1016/j.ypmed.2015.11.028
- Deforche, B., Van Dyck, D., Deliens, T., & De Bourdeaudhuij, I. (2015). Changes in weight, physical activity, sedentary behaviour and dietary intake during the transition to higher education: A prospective study. *International Journal of*

- Behavioral Nutrition and Physical Activity, 12(1). https://doi.org/10.1186/s12966-015-0173-9
- Deliens, T., Clarys, P., De Bourdeaudhuij, I., & Deforche, B. (2013). Weight, sociodemographics, and health behaviour related correlates of academic performance in first year university students. *Nutr J*, *12*, 162. https://doi.org/10.1186/1475-2891-12-162
- Delk, J., Creamer, M. L. R., Perry, C. L., & Harrell, M. B. (2018). Weight Status and Cigarette and Electronic Cigarette Use in Adolescents. *American Journal of Preventive Medicine*, *54*(1), e31–e35. https://doi.org/10.1016/j.amepre.2017.09.007
- DeRuiter, W. K., Cairney, J., Leatherdale, S. T., & Faulkner, G. (2016). The period prevalence of risk behavior co-occurrence among Canadians. *Prev Med*, 85, 11–16. https://doi.org/10.1016/j.ypmed.2015.11.026
- DeRuiter, W. K., Cairney, J., Leatherdale, S. T., & Faulkner, G. E. (2014). A longitudinal examination of the interrelationship of multiple health behaviors. *Am J Prev Med*, 47(3), 283–289. https://doi.org/10.1016/j.amepre.2014.04.019
- Devis-Devis, J., Lizandra, J., Valencia-Peris, A., Perez-Gimeno, E., Garcia-Masso, X., & Peiro-Velert, C. (2017). Longitudinal changes in physical activity, sedentary behavior and body mass index in adolescence: Migrations towards different weight cluster. *PloS One*, *12*(6), e0179502. https://doi.org/10.1371/journal.pone.0179502
- Donovan, J. E. (2005). Problem Behavior Theory. In C. B. Fisher & R. M. Lerner (Eds.), *Encyclopedia of Applied Developmental Science* (Volume 2, pp. 872–877). Thousand Oaks California 91320 United States: SAGE Publications, Inc. https://doi.org/10.4135/9781412950565.n336
- Donovan, J. E. (2009). Estimated Blood Alcohol Concentrations for Child and Adolescent Drinking and Their Implications for Screening Instruments. *PEDIATRICS*. https://doi.org/10.1542/peds.2008-0027
- Eik-Nes, T. T., Austin, S. B., Blashill, A. J., Murray, S. B., & Calzo, J. P. (2018). Prospective health associations of drive for muscularity in young adult males. *International Journal of Eating Disorders*. https://doi.org/10.1002/eat.22943
- Eime, R. M., Young, J. A., Harvey, J. T., Charity, M. J., & Payne, W. R. (2013). A systematic review of the psychological and social benefits of participation in sport

- for adults: Informing development of a conceptual model of health through sport. *International Journal of Behavioral Nutrition and Physical Activity*, *10*(1), 98. https://doi.org/10.1186/1479-5868-10-135
- Espelage, D. L., & De La Rue, L. (2012). School bullying: Its nature and ecology. *International Journal of Adolescent Medicine and Health*. https://doi.org/10.1515/ijamh.2012.002
- Etchison, W. C., Bloodgood, E. A., Minton, C. P., Thompson, N. J., Collins, M. A., Hunter, S. C., & Dai, H. (2011). Body mass index and percentage of body fat as indicators for obesity in an adolescent athletic population. *Sports Health*, *3*(3), 249–252. https://doi.org/10.1177/1941738111404655
- Faught, E. L., Gleddie, D., Storey, K. E., Davison, C. M., & Veugelers, P. J. (2017). Healthy lifestyle behaviours are positively and independently associated with academic achievement: An analysis of self-reported data from a nationally representative sample of Canadian early adolescents. *PLoS ONE*, *12*(7), e0181938. https://doi.org/10.1371/journal.pone.0181938
- Fazzino, T. L., Fleming, K., Sher, K. J., Sullivan, D. K., & Befort, C. (2017). Heavy
 Drinking in Young Adulthood Increases Risk of Transitioning to Obesity. *American Journal of Preventive Medicine*, 53(2), 169–175.
 https://doi.org/10.1016/j.amepre.2017.02.007
- Fleary, S. A. (2017). Combined Patterns of Risk for Problem and Obesogenic Behaviors in Adolescents: A Latent Class Analysis Approach. *Journal of School Health*, 87(3), 182–193. https://doi.org/10.1111/josh.12481
- Fletcher, A., Bonell, C., & Hargreaves, J. (2008). School Effects on Young People's Drug Use: A Systematic Review of Intervention and Observational Studies. *Journal of Adolescent Health*. https://doi.org/10.1016/j.jadohealth.2007.09.020
- Freedman, D. S., Khan, L. K., Serdula, M. K., Dietz, W. H., Srinivasan, S. R., & Berenson, G. S. (2005). The Relation of Childhood BMI to Adult Adiposity: The Bogalusa Heart Study. *Pediatrics*, 115(1), 22–27. https://doi.org/10.1542/peds.2004-0220
- Funtikova, A. N., Navarro, E., Bawaked, R. A., Fito, M., & Schroder, H. (2015). Impact of diet on cardiometabolic health in children and adolescents. *Nutr J*, *14*, 118.

- https://doi.org/10.1186/s12937-015-0107-z
- Gaete, J., Tornero, B., Valenzuela, D., Rojas-Barahona, C. A., Salmivalli, C., Valenzuela, E., & Araya, R. (2017). Substance use among adolescents involved in bullying: A cross-sectional multilevel study. *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2017.01056
- Gorber, S. C., Shields, M., Tremblay, M. S., & McDowell, I. (2008). *The feasibility of establishing correction factors to adjust self-reported estimates of obesity. Health Reports* (Vol. 82-003–X). Statistics Canada. Retrieved from http://www.statcan.gc.ca/pub/82-624-x/2014001/article/11922-eng.htm
- Gordon-Larsen, P., Nelson, M. C., & Popkin, B. M. (2004). Longitudinal physical activity and sedentary behavior trends: Adolescence to adulthood. *American Journal of Preventive Medicine*, 27(4), 277–283. https://doi.org/10.1016/j.amepre.2004.07.006
- Gordon-Larsen, P., The, N. S., & Adair, L. S. (2010). Longitudinal trends in obesity in the United States from adolescence to the third decade of life. *Obesity*, *18*(9), 1801–1804. https://doi.org/10.1038/oby.2009.451
- Government of Canada, Health Canada, Healthy Environments and Consumer Safety Branch, T. and D. D. (2012). Canadian Alcohol and Drug Use Monitoring Survey: Summary of Results for 2012 Health Canada. (C. S. and T. D. Office of Research and Surveillance, Ed.). Ottawa, ON: Health Canada. Retrieved from http://www.hc-sc.gc.ca/hc-ps/drugs-drogues/stat/_2012/tables-tableaux-eng.php#t2
- Govindan, M., Gurm, R., Mohan, S., Kline-Rogers, E., Corriveau, N., Goldberg, C., ... Jackson, E. a. (2013). Gender differences in physiologic markers and health behaviors associated with childhood obesity. *Pediatrics*, *132*, 468–474. https://doi.org/10.1542/peds.2012-2994
- Greenland, S., Mansournia, M. A., & Altman, D. G. (2016). Sparse data bias: A problem hiding in plain sight. *BMJ (Online)*. https://doi.org/10.1136/bmj.i1981
- Gwozdz, W., Nie, P., Sousa-Poza, A., DeHenauw, S., Felső, R., Hebestreit, A., ... Foraita, R. (2019). Peer Effects on Weight Status, Dietary Behaviour and Physical Activity among Adolescents in Europe: Findings from the I.Family Study. *Kyklos*, 72(2), 270–296. https://doi.org/10.1111/kykl.12197

- Haerens, L., Vereecken, C., Maes, L., & De Bourdeaudhuij, I. (2010). Relationship of physical activity and dietary habits with body mass index in the transition from childhood to adolescence: a 4-year longitudinal study. *Public Health Nutr*, *13*(10A), 1722–1728. https://doi.org/10.1017/S1368980010002284
- Hammami, N., Chaurasia, A., Bigelow, P., & Leatherdale, S. T. (2019a). A gender-stratified, multilevel latent class assessment of chronic disease risk behaviours' association with BMI among youth in the COMPASS study. *Preventive Medicine*, 126(C). https://doi.org/10.1016/j.ypmed.2019.105758
- Hammami, N., Chaurasia, A., Bigelow, P., & Leatherdale, S. T. (2019b). Gender differences in the longitudinal association between classes of chronic disease risk behaviours and Body Mass Index among youth in the COMPASS study. *Working Paper*,.
- Harvey, A., Faulkner, G., Giangregorio, L., & Leatherdale, S. T. (2017). An examination of school- and student-level characteristics associated with the likelihood of students' meeting the Canadian physical activity guidelines in the COMPASS study. *Canadian Journal of Public Health*, 108(4), e348–e354. https://doi.org/10.17269/cjph.108.5925
- Hay, C., Meldrum, R., & Mann, K. (2010). Traditional bullying, cyber bullying, and deviance: A general strain theory approach. *Journal of Contemporary Criminal Justice*. https://doi.org/10.1177/1043986209359557
- Health Canada. (2018a). Detailed tables for the Canadian Student Tobacco, Alcohol and Drugs Survey 2016-17 Canada.ca. Retrieved December 3, 2018, from https://www.canada.ca/en/health-canada/services/canadian-student-tobacco-alcoholdrugs-survey/2016-2017-supplementary-tables.html
- Health Canada. (2018b). Summary of results for the Canadian Student Tobacco, Alcohol and Drugs Survey 2016-17 Canada.ca. Retrieved December 2, 2018, from https://www.canada.ca/en/health-canada/services/canadian-student-tobacco-alcoholdrugs-survey/2016-2017-summary.html
- Health Canada. (2019). Canada's food guide. Retrieved from https://food-guide.canada.ca/en/
- Hedeker, D., & Gibbons, R. D. (2006). Longitudinal Data Analysis. Longitudinal Data

- Analysis. https://doi.org/10.1002/0470036486
- Hemphill, S. A., & Heerde, J. A. (2014). Adolescent predictors of young adult cyberbullying perpetration and victimization among australian youth. *Journal of Adolescent Health*. https://doi.org/10.1016/j.jadohealth.2014.04.014
- Henry, K. L., & Muthén, B. (2010a). Multilevel latent class analysis: An application of adolescent smoking typologies with individual and contextual predictors. *Structural Equation Modeling*. https://doi.org/10.1080/10705511003659342
- Henry, K. L., & Muthén, B. (2010b). Multilevel Latent Class Analysis: An Application of Adolescent Smoking Typologies with Individual and Contextual Predictors. *Struct Equ Modeling*, 17(2), 193–215. https://doi.org/10.1080/10705511003659342
- Heo, M, Kim, R. S., Wylie-Rosett, J., Allison, D. B., Heymsfield, S. B., & Faith, M. S. (2011). Inverse association between fruit and vegetable intake and BMI even after controlling for demographic, socioeconomic and lifestyle factors. *Obes Facts*, 4(6), 449–455. https://doi.org/10.1159/000335279
- Heo, Moonseong, Jimenez, C. C., Lim, J., Isasi, C. R., Blank, A. E., Lounsbury, D. W., ... Wylie-Rosett, J. (2018). Effective nationwide school-based participatory extramural program on adolescent body mass index, health knowledge and behaviors. *BMC Pediatrics*, 18(1), 7. https://doi.org/10.1186/s12887-017-0975-9
- Hertz, M. F., Everett Jones, S., Barrios, L., David-Ferdon, C., & Holt, M. (2015).
 Association Between Bullying Victimization and Health Risk Behaviors Among High School Students in the United States. *Journal of School Health*.
 https://doi.org/10.1111/josh.12339
- Hong, J. S., & Espelage, D. L. (2012). A review of research on bullying and peer victimization in school: An ecological system analysis. *Aggression and Violent Behavior*, 17(4), 311–322. https://doi.org/10.1016/J.AVB.2012.03.003
- Hruby, A., & Hu, F. B. (2015). The Epidemiology of Obesity: A Big Picture. *PharmacoEconomics*. https://doi.org/10.1007/s40273-014-0243-x
- Huang, D. Y. C., Lanza, H. I., & Anglin, M. D. (2013). Association Between Adolescent Substance Use And Obesity In Young Adulthood: A Group-Based Dual Trajectory Analysis. *Addictive Behaviors*, 38(11), 2653–2660. https://doi.org/10.1016/j.addbeh.2013.06.024

- Huang, D. Y. C., Lanza, H. I., Wright-Volel, K., & Anglin, M. D. (2013). Developmental trajectories of childhood obesity and risk behaviors in adolescence. *Journal of Adolescence*, *36*(1), 139–148. https://doi.org/10.1016/j.adolescence.2012.10.005
- Huh, J., Riggs, N. R., Spruijt-Metz, D., Chou, C.-P., Huang, Z., & Pentz, M. (2011).
 Identifying Patterns of Eating and Physical Activity in Children: A Latent Class Analysis of Obesity Risk. *Obesity*, 19(3), 652–658.
 https://doi.org/10.1038/oby.2010.228
- Ibrahim, J. G., & Molenberghs, G. (2009). Missing data methods in longitudinal studies: A review. *Test*. https://doi.org/10.1007/s11749-009-0138-x
- Jackson, S. L., & Cunningham, S. A. (2017). The stability of children's weight status over time, and the role of television, physical activity, and diet. *Preventive Medicine*, 100, 229–234. https://doi.org/10.1016/j.ypmed.2017.04.026
- Janssen, I., Craig, W. M., Boyce, W. F., & Pickett, W. (2004). Associations Between Overweight and Obesity With Bullying Behaviors in School-Aged Children. *PEDIATRICS*. https://doi.org/10.1140/epjad/s2005-04-035-9
- Janssen, I., Roberts, K. C., & Thompson, W. (2017). Adherence to the 24-Hour Movement Guidelines among 10- to 17-year-old Canadians. *Health Promotion and Chronic Disease Prevention in Canada*. https://doi.org/10.24095/hpcdp.37.11.01
- Jessor, R. (1991). Risk behavior in adolescence: a psychosocial framework for understanding and action. *J Adolesc Health*, *12*(8), 597–605. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/1799569
- Jessor, R. (2014). Problem Behavior Theory: A Half-Century of Research on Adolescent Behavior and Development. In R. Lerner & A. C. Petersen (Eds.), *The* developmental science of adolescence: History through autobiography. New York: Psychology Press.
- Jessor, R., & Jessor, S. L. (1977). *Problem behavior and psychosocial development: a longitudinal study of youth.* New York: Academic Press.
- Kang, J., Ciecierski, C. C., Malin, E. L., Carroll, A. J., Gidea, M., Craft, L. L., ... Hitsman, B. (2014). A latent class analysis of cancer risk behaviors among U.S. college students. *Preventive Medicine*, 64, 121–125. https://doi.org/10.1016/j.ypmed.2014.03.023

- Kaplan, H. B. (1976). Self-attitudes and deviant response. *Social Forces*. https://doi.org/10.1093/sf/54.4.788
- Katapally, T. R., Thorisdottir, A. S., Laxer, R., Qian, W., & Leatherdale, S. T. (2018). The association of school connectedness and bullying involvement with multiple screen-time behaviours among youth in two Canadian provinces: a COMPASS study. *Health Promotion and Chronic Disease Prevention in Canada*, 38(10), 368–379. https://doi.org/10.24095/hpcdp.38.10.03
- Katapally, T. R., Laxer, R. E., Qian, W., & Leatherdale, S. T. (2018). Do school physical activity policies and programs have a role in decreasing multiple screen time behaviours among youth? *Preventive Medicine*, *110*, 106–113. https://doi.org/10.1016/J.YPMED.2017.11.026
- Kim, Y. K., Okumu, M., Small, E., Nikolova, S. P., & Mengo, C. (2018). The association between school bullying victimization and substance use among adolescents in Malawi: The mediating effect of loneliness. *International Journal of Adolescent Medicine and Health*. https://doi.org/10.1515/ijamh-2017-0229
- Kritsotakis, G., Papanikolaou, M., Androulakis, E., & Philalithis, A. E. (2017).

 Associations of Bullying and Cyberbullying With Substance Use and Sexual Risk
 Taking in Young Adults. *Journal of Nursing Scholarship*.

 https://doi.org/10.1111/jnu.12299
- Kritsotakis, G., Psarrou, M., Vassilaki, M., Androulaki, Z., & Philalithis, A. E. (2016). Gender differences in the prevalence and clustering of multiple health risk behaviours in young adults. *Journal of Advanced Nursing*, 72(9), 2098–2113. https://doi.org/10.1111/jan.12981
- Lamont, A. E., Woodlief, D., & Malone, P. S. (2014). Predicting high-risk versus higher-risk substance use during late adolescence from early adolescent risk factors using Latent Class Analysis. *Addict Res Theory*, 22(1), 78–89. https://doi.org/10.3109/16066359.2013.772587
- Landsberg, B., Plachta-Danielzik, S., Lange, D., Johannsen, M., Seiberl, J., & Muller, M. J. (2010). Clustering of lifestyle factors and association with overweight in adolescents of the Kiel Obesity Prevention Study. *Public Health Nutr*, 13(10A), 1708–1715. https://doi.org/10.1017/S1368980010002260

- Lanza, H. I., Grella, C. E., & Chung, P. J. (2014). Does adolescent weight status predict problematic substance use patterns? *American Journal of Health Behavior*, *38*(5), 708–716. https://doi.org/10.5993/AJHB.38.5.8
- Lanza, H. I., Pittman, P., & Batshoun, J. (2017). Obesity and cigarette smoking: Extending the link to E-cigarette/vaping use. *American Journal of Health Behavior*, 41(3), 338–347. https://doi.org/10.5993/AJHB.41.3.13
- Lanza, S. T., Collins, L. M., Lemmon, D. R., & Schafer, J. L. (2007). PROC LCA: A SAS Procedure for Latent Class Analysis PROC LCA: A SAS Procedure for Latent Class Analysis. *Structural Equation Modeling*, *14*(4), 671–694. https://doi.org/10.1080/10705510701575602
- Larson, N. I., Story, M., Perry, C. L., Neumark-Sztainer, D., & Hannan, P. J. (2007). Are diet and physical activity patterns related to cigarette smoking in adolescents?Findings from Project EAT. *Prev. Chronic. Dis.*, 4(3), A51. https://doi.org/A51 [pii]
- Laska, M. N., Pasch, K. E., Lust, K., Story, M., & Ehlinger, E. (2009). Latent class analysis of lifestyle characteristics and health risk behaviors among college youth. *Prevention Science*, *10*(4), 376–386. https://doi.org/10.1007/s11121-009-0140-2
- Laxer, R. E., Brownson, R. C., Dubin, J. A., Cooke, M., Chaurasia, A., & Leatherdale, S. T. (2017). Clustering of risk-related modifiable behaviours and their association with overweight and obesity among a large sample of youth in the COMPASS study. *BMC Public Health*, 17(1), 102. https://doi.org/10.1186/s12889-017-4034-0
- Laxer, R. E., Cooke, M., Dubin, J. A., Brownson, R. C., Chaurasia, A., & Leatherdale, S. T. (2018). Behavioural patterns only predict concurrent BMI status and not BMI trajectories in a sample of youth in Ontario, Canada. *PLoS ONE*, 13(1). https://doi.org/10.1371/journal.pone.0190405
- Leatherdale, S. T. (2015). An examination of the co-occurrence of modifiable risk factors associated with chronic disease among youth in the COMPASS study. *Cancer Causes and Control*, 26(4), 519–528. https://doi.org/10.1007/s10552-015-0529-0
- Leatherdale, S. T., & Ahmed, R. (2011). Screen-based sedentary behaviours among a nationally representative sample of youth: are Canadian kids couch potatoes? *Chronic Diseases and Injuries in Canada*, 31(4), 141–146.
- Leatherdale, S. T., Brown, K. S., Carson, V., Childs, R. A., Dubin, J. A., Elliott, S. J., ...

- Thompson-Haile, A. (2014). The COMPASS study: A longitudinal hierarchical research platform for evaluating natural experiments related to changes in school-level programs, policies and built environment resources. *BMC Public Health*, *14*(1), 331. https://doi.org/10.1186/1471-2458-14-331
- Leatherdale, S. T., & Burkhalter, R. (2012). The substance use profile of Canadian youth: Exploring the prevalence of alcohol, drug and tobacco use by gender and grade.

 *Addictive Behaviors, 37(3), 318–322. https://doi.org/10.1016/j.addbeh.2011.10.007
- Leatherdale, S. T., & Laxer, R. E. (2013). Reliability and validity of the weight status and dietary intake measures in the COMPASS questionnaire: are the self-reported measures of body mass index (BMI) and Canada's food guide servings robust? *The International Journal of Behavioral Nutrition and Physical Activity*, 10. https://doi.org/10.1186/1479-5868-10-42
- Leatherdale, S. T., Laxer, R. E., & Faulkner, G. (2014). Reliability and validity of the physical activity and sedentary behaviour measures in the COMPASS study.

 Compass Technical Report Series (Vol. 2). Retrieved from www.compass.uwaterloo.ca
- Leatherdale, S. T., & Rynard, V. (2013). A cross-sectional examination of modifiable risk factors for chronic disease among a nationally representative sample of youth:

 Are Canadian students graduating high school with a failing grade for health? *BMC Public Health*, *13*(1), 569. https://doi.org/10.1186/1471-2458-13-569
- Lee, K. S., & Vaillancourt, T. (2018a). Body mass index, peer victimization, and body dissatisfaction across 7 years of childhood and adolescence: Evidence of moderated and mediated pathways. *Developmental Science*. https://doi.org/10.1111/desc.12734
- Lee, K. S., & Vaillancourt, T. (2018b). Developmental pathways between peer victimization, psychological functioning, disordered eating behavior, and body mass index: A review and theoretical model. *Aggression and Violent Behavior*. https://doi.org/10.1016/j.avb.2018.01.004
- Leech, R. M., McNaughton, S. A., & Timperio, A. (2014). The clustering of diet, physical activity and sedentary behavior in children and adolescents: A review. *International Journal of Behavioral Nutrition and Physical Activity*, 11(1), 4. https://doi.org/10.1186/1479-5868-11-4

- Lester, L., Cross, D., & Shaw, T. (2012). Problem behaviours, traditional bullying and cyberbullying among adolescents: Longitudinal analyses. *Emotional and Behavioural Difficulties*. https://doi.org/10.1080/13632752.2012.704313
- Lippke, S., Nigg, C. R., & Maddock, J. E. (2012). Health-promoting and health-risk behaviors: Theory-driven analyses of multiple health behavior change in three international samples. *International Journal of Behavioral Medicine*. https://doi.org/10.1007/s12529-010-9135-4
- Little, R. J. A., & Rubin, D. B. (2002). Statistical Analysis with Missing Data: Second Edition. Wiley Series in Probability and Statistics.
- Lloyd, L. J., Langley-Evans, S. C., & McMullen, S. (2012). Childhood obesity and risk of the adult metabolic syndrome: a systematic review. *Int J Obes (Lond)*, *36*(1), 1–11. https://doi.org/10.1038/ijo.2011.186
- Lloyd, L., Langley-Evans, S., & McMullen, S. (2012). Childhood obesity and risk of the adult metabolic syndrome: a systematic review. *Int J Obes*, *36*(1), 1–11. https://doi.org/10.1038/ijo.2011.186
- Luk, J. W., Wang, J., & Simons-Morton, B. G. (2010). Bullying Victimization and Substance Use Among U.S. Adolescents: Mediation by Depression. *Prevention Science*. https://doi.org/10.1007/s11121-010-0179-0
- Luo, J., Agley, J., Hendryx, M., Gassman, R., & Lohrmann, D. (2015). Risk Patterns Among College Youth: Identification and Implications for Prevention and Treatment. *Health Promotion Practice*, 16(1), 132–141. https://doi.org/10.1177/1524839914520702
- Magee, C. A., Caputi, P., & Iverson, D. C. (2013). Identification of distinct body mass index trajectories in Australian children. *Pediatric Obesity*, 8(3), 189–198. https://doi.org/10.1111/j.I2047T-6310.201Y2.00112.x
- Magee, Christopher A., Caputi, P., & Iverson, D. C. (2013). Patterns of health behaviours predict obesity in Australian children. *Journal of Paediatrics and Child Health*, 49(4), 291–296. https://doi.org/10.1111/jpc.12163
- Maggio, A. B., Martin, X. E., Saunders Gasser, C., Gal-Duding, C., Beghetti, M., Farpour-Lambert, N. J., & Chamay-Weber, C. (2014). Medical and non-medical complications among children and adolescents with excessive body weight. *BMC*

- Pediatr, 14, 232. https://doi.org/10.1186/1471-2431-14-232
- Makel, M. C., Plucker, J. A., & Hegarty, B. (2012). Replications in Psychology Research: How Often Do They Really Occur? *Perspectives on Psychological Science*, 7(6), 537–542. https://doi.org/10.1177/1745691612460688
- Malhotra, R., Østbye, T., Riley, C. M., & Finkelstein, E. A. (2013). Young adult weight trajectories through midlife by body mass category. *Obesity*, *21*(9), 1923–1934. https://doi.org/10.1002/oby.20318
- Mamun, A. A., O'Callaghan, M. J., Williams, G. M., & Najman, J. M. (2013).

 Adolescents bullying and young adults body mass index and obesity: A longitudinal study. *International Journal of Obesity*. https://doi.org/10.1038/ijo.2012.182
- Martins, J., Marques, A., Sarmento, H., & Carreiro Da Costa, F. (2014). Adolescents' perspectives on the barriers and facilitators of physical activity: A systematic review of qualitative studies. *Health Education Research*. https://doi.org/10.1093/her/cyv042
- McAloney, K., Graham, H., Law, C., & Platt, L. (2013). A scoping review of statistical approaches to the analysis of multiple health-related behaviours. *Preventive Medicine*, *56*(6), 365–371. https://doi.org/10.1016/j.ypmed.2013.03.002
- Mei, H., Xiong, Y., Xie, S., Guo, S., Li, Y., Guo, B., & Zhang, J. (2016). The impact of long-term school-based physical activity interventions on body mass index of primary school children A meta-analysis of randomized controlled trials. *BMC Public Health*, 16(1), 205. https://doi.org/10.1186/s12889-016-2829-z
- Mejia, D., Berchtold, A., Belanger, R. E., Kuntsche, E. N., Michaud, P. A., & Suris, J. C. (2013). Frequency and effects of meeting health behaviour guidelines among adolescents. *European Journal of Public Health*, 23(1), 8–13. https://doi.org/10.1093/eurpub/cks050
- Melkevik, O., Haug, E., Rasmussen, M., Fismen, A. S., Wold, B., Borraccino, A., ... Samdal, O. (2015). Are associations between electronic media use and BMI different across levels of physical activity? *BMC Public Health*, *15*(1), 497. https://doi.org/10.1186/s12889-015-1810-6
- Merrill, R. M., & Hanson, C. L. (2016). Risk and protective factors associated with being bullied on school property compared with cyberbullied. *BMC Public Health*.

- https://doi.org/10.1186/s12889-016-2833-3
- Milicic, S., Piérard, E., DeCicca, P., & Leatherdale, S. T. (2017). Examining the Association Between Physical Activity, Sedentary Behavior and Sport Participation With E-Cigarette Use and Smoking Status in a Large Sample of Canadian Youth.

 Nicotine & Tobacco Research. https://doi.org/10.1093/ntr/ntx238
- Minaker, L., & Hammond, D. (2016). Low Frequency of Fruit and Vegetable Consumption Among Canadian Youth: Findings From the 2012/2013 Youth Smoking Survey. *Journal of School Health*, 86(2), 135–142. https://doi.org/10.1111/josh.12359
- Mistry, R., McCarthy, W. J., Yancey, A. K., Lu, Y., & Patel, M. (2009). Resilience and patterns of health risk behaviors in California adolescents. *Preventive Medicine*, 48(3), 291–297. https://doi.org/10.1016/j.ypmed.2008.12.013
- Mobley, M., & Chun, H. (2013). Testing Jessor's problem behavior theory and syndrome: a nationally representative comparative sample of Latino and African American adolescents. *Cultur Divers Ethnic Minor Psychol*, *19*(2), 190–199. https://doi.org/10.1037/a0031916
- Monteiro, R., & Azevedo, I. (2010). Chronic inflammation in obesity and the metabolic syndrome. *Mediators Inflamm*, 2010. https://doi.org/10.1155/2010/289645
- Moore, S. E., Norman, R. E., Suetani, S., Thomas, H. J., Sly, P. D., & Scott, J. G. (2017). Consequences of bullying victimization in childhood and adolescence: A systematic review and meta-analysis. *World Journal of Psychiatry*. https://doi.org/10.5498/wjp.v7.i1.60
- Moore, L. V., Thompson, F. E., & Demissie, Z. (2017). Percentage of Youth Meeting Federal Fruit and Vegetable Intake Recommendations, Youth Risk Behavior Surveillance System, United States and 33 States, 2013. *Journal of the Academy of Nutrition and Dietetics*, 117(4), 545-553.e3. https://doi.org/10.1016/j.jand.2016.10.012
- Must, A., & Anderson, S. E. (2006). Body mass index in children and adolescents: considerations for population-based applications. *International Journal of Obesity*. https://doi.org/10.1038/sj.ijo.0803300
- Muthén, L. K., & Muthén, B. (2018). Mplus. Los Angeles. Retrieved from

- https://www.statmodel.com/
- Muthén, L. K., & Muthén, B. O. (2009). Mplus Short Courses Topic 5 Categorical Latent Variable Modeling Using Mplus: Cross-Sectional Data Mplus Background Statistical Analysis With Latent Variables A General Modeling Framework Statistical Concepts Captured By Latent Variables. Slides. Retrieved from www.statmodel.com
- Ndugwa, R. P., Kabiru, C. W., Cleland, J., Beguy, D., Egondi, T., Zulu, E. M., & Jessor, R. (2011). Adolescent problem behavior in Nairobi's informal settlements: applying problem behavior theory in sub-Saharan Africa. *J Urban Health*, 88 Suppl 2, S298-317. https://doi.org/10.1007/s11524-010-9462-4
- Neumark-Sztainer, D., Wall, M., Story, M., & Standish, A. R. (2012). Dieting and unhealthy weight control behaviors during adolescence: Associations with 10-year changes in body mass index. *Journal of Adolescent Health*, *50*(1), 80–86. https://doi.org/10.1016/j.jadohealth.2011.05.010
- Ngun, T. C., Ghahramani, N., Sánchez, F. J., Bocklandt, S., & Vilain, E. (2011). The genetics of sex differences in brain and behavior. *Frontiers in Neuroendocrinology*. https://doi.org/10.1016/j.yfrne.2010.10.001
- Nuutinen, T., Lehto, E., Ray, C., Roos, E., Villberg, J., & Tynjälä, J. (2017). Clustering of energy balance-related behaviours, sleep, and overweight among Finnish adolescents. *International Journal of Public Health*, 62(8), 929–938. https://doi.org/10.1007/s00038-017-0991-4
- Park, M. H., Falconer, C., Viner, R. M., & Kinra, S. (2012). The impact of childhood obesity on morbidity and mortality in adulthood: A systematic review. *Obesity Reviews*, *13*(11), 985–1000. https://doi.org/10.1111/j.1467-789X.2012.01015.x
- Parliament of Canada. (2018). Cannabis Act C-45 (42-1). Retrieved June 28, 2019, from https://www.parl.ca/DocumentViewer/en/42-1/bill/C-45/royal-assent
- Pasch, K. E., Velazquez, C. E., Cance, J. D., Moe, S. G., & Lytle, L. A. (2012). Youth Substance Use and Body Composition: Does Risk in One Area Predict Risk in the Other? *Journal of Youth and Adolescence*, 41(1), 14–26. https://doi.org/10.1007/s10964-011-9706-y
- Pearson, N., Griffiths, P., Biddle, S. J., Johnston, J. P., McGeorge, S., & Haycraft, E.

- (2017). Clustering and correlates of screen-time and eating behaviours among young adolescents. *BMC Public Health*, *17*(1), 533. https://doi.org/10.1186/s12889-017-4441-2
- Peirson, L., Fitzpatrick-Lewis, D., Morrison, K., Ciliska, D., Kenny, M., Usman Ali, M., & Raina, P. (2015). Prevention of overweight and obesity in children and youth: a systematic review and meta-analysis. *CMAJ Open*, 3(1), E23-33. https://doi.org/10.9778/cmajo.20140053
- Penedo, F. J., & Dahn, J. R. (2005). Exercise and well-being: A review of mental and physical health benefits associated with physical activity. *Current Opinion in Psychiatry*. https://doi.org/10.1097/00001504-200503000-00013
- Piggott, T., Harrington, D., Mann, R., Hamilton, H. A., Donnelly, P. D., & Manson, H. (2018). Youth violence victims and perpetrators in Ontario: identifying a high-risk group and a focus for public health prevention. *Canadian Journal of Public Health*, 109(2), 195–203. https://doi.org/10.17269/s41997-018-0061-6
- Plotnikoff, R. C., Karunamuni, N., Spence, J. C., Storey, K., Forbes, L., Raine, K., ... McCargar, L. (2009). Chronic Disease-Related Lifestyle Risk Factors in a Sample of Canadian Adolescents. *Journal of Adolescent Health*, *44*(6), 606–609. https://doi.org/10.1016/j.jadohealth.2008.11.004
- Poitras, V. J., Gray, C. E., Borghese, M. M., Carson, V., Chaput, J. P., Janssen, I., ... Tremblay, M. S. (2016). Systematic review of the relationships between objectively measured physical activity and health indicators in school-aged children and youth. *Appl Physiol Nutr Metab*, 41(6 Suppl 3), S197-239. https://doi.org/10.1139/apnm-2015-0663
- Priesman, E., Newman, R., & Ford, J. A. (2018). Bullying Victimization, Binge
 Drinking, and Marijuana Use among Adolescents: Results from the 2013 National
 Youth Risk Behavior Survey. *Journal of Psychoactive Drugs*.
 https://doi.org/10.1080/02791072.2017.1371362
- Prochaska, J. J., Velicer, W. F., Prochaska, J. O., Delucchi, K., & Hall, S. M. (2006). Comparing intervention outcomes in smokers treated for single versus multiple behavioral risks. *Health Psychol*, 25(3), 380–388. https://doi.org/10.1037/0278-6133.25.3.380

- Public Health Agency of Canada. (2011). Obesity in Canada: Determinants and Contributing Factors. Retrieved from http://www.phac-aspc.gc.ca/hp-ps/hl-mvs/oic-oac/index-eng.php
- Public Health England. (n.d.). Health risks of childhood obesity. Retrieved from https://www.noo.org.uk/NOO_about_obesity/obesity_and_health/health_risk_child
- Qian, W., Battista, K., Bredin, C., Brown, K. S., & Leatherdale, S. T. (2015). *Assessing longitudinal data linkage results in the COMPASS study* (Vol. 3). University of Waterloo,. Retrieved from https://uwaterloo.ca/compass-system/sites/ca.compass-system/files/uploads/files/compass_report_-
 - _assessing_longitudinal_data_linkage_results_-_volume_3_issue_4.pdf
- Quick, V., Wall, M., Larson, N., Haines, J., & Neumark-Sztainer, D. (2013). Personal, behavioral and socio-environmental predictors of overweight incidence in young adults: 10-yr longitudinal findings. *International Journal of Behavioral Nutrition and Physical Activity*, 10, 37. https://doi.org/10.1186/1479-5868-10-37
- Raffoul, A., Leatherdale, S. T., & Kirkpatrick, S. I. (2018). Dieting predicts engagement in multiple risky behaviours among adolescent Canadian girls: a longitudinal analysis. *Canadian Journal of Public Health*, 109(1), 61–69. https://doi.org/10.17269/s41997-018-0025-x
- Raj, M., & Kumar, R. K. (2010). Obesity in children & adolescents. *Indian J Med Res*, 132, 598–607. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/21150012
- Rankin, J., Matthews, L., Cobley, S., Han, A., Sanders, R., Wiltshire, H. D., & Baker, J. S. (2016). Psychological consequences of childhood obesity: psychiatric comorbidity and prevention. *Adolescent Health, Medicine and Therapeutics*. https://doi.org/10.2147/AHMT.S101631
- Ritchie, L. D. (2012). Less frequent eating predicts greater BMI and waist circumference in female adolescents. *American Journal of Clinical Nutrition*, 95(2), 290–296. https://doi.org/10.3945/ajcn.111.016881
- Roberts, K. C., Shields, M., de Groh, M., Aziz, A., & Gilbert, J. A. (2012). Overweight and obesity in children and adolescents: results from the 2009 to 2011 Canadian Health Measures Survey. *Health Reports / Statistics Canada, Canadian Centre for Health Information = Rapports Sur La Santé / Statistique Canada, Centre Canadien*

- d'information Sur La Santé, 23(3), 37-41. https://doi.org/82-003-XPE
- Rodd, C., & Sharma, A. K. (2016). Recent trends in the prevalence of overweight and obesity among Canadian children. *CMAJ: Canadian Medical Association Journal = Journal de l'Association Medicale Canadienne*, 188(13), 313–320. https://doi.org/10.1503/cmaj.150854
- Rubin, D. B. (1976). Inference and missing data. *Biometrika*, *63*(3), 581–592. https://doi.org/10.1093/biomet/63.3.581
- Sakuma, K. L. K., Riggs, N. R., & Pentz, M. A. (2012). Translating evidence based violence and drug use prevention to obesity prevention: Development and construction of the Pathways program. *Health Education Research*, 27(2), 343–358. https://doi.org/10.1093/her/cyr095
- SAS Institute Inc. (2013). SAS 9.4. Cary, NC: SAS Institute Inc.,.
- Saunders, T. J., Chaput, J. P., & Tremblay, M. S. (2014). Sedentary behaviour as an emerging risk factor for cardiometabolic diseases in children and youth. *Canadian Journal of Diabetes*, *38*(1), 53–61. https://doi.org/10.1016/j.jcjd.2013.08.266
- Sayon-Orea, C., Martinez-Gonzalez, M. A., & Bes-Rastrollo, M. (2011). Alcohol consumption and body weight: a systematic review. *Nutr Rev*, 69(8), 419–431. https://doi.org/10.1111/j.1753-4887.2011.00403.x
- Schilling, L., Zeeb, H., Pischke, C., Helmer, S., Schmidt-Pokrzywniak, A., Reintjes, R., ... Schneider, S. (2017). Licit and illicit substance use patterns among university students in Germany using cluster analysis. *Substance Abuse Treatment, Prevention, and Policy*, *12*(1), 44. https://doi.org/10.1186/s13011-017-0128-z
- Senate of Canada. (2016). *Obesity in Canada: A Whole-of-Society Approach for a Healthier Canada*. Ottawa, Ontario, Canada: The Standing Senate Committee on Social Affairs, Science and Technology Senate. Retrieved from http://www.senate-senat.ca/social.asp
- Shakir, R. N., Coates, A. M., Olds, T., Rowlands, A., & Tsiros, M. D. (2018). Not all sedentary behaviour is equal: Children's adiposity and sedentary behaviour volumes, patterns and types. *Obesity Research and Clinical Practice*. https://doi.org/10.1016/j.orcp.2018.09.001
- Sherry, B., Jefferds, M. E., & Grummer-Strawn, L. M. (2007). Accuracy of adolescent

- self-report of height and weight in assessing overweight status: A literature review. Archives of Pediatrics and Adolescent Medicine. https://doi.org/10.1001/archpedi.161.12.1154
- Sherry, B., Jefferds, M. E., Grummer-Strawn, L. M., Sherry, Jefferds, M. E., & Grummer-Strawn, L. M. (2007). Accuracy of adolescent self-report of height and weight in assessing overweight status: A literature review. Archives of Pediatrics and Adolescent Medicine, 161(12), 1154–1161. https://doi.org/10.1001/archpedi.161.12.1154
- Shi, Y., Lenzi, M., & An, R. (2015). Cannabis liberalization and adolescent cannabis use: A cross-national study in 38 countries. *PLoS ONE*, *10*(11), e0143562. https://doi.org/10.1371/journal.pone.0143562
- Silva, K. S., Barbosa Filho, V. C., Del Duca, G. F., de Anselmo Peres, M. A., Mota, J., Lopes, A. da S., & Nahas, M. V. (2014a). Gender differences in the clustering patterns of risk behaviours associated with non-communicable diseases in Brazilian adolescents. *Preventive Medicine*, 65, 77–81. https://doi.org/10.1016/j.ypmed.2014.04.024
- Silva, K. S., Barbosa Filho, V. C., Del Duca, G. F., de Anselmo Peres, M. A., Mota, J., Lopes, A. da S., & Nahas, M. V. (2014b). Gender differences in the clustering patterns of risk behaviours associated with non-communicable diseases in Brazilian adolescents. *Preventive Medicine*, 65, 77–81. https://doi.org/10.1016/j.ypmed.2014.04.024
- Simen-Kapeu, A., & Veugelers, P. J. (2010). Should public health interventions aimed at reducing childhood overweight and obesity be gender-focused? *BMC Public Health*, 10(1), 340. https://doi.org/10.1186/1471-2458-10-340
- Simonton, A. J., Young, C. C., & Johnson, K. E. (2018). Physical Activity Interventions to Decrease Substance Use in Youth: A Review of the Literature. *Substance Use & Misuse*, 1–17. https://doi.org/10.1080/10826084.2018.1452338
- Sisson, S. B., Krampe, M., Anundson, K., & Castle, S. (2016). Obesity prevention and obesogenic behavior interventions in child care: A systematic review. *Prev Med*. https://doi.org/10.1016/j.ypmed.2016.02.016
- Skalamera, J., & Hummer, R. A. (2016). Educational attainment and the clustering of

- health-related behavior among U.S. young adults. *Preventive Medicine*, *84*, 83–89. https://doi.org/10.1016/j.ypmed.2015.12.011
- Skara, S., & Sussman, S. (2003). A review of 25 long-term adolescent tobacco and other drug use prevention program evaluations. *Preventive Medicine*. https://doi.org/10.1016/S0091-7435(03)00166-X
- Smith, P. K. (2016). Bullying: Definition, Types, Causes, Consequences and Intervention. Social and Personality Psychology Compass. https://doi.org/10.1111/spc3.12266
- Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling* (2nd ed.). Sage Publications, Inc.
- Spengler, S., Mess, F., Mewes, N., Mensink, G. B. M., & Woll, A. (2012). A cluster-analytic approach towards multidimensional health-related behaviors in adolescents: The MoMo-Study. *BMC Public Health*. https://doi.org/10.1186/1471-2458-12-1128
- Spring, B., Moller, A. C., & Coons, M. J. (2012). Multiple health behaviours: overview and implications. *J Public Health (Oxf)*, *34 Suppl 1*, i3-10. https://doi.org/10.1093/pubmed/fdr111
- Statistics Canada. (2015). Body mass index of children and youth, 2012 to 2013.

 Retrieved from http://www.statcan.gc.ca/pub/82-625-x/2014001/article/14105-eng.htm
- Suppli, C. H., Due, P., Henriksen, P. W., Rayce, S. L., Holstein, B. E., & Rasmussen, M. (2013). Low vigorous physical activity at ages 15, 19 and 27: childhood socioeconomic position modifies the tracking pattern. *Eur J Public Health*, 23(1), 19–24. https://doi.org/10.1093/eurpub/cks040
- Te Velde, S. J., De Bourdeaudhuij, I., Thorsdottir, I., Rasmussen, M., Hagströmer, M., Klepp, K. I., & Brug, J. (2007). Patterns in sedentary and exercise behaviors and associations with overweight in 9-14-year-old boys and girls A cross-sectional study. *BMC Public Health*, 7, 16. https://doi.org/10.1186/1471-2458-7-16
- Thompson-Haile, A., Bredin, C., & Leatherdale, S. T. (2013). *Rationale for using active-information passive-consent permission protocol in COMPASS. Compass Technical Report Series* (Vol. 1). Waterloo, Ontario: University of Waterloo. Retrieved from https://uwaterloo.ca/compass-system/

- Tomczyk, S., Isensee, B., & Hanewinkel, R. (2016). Latent classes of polysubstance use among adolescents-a systematic review. *Drug and Alcohol Dependence*, *160*, 12–29. https://doi.org/10.1016/j.drugalcdep.2015.11.035
- Tomczyk, S., Pedersen, A., Hanewinkel, R., Isensee, B., & Morgenstern, M. (2016). Polysubstance use patterns and trajectories in vocational students A latent transition analysis. *Addictive Behaviors*, *58*, 136–141. https://doi.org/10.1016/j.addbeh.2016.02.027
- Traversy, G., & Chaput, J. P. (2015). Alcohol Consumption and Obesity: An Update.

 Current Obesity Reports, 4(1), 122–130. https://doi.org/10.1007/s13679-014-0129-4
- Tremblay, M. S., Carson, V., Chaput, J. P., Connor Gorber, S., Dinh, T., Duggan, M., ...
 Zehr, L. (2016). Canadian 24-Hour Movement Guidelines for Children and Youth:
 An Integration of Physical Activity, Sedentary Behaviour, and Sleep. *Appl Physiol Nutr Metab*, 41(6 Suppl 3), S311-27. https://doi.org/10.1139/apnm-2016-0151
- Tremblay, M. S., LeBlanc, A. G., Kho, M. E., Saunders, T. J., Larouche, R., Colley, R.
 C., ... Connor Gorber, S. (2011). Systematic review of sedentary behaviour and health indicators in school-aged children and youth. *Int J Behav Nutr Phys Act*, 8, 98. https://doi.org/10.1186/1479-5868-8-98
- Van Kann, D. H. H., de Vries, S., Schipperijn, J., de Vries, N. K., Jansen, M. W. J., & Kremers, S. P. J. (2017). A Multicomponent Schoolyard Intervention Targeting Children's Recess Physical Activity and Sedentary Behavior: Effects After One Year. *Journal of Physical Activity and Health*, 1–32. https://doi.org/10.1123/jpah.2016-0656
- Vasques, C., Magalhães, P., Cortinhas, A., Mota, P., Leitão, J., & Lopes, V. P. (2014).
 Effects of Intervention Programs on Child and Adolescent BMI: A Meta-Analysis
 Study. *Journal of Physical Activity and Health*, 11(2), 426–444.
 https://doi.org/10.1123/jpah.2012-0035
- Vazsonyi, A. T., Chen, P., Jenkins, D. D., Burcu, E., Torrente, G., & Sheu, C. J. (2010). Jessor's problem behavior theory: Cross-national evidence from Hungary, the Netherlands, Slovenia, Spain, Switzerland, Taiwan, Turkey, and the United States. *Dev Psychol*, 46(6), 1779–1791. https://doi.org/10.1037/a0020682
- Veliz, P., McCabe, S. E., & Boyd, C. J. (2016). Extreme Binge Drinking among

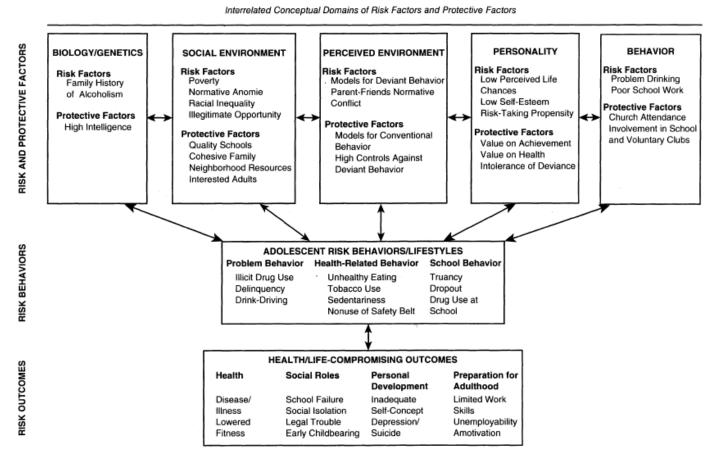
- Adolescent Athletes: A Cause for Concern? *American Journal on Addictions*. https://doi.org/10.1111/ajad.12323
- Wang, C., Li, Y., Li, K., & Seo, D. C. (2018). Body weight and bullying victimization among US adolescents. *American Journal of Health Behavior*. https://doi.org/10.5993/AJHB.42.1.1
- Watts, A. W., Mason, S. M., Loth, K., Larson, N., & Neumark-Sztainer, D. (2016).
 Socioeconomic differences in overweight and weight-related behaviors across adolescence and young adulthood: 10-year longitudinal findings from Project EAT.
 Preventive Medicine, 87, 194–199. https://doi.org/10.1016/j.ypmed.2016.03.007
- Wilson, D. B., Smith, B. N., Speizer, I. S., Bean, M. K., Mitchell, K. S., Uguy, L. S., & Fries, E. A. (2005). Differences in food intake and exercise by smoking status in adolescents. *Preventive Medicine*. https://doi.org/10.1016/j.ypmed.2004.10.005
- Wing Lo, T., Cheng, C. H. K., Wong, D. S. W., Rochelle, T. L., & Kwok, S. I. (2012).
 Self-Esteem, Self-Efficacy and Deviant Behaviour of Young People in Hong Kong.
 Advances in Applied Sociology. https://doi.org/10.4236/aasoci.2011.11004
- Wong, S. L., Shields, M., Leatherdale, S. T., Malaison, E., & Hammond, D. (2012).

 Assessment of validity of self-reported smoking status. *Health Reports / Statistics Canada, Canadian Centre for Health Information = Rapports Sur La Sant?? / Statistique Canada, Centre Canadien d'information Sur La Sant??*, 23(1), 47–53.

 Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/22590805
- World Health Organization. (2007). Children Growth Reference. Retrieved from http://www.who.int/growthref/who2007_bmi_for_age/en/index.html.
- World Health Organization. (2015). Assessing national capacity for the prevention and control of noncommunicable diseases: report of the 2015 global survey. Geneva, Switzerland. https://doi.org/ISBN 978 92 4 156536 3
- Zeller, M. H., Reiter-Purtill, J., Peugh, J. L., Wu, Y., & Becnel, J. N. (2015). Youth Whose Weight Exceeds Healthy Guidelines Are High-Risk Targets for Tobacco Prevention Messaging and Close Monitoring of Cigarette Use. *Childhood Obesity*. https://doi.org/10.1089/chi.2014.0113

Appendix A Conceptual Framework for Problem Behaviour Theory

Supplementary Figure 1 Problem Behaviour Theory conceptual framework. Adapted from "Problem Behaviour Theory: A Half-Century of Research on Adolescent Behaviour and Development" by R. Jessor, in "The developmental science of adolescence: History through autobiography." New York: Psychology Press. Pp. 250. Reprinted with permission.



Appendix B COMPASS Student Questionnaire



- This is NOT a test. All of your answers will be kept confidential.
 No one, not even your parents or teachers, will ever know what you answered. So, please be honest when you answer the questions.
- Mark only one option per question unless the instructions tell you to do something else.
- Choose the option that is the closest to what you think/feel is true for you.

Please, use an HB pencil





Please read each sentence below carefully and write the correct letter or number for each question on the line and then fill in the corresponding circle.

The first letter of your middle name (if you have more than one middle name use your first middle name, if you don't have a middle name use "Z"):	The first letter of the month in which you were born:	The last letter of your full first name:	The second letter of your last name:	The number of <u>older</u> brothers you have (alive and deceased):
000000000000000000000000000000000000000	0000000	00000000000000000000000000000000000000	00000000 0000000 00000000	G0000000



[serial]

About You	
1. What grade are you in? Grade 9 Grade 10 Grade 11 Grade 12	
2. How old are you today? 13 years or younger 14 years 15 years 16 years 17 years 18 years or older	
3. Are you female or male? O Female O Male	
4. How would you describe yourself? (Mar	k all that apply)
5. About how much money do you usually (Remember to include all money from allowand Zero \$1 to \$5 \$6 to \$10 \$11 to \$20 \$21 to \$40 \$41 to \$100 More than \$100 I do not know how much money I get each	get each week to spend on yourself or to save? es and jobs like baby-sitting, delivering papers, etc.) week
6. How do you <u>usually</u> travel to and from s	chool?
To school By car (as a passenger) By car (as a driver) By school bus By public bus By walking By bicycling By subway or streetcar Other	From school By car (as a passenger) By car (as a driver) By school bus By public bus By walking By bicycling By subway or streetcar Other

O I do not know how tall I am			_		Feet	eight Inch			Centir			F	Height Heig eet	ght Inche
"My height isfeet OR "My height iscentime	inch				00000000	000	0	OR	000					●000000000000000000000000000000000000
How much do you weigh with										wei	ght in	E	катр	a:
O I do not know how much i we	_				Pou	ight nds		KI	Weight logram	15		F	Veight is Veigh Ound:	t s o
"My weight ispound OR					00	90	OR		00 00 00	0			3 3 3 3 6	② ③ ④
"My weight iskilogr	rams	•"		,		00			00				(0)	0
] ·		0	00 00 00			9 (0 (0)				9 0	◉
How much time per day do yo For example: If you spend about 3 l the 0 minute circle as	hours	wato	hing '	_	d doi	ing t			0 0 0 0 ving	activ		circle,	(0) (a)	0
For example: If you spend about 3 i	hours s show	wate vn be	hing low:	_	d doi	ing t		need	o (ing	activ		circle,	0	0
For example: If you spend about 3 in the 0 minute circle as a) Watching/streaming TV shows or movies	hours s show	wate vn be	ching low:	TV ea	d doi	ing t	@	©	ving to fill i	active of the	3 hour	circle, Min ③	and utes	© © :
For example: If you spend about 3 if the 0 minute circle as a) Watching/streaming TV shows or movies a) Watching/streaming TV shows or movies	hours s show	wate vn be	shing slow:	TV es	Hor	ing to	(3)	⑦	ving to fill i	active of the original of the	3 hour	Min Min Min	and sutes	© 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
For example: If you spend about 3 the 0 minute circle as a) Watching/streaming TV shows or movies a) Watching/streaming TV shows or movies b) Playing video/computer games	o o	wate vn be	shing slow:	TV ea	Hora	ing to	(a)	o O O	ving to fill i	active of the control	3 hour	Min (3) Min (3)	and sutes	0
For example: If you spend about 3 the 0 minute circle as a) Watching/streaming TV shows or movies a) Watching/streaming TV shows or movies b) Playing video/computer games c) Doing homework	o o o	o watco	shing slow: ② ③ ③	① ③ ③	Hoo	ing ti	(a)	o o o	o o o o o o o o o o o o o o o o o o o	active of the control	3 hour	Min (3) Min (3) (4)	and utes	(a)
For example: If you spend about 3 the 0 minute circle as a) Watching/streaming TV shows or movies a) Watching/streaming TV shows or movies b) Playing video/computer games c) Doing homework d) Talking on the phone	hours s show 0 0 0	watdown be	shing slow: ③ ③ ③ ③ ③	① ③ ③ ③	Hoo o	on the state of th	(a) (b) (c) (c) (c) (c) (c) (c) (c) (c) (c) (c	© © ©	of o	activing the	3 hour	Min 3 Min 3 3 3	and sutes	(a)
For example: If you spend about 3 the 0 minute circle as a) Watching/streaming TV shows or movies a) Watching/streaming TV shows or movies b) Playing video/computer games c) Doing homework	o o o o	o watco	shing slow: ② ③ ③	① ③ ③	Hoo	ing ti	(a)	o o o	o o o o o o o o o o o o o o o o o o o	active of the control	3 hour	Min 3 Min 3 3 3	and utes	

Physical Activity

HARD physical activities include jogging, team sports, fast dancing, jump-rope and <u>any other</u> physical activities that increase your heart rate and make you breathe hard and sweat.

MODERATE physical activities include lower intensity activities such as walking, biking to school, and recreational swimming.

Mark how many minutes of <u>HARD</u> physical activity you did on <u>each of the last 7 days</u>.
 This includes physical activity during physical education class, lunch, after school, evenings, and spare time.



For example: If you did 45 minutes of hard physical activity on Monday, you will need to fill in the 0 hour circle and the 45 minute circle, as shown below:

Hours

Minutes

Monday

① ② ③ ④ ④ ④ ④

 Mark how many minutes of <u>MODERATE</u> physical activity you did on <u>each of the last 7</u> <u>days</u>. This includes physical activity during physical education class, lunch, after school, evenings, and spare time. <u>Do not include time spent doing hard physical activities</u>.

	Hours						Minu	tes	
Monday	0	①	2	(3)	(4)	0	(1)	(3)	(4)
Tuesday	0	0	②	<u>(3)</u>	<u>@</u>	0	<u> </u>	0	(4)
Wednesday	0	0	(2)	(3)	(4)	0	0	(3)	(4)
Thursday	0	0	(2)	(3)	(4)	0	0	@	(4)
Friday	0	0	(2)	(1)	(1)	0	(1)	(2)	@
Saturday	0	0	@	(3)	(4)	0	•	0	(4)
Sunday	0	0	2	3	(4)	0	0	0	0

For example: If you did 1 hour and 30 minutes of moderate physical activity on Monday, you will need to fill in the 1 hour circle and the 30 minute circle, as shown below:



- 12. Were the <u>last 7 days</u> a typical week in terms of the amount of physical activity that you usually do?
 - O Yes
 - O No, I was more active in the last 7 days
 - No, I was less active in the last 7 days
- 13. Your closest friends are the friends you like to spend the most time with. How many of your closest friends are <u>physically active</u>?
 - O None
 - O 1 friend
 - O 2 friends
 - 3 friends
 - O 4 friends
 - 5 or more friends
- 14. Are you taking a physical education class at school this year?
 - O Yes, I am taking one this term
 - O Yes, I will be taking one or have taken one this school year, but not this term.
 - No, I am not taking a physical education class at school this year

15. Do you participate in before-school, noon hour, or after-school physical activities organized by your school? (e.g., intramurals, non-competitive clubs) Yes
O No O None offered at my school
16. Do you participate in competitive school sports teams that compete against other schools? (e.g., junior varsity or varsity sports) O Yes O No O None offered at my school
17. Do you participate in league or team sports outside of school? O Yes O No O There are none available where I live
18. On how many days in the last 7 days did you do exercises to strengthen or tone your muscles? (e.g., push-ups, sit-ups, or weight-training)
○ 0 days ○ 4 days ○ 1 day ○ 5 days ○ 2 days ○ 6 days ○ 3 days ○ 7 days
19. How do you describe your weight? O Very underweight O Slightly underweight O About the right weight O Slightly overweight O Very overweight O Very overweight
20. Which of the following are you trying to do about your weight? Caln weight Stay the same weight I am not trying to do anything about my weight
21. How much do your parents, step-parents, or guardians encourage you to be physically active?
O Strongly encourage Encourage Do not encourage or discourage Discourage Strongly discourage
22. How much do your parents, step-parents, or guardians support you in being physically active? (e.g., driving you to team games, buying you sporting equipment)
O Very supportive O Supportive O Unsupportive O Very unsupportive

Healthy Eating

23.	If you do not eat breakfast every day, why do you sk I eat breakfast every day	ip brea	kfast?	(Mari	k all tha	t apply)	
	I don't have time for breakfast The bus comes too early I sleep in I'm not hungry in the morning I feel sick when I eat breakfast I'm trying to lose weight There is nothing to eat at home Other							
24.	In a <i>usual</i> school week <i>(Monday to Friday),</i> on how many days do you do the following?	None	1 day	days	days	4 days	days	J
a)	Eat breakfast	0	Ŏ	O	O	0	0	
b)	Eat breakfast provided to you as part of a school program	0	0	0	0	0	0	
c)	Eat lunch at school - lunch packed and brought from home	0	0	0	0	0	0	
d)	Eat lunch at school - lunch <u>purchased in the cafeteria</u>	0	0	0	0	0	0	
0)	Eat lunch purchased at a fast food place or restaurant	0	0	0	0	0	0	
f)	Eat snacks purchased from a vending machine In your school	0	0	0	0	0	0	
g)	Eat snacks purchased from a vending machine, corner store, snack bar, or canteen off school property	0	0	0	0	0	0	
	Drink sugar-sweetened beverages (soda pop, Kool-Aid, Gatorade, etc.) <u>Do not include diet/sugar-free drinks</u>	0	0	0	0	0	0	
·	Drink high-energy drinks (Red Bull, Monster, Rock Star, etc.)	0	0	0	0	0	0	
_	Drink coffee or tea With sugar (include cappuccino, frappuccino, iced-tea, iced-coffees, etc.)	0	0	0	0	0	0	
k)	Drink coffee or tea without sugar	0	0	0	0	0	0	Ļ
25.	On a usual weekend (Saturday and Sunday), on how days do you do the following?	many		1	None	day (days	
a)	Eat breakfast				0	0	0	
b)	Eat lunch				0	0	0	
c)	Eat foods purchased at a fast food place or restaurant				0	0	0	
d)	Eat snacks purchased from a vending machine, corner store, or canteen	snack b	ar,		0	0	0	
e)	Drink sugar-sweetened beverages (soda pop, Kool-Aid, Gato include diet/sugar-free drinks	rade, et	c.) <u>Do ı</u>	<u>not</u>	0	0	0	
f)	Drink high energy drinks (Red Bull, Monster, Rock Star, etc.)				0	0	0	
g)	Drink coffee or tea with sugar (include cappuccino, frappucciced-coffees, etc.)	ino, iceo	d-tea,		0	0	0	
h)	Drink coffee or tea without sugar				0	0	0	

26. YESTERDAY, from the time you woke up until the time you went to bed, how many servings of meats and alternatives did you have? One 'Food Guide' serving of meat and alternatives includes cooked fish, chicken, beef, pork, or game meat, eggs, nuts or seeds, peanut butter or nut butters, legumes (beans), and tofu. Canada's Food Guide Serving Sizes of Meats and Alternatives None 1 servina 2 servings 3 servings 4 servings Cooked fish, shellfish, 175 mL (14 cup) Peanut or nut butters Shelled nuts Eggs 5 or more servings 75g (2½ oz.) / 125 mL (½ cup) 30 mL (2 Thep) 27. YESTERDAY, from the time you woke up until the time you went to bed, how many servings of vegetables and fruits did you have? One 'Food Guide' serving of vegetables and fruit includes pieces of fresh vegetable or fruit, salad or raw leafy greens, cooked leafy green vegetables, dried or canned or frozen fruit, and 100% fruit or vegetable juice. Canada's Food Guide Serving Sizes of Vegetables and Fruits None 1 serving 2 servings 3 servings 4 servings 5 servings Fresh, frozen or canned vegetables 🚌 Fresh, frazen or Leafy vegetables 100% Juice 6 servings 125 ml (½ cup) Cooked: 125 mL (½ cup) 🚭 canned fruits 7 servings 125 ml. (% cup) Raw: 250 mL (1 cup) 1 fruit or 125 mL (½ cup) 8 servings 9 or more servings 28. YESTERDAY, from the time you woke up until the time you went to bed, how many servings of milk and alternatives did you have? One 'Food Guide' serving of milk or milk alternatives includes milk, fortified soy beverage, reconstituted powdered milk, canned (evaporated) milk. yogurt or kefir (another type of cultured milk product), and cheese. None Canada's Food Guide Serving Sizes of Milk and Alternatives 1 serving 2 servings 3 servings O 4 servings 5 servings Fortified soy Milk or powdered Yogurt 6 or more servings milk (reconstituted) beverage 175 mL 175 mL 50g (1½ oz.) (½ cup) 250 mL (1 cup) 250 mL (1 cup) 29. YESTERDAY, from the time you woke up until the time you went to bed, how many servings of grain products did you have? One 'Food Guide' serving of grain products includes bread, bagels, flatbread such as tortilla, pita, cooked rice or pasta, and cold cereal. Canada's Food Guide Serving Sizes of Grain Products None 1 serving 2 servings 3 servings 4 servings 5 servings 6 servings Cereal Cooked pasta Cooked rice, Bagel Bread 7 servings Cold: 30g Hot: 175 mL (1/4 cup) 1 slice (35 q) 1/2 bagel (45 g) bulgur or quinoa 125 mL (½ cup) or couscous 8 servings 9 or more servings

Your Experience with Smoking

30. Have you ever tried cigarette smoking, even just a few puffs? O Yes O No
31. How old were you when you first tried smoking cigarettes, even just a few puffs? O I have never done this O I do not know
O 8 years or younger O 14 years O 9 years O 15 years O 10 years O 16 years O 11 years O 17 years O 12 years O 18 years or older O 13 years
32. Do you think in the future you might try smoking cigarettes?
O Definitely yes O Probably yes O Probably not O Definitely not
33. If one of your best friends was to offer you a cigarette, would you smoke it? Definitely yes Probably yes Probably not Definitely not
34. At any time during the next year do you think you will smoke a cigarette? O Definitely yes O Probably yes O Probably not O Definitely not
35. Do you think it would be difficult or easy for you to get cigarettes if you wanted to smoke? O Difficult O Easy O I do not know
36. Have you ever smoked a whole cigarette? O Yes O No
37. Have you ever smoked 100 or more whole cigarettes in your life? O Yes O No

38. Have	you ever smoked <u>every day</u> for at least 7 days in a row?
O Yes	
O No	
39. On ho	ow many of the <u>last 30 days</u> did you smoke one or more cigarettes?
O No	ne
O 1 d	ay
	o 3 days
	o 5 days
	o 10 days
	to 20 days
	to 29 days
O 30	days (every day)
0. Think	ing back over the <u>last 30 days</u> , on the days that you smoked, how many cigarettes did
_	
O No	
	ew puffs to one whole cigarette
0 210	o 3 cigarettes o 5 cigarettes
	o 10 cigarettes
Ö 11	to 20 cigarettes
	to 29 cigarettes
	or more cigarettes
O No O 1 fr O 2 fr O 3 fr	iend iends
O 4 fr	
	r more friends
2. Have	you <u>ever</u> tried to quit smoking cigarettes?
	ave never smoked
	eve only smoked a few times
	eve never tried to quit
	eve tried to quit once
	eve tried to quit 2 or 3 times
	ave tried to quit 4 or 5 times
OTH	ave tried to quit 6 or more times
2 In the	last 30 days, did you use any of the following? (Mark all that apply)
	e tobacco
	arillos or little cigars (plain or flavoured)
O Gig	ars (not including cigarillos or little cigars, plain or flavoured)
	Il-your-own cigarettes (tobacco only)
	ose tobacco mixed with marijuana
O 8m	is (little flavoured cigarettes that are hand-rolled in leaves and tied at the ends with string) tokeless tobacco (chewing tobacco, pinch, snuff, or snus)
	otine patches, nicotine gum, nicotine lozenges, or nicotine inhalers
	okah (water-pipe) to smoke tobacco
O Ho	okan (water-pipe) to smoke tobacco okah (water-pipe) to smoke herbal sheesha/shisha
	nt wraps (a sheet or tube made of tobacco used to roll cigarette tobacco)
	ave not used any of these things in the last 30 days

Alcohol and Marijuana Use

Rease remember that we will keep your answers completely confidential.

A DRINK means: 1 regular sized bottle, can, or draft of beer; 1 glass of wine; 1 bottle of cooler; 1 shot of liquor (rum, whiskey, etc); or 1 mixed drink (1 shot of liquor with pop, juice, energy drink).

44. In the last 12 months, how often did you have a drink of alcohol that was more than just a sip?	45. How old were you when you first had a drink of alcohol that was more than just a sip?
	I have never drunk alcohol
I have never drunk alcohol	I have only had a sip of alcohol
 I did not drink alcohol in the last 12 months 	O I do not know
 I have only had a sip of alcohol 	
,,	8 years or younger
 Less than once a month 	O 9 years O 16 years
O Once a month	O 10 years O 17 years
O 2 or 3 times a month	O 11 years O 18 years or older
	O 10 years of older
Once a week	0 12 years
O 2 or 3 times a week	O 13 years
4 to 6 times a week	O 14 years
O Every day	
4C In the lest 40 menths, how often did you b	ave E drinks of alaskal as man an ana assasianO
46. In the last 12 months, now often did you no	ave 5 drinks of alcohol or more on one occasion?
 I have never done this 	
 I did not have 5 or more drinks on one occasion 	n in the last 12 months
O Less than once a month	
O Once a month	
O 2 to 3 times a month	
Once a week	
2 to 5 times a week	
Daily or almost daily	
A7. In the last 12 months, have you had alcohous Red Bull, Rock Star, Monster, or another like I have never done this I did not do this in the last 12 months Yes I do not know	ol mixed or pre-mixed with an energy drink such brand?
48. In the last 12 months, how often did you us marijuana or cannabis? (a joint, pot, weed,	hash) marijuana or cannabis?
I have never used marijuana I have used marijuana but not in the last 12 m Less than once a month	O I have never used marijuana onths O I do not know
Once a month	 8 years or younger 14 years
O 2 or 3 times a month	O 9 years O 15 years
O Once a week	O 10 years O 16 years
O 2 or 3 times a week	O 11 years O 17 years
O 4 to 6 times a week	0 11 years 0 17 years 0 18 years or older
O Every day	O 13 years
50. Do you think it would be difficult or easy fo Difficult Easy I do not know	or you to get marijuana if you wanted some?

Your School and You					
51. How strongly do you agree or disagree with each of the following?	Strongl	y A	gree	Disagree	Strongly Disagree
I feel close to people at my school.	0		O	0	0
b) I feel I am part of my school.	_ 0		0000	0000	_ 2
c) I am happy to be at my school. d) I feel the teachers at my school treat me fairly.	×		X	8	8
e) I feel safe in my school.	000		ŏ	ŏ	00000
f) Getting good grades is important to me.	0		0	0	0
52. In the last 30 days, in what ways were you bullion. I have not been bullied in the last 30 days. Physical attacks (e.g., getting beaten up, pushed, or verbal attacks (e.g., getting teased, threatened, or compared to the compared teased. The compared teased is the compared teased. The compared teased is the compared teased. The compared teased is the compared teased. The compared teased teased teased teased teased. The compared teased tease	r kicked) naving rum s or having	ours sp	read abou	ut you)	
53. In the last 30 days, how often have you been but I have not been bullied by other students in the last Less than once a week About once a week 2 or 3 times a week Daily or almost daily	_	other s	tudents'	?	
I did not bully other students in the last 30 days Physical attacks (e.g., beat up, pushed, or kicked th Verbal attacks (e.g., teased, threatened, or spread of the companies of the	umours at			n the intern	et)
55. In the last 30 days, how often have you taken p I did not bully other students in the last 30 days Less than once a week About once a week 2 or 3 times a week Daily or almost daily	art in bul	lying o	ther stu	dents?	
56. How supportive is your school of the following:	Versuppo	ry ortive	Supportive	Unsupportiv	Very unsupportive
Making sure there are opportunities for students to be physically active	C	5	0	0	0
 b) Making sure students have access to healthy foods and 	drinks 🤇)	Q	O	8
c) Making sure no one is bullied at school	obacco C	3	0	8	8
 d) Giving students the support they need to resist or quit to e) Giving students the support they need to resist or quit of and/or alcohol 			ŏ	ŏ	ŏ
57. What academic level was your current or most O Applied O Academic O Other	recent M	ath co	urse?		

58. In your current or most recent Math course, what is your approximate overall mark? (Think about last year if you have not taken math yet this year)
○ 90% - 100% ○ 55% - 59% ○ 80% - 89% ○ 50% - 54% ○ 70% - 79% ○ Less than 50% ○ 60% - 69%
59. In your current or most recent English course, what is your approximate overall mark? (Think about last year if you have not taken English yet this year)
O 90% - 100% O 55% - 59% O 80% - 89% O 50% - 54% O 70% - 79% O Less than 50% O 60% - 69%
60. What is the highest level of education you would like to get?
Some high school or less High school diploma or graduation equivalency
College/trade/vocational certificate University Bachelor's degree
University Master's / PhD / law school / medical school / teachers' college degree
61. What is the highest level of education you think you will get?
Some high school or less High school diploma or graduation equivalency
College/trade/vocational certificate University Bachelor's degree
O University Master's / PhD / law school / medical school / teachers' college degree O I don't know
62. In the last 4 weeks, how many days of school did you miss because of your health?
○ 0 days ○ 1 or 2 days
O 3 to 5 days
O 6 to 10 days 11 or more days
63. In the last 4 weeks, how many classes did you skip when you were not supposed to?
O classes
O 1 or 2 classes O 3 to 5 classes
O 6 to 10 classes
O 11 to 20 classes O More than 20 classes
64. How often do you go to class without your homework complete?
O Never
O Seldom O Often
Usually

Appendix C Supplementary Material for Chapter 5

Supplementary Table 1 Results from the chi-square tests assessing for differences across gender in chronic disease risk behaviours across years 2013-2015 among youth participating in COMPASS in Ontario, Canada.

	Chi-square value	P-value	Degree(s) of freedom
		2013	
Physical activity (PA)	671.5	< 0.0001	1
Binge drinking	88.0	< 0.0001	1
Marijuana use	219.9	< 0.0001	1
Cigarette smoking	155.1	< 0.0001	1
Overweight/obesity	568.1	< 0.0001	1
		2014	
PA	696.7	< 0.0001	1
Binge drinking	101.5	< 0.0001	1
Marijuana use	205.6	< 0.0001	1
Cigarette smoking	107.7	< 0.0001	1
Overweight/obesity	559.7	< 0.0001	1
		2015	
PA	665.0	< 0.0001	1
Binge drinking	73.6	< 0.0001	1
Marijuana use	218.3	< 0.0001	1
Cigarette smoking	144.8	< 0.0001	1
Overweight/obesity	464.1	< 0.0001	1

Supplementary Table 2 Fit statistics for the multilevel latent class analysis among male youth in 2013 participating in COMPASS from Ontario, Canada.

Tixed effects mode Number of free parameters		Number of student (level 1) latent classes			
Number of free parameters 4 9 14 Log-likelihood -42621.8 -38515.2 -38423.7 BIC 85283.3 77119.6 76986.2 Entropy 1 0.779 0.923 Random effects nonparametric multilevel latent classes sanalysis models 2 school (level 2) latent classes Number of free parameters 5 11 17 Log-likelihood -42621.8 -38437.3 -38284.2 BIC 85293.2 76983.7 76736.9 Entropy 0.918 0.814 0.956 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -42621.8 -38415.5 -38244.0 BIC 85303.1 76959.8 76686.3 Entropy 0.341 0.857 0.915 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -38211.6 BIC 85313 76963.2 76651.1 Entropy 0.606		1	2	3	
Cog-likelihood A-2621.8 A-38515.2 A-38423.7 BIC B5283.3 A-77119.6 A-76986.2 Entropy 1 0.779 0.923 Entropy 1 0.779 0.923 Entropy 1 0.779 0.923 Entropy 1 0.779 0.923 Entropy 1 1 1.7 School (level 2) latent classes Number of free parameters 5 11 17 Log-likelihood A-2621.8 -38437.3 -38284.2 BIC 85293.2 76983.7 76736.9 Entropy 0.918 0.814 0.956 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood A-2621.8 -38415.5 -38244.0 BIC 85303.1 76959.8 76686.3 Entropy 0.341 0.857 0.915 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood A-2621.8 -38407.3 -38211.6 BIC 85313 76963.2 76651.1 Entropy 0.606 0.84 0.866 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators School (level 2) latent classes Number of free parameters 15 21 Log-likelihood A-38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood A-38219.7 -38110.4 BIC A-6607.9 76458.7 Entropy 0.85 0.7007 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood A-38211.4 -38085.4 BIC A-38085.4 BIC A-3808	Fixed effects model				
BIC 85283.3 77119.6 76986.2 Entropy 1 0.779 0.923 Random effects nonparametric multilevel latent class analysis models 2 school (level 2) latent classes Number of free parameters 5 11 17 Log-likelihood -42621.8 -38437.3 -38284.2 BIC 85293.2 76983.7 76736.9 Entropy 0.918 0.814 0.956 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -42621.8 -38415.5 -38244.0 BIC BIC 85303.1 76959.8 76686.3 Entropy 0.341 0.857 0.915 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -42621.8 -38407.3 -38211.6 BIC 85313 76959.2 76651.1 Entropy 0.606 0.84 0.866 Random effects n	Number of free parameters	4	9	14	
Entropy	Log-likelihood	-42621.8	-38515.2	-38423.7	
Random effects nonparametric multilevel latent class analysis models 2 school (level 2) latent classes Number of free parameters 5 11 17 17 18 18 18 18 19 19 19 19	BIC	85283.3	77119.6	76986.2	
Number of free parameters	Entropy	1	0.779	0.923	
Number of free parameters 5 11 17 Log-likelihood -42621.8 -38437.3 -38284.2 BIC 85293.2 76983.7 76736.9 Entropy 0.918 0.814 0.956 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -42621.8 -38415.5 -38244.0 BIC 85303.1 76959.8 76686.3 Entropy 0.341 0.857 0.915 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -42621.8 -38407.3 -38211.6 BIC 85313 76963.2 76651.1 Entropy 0.606 0.84 0.866 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicator -38237.8 -38146.1 BIC 76624.3 76500.4 -38237.8 -38146.1 BIC 76624.3 76500.4 -38217.9 -38	Random effects nonparametric	multilevel laten	t class analysis	models	
Log-likelihood -42621.8 -38437.3 -38284.2 BIC 85293.2 76983.7 76736.9 Entropy 0.918 0.814 0.956 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -42621.8 -38415.5 -38244.0 BIC 85303.1 76959.8 76686.3 Entropy 0.341 0.857 0.915 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -42621.8 -38407.3 -38211.6 BIC 85313 76963.2 76651.1 Entropy 0.606 0.84 0.866 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators -38237.8 -38146.1 BIC 76624.3 76500.4 -38237.8 -38146.1 BIC 76624.3 76500.4 -38237.8 -38146.1 BIC 76607.9 76458.7 -38210.	2 school (level 2) latent classes				
BIC 85293.2 76983.7 76736.9 Entropy 0.918 0.814 0.956 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -42621.8 -38415.5 -38244.0 BIC 85303.1 76959.8 76686.3 Entropy 0.341 0.857 0.915 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -42621.8 -38407.3 -38211.6 BIC 85313 76963.2 76651.1 Entropy 0.606 0.84 0.866 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 21 Log-likelihood -38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7	Number of free parameters	5	11	17	
Entropy	Log-likelihood	-42621.8	-38437.3	-38284.2	
Number of free parameters	BIC	85293.2	76983.7	76736.9	
Number of free parameters 6 13 20 Log-likelihood -42621.8 -38415.5 -38244.0 BIC 85303.1 76959.8 76686.3 Entropy 0.341 0.857 0.915 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -42621.8 -38407.3 -38211.6 BIC 85313 76963.2 76651.1 Entropy 0.606 0.84 0.866 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 2 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 7645	Entropy	0.918	0.814	0.956	
Log-likelihood -42621.8 -38415.5 -38244.0 BIC 85303.1 76959.8 76686.3 Entropy 0.341 0.857 0.915 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -42621.8 -38407.3 -38211.6 BIC 85313 76963.2 76651.1 Entropy 0.606 0.84 0.866 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators Vumber of free parameters 15 21 Log-likelihood -38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes Number of free parameters 19 27 Log-lik	3 school (level 2) latent classes				
BIC 85303.1 76959.8 76686.3 Entropy 0.341 0.857 0.915 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -42621.8 -38407.3 -38211.6 BIC 85313 76963.2 76651.1 Entropy 0.606 0.84 0.866 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -38211.4 -38085.4 BIC -38211.4 -38085.4 BIC -38211.4 -38085.4 BIC -38211.4 -38085.4 BIC -36611.2 76438.4	Number of free parameters	6	13	20	
Company Comp	Log-likelihood	-42621.8	-38415.5	-38244.0	
A school (level 2) latent classes Number of free parameters 7 15 23	BIC	85303.1	76959.8	76686.3	
Number of free parameters 7 15 23 Log-likelihood -42621.8 -38407.3 -38211.6 BIC 85313 76963.2 76651.1 Entropy 0.606 0.84 0.866 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	Entropy	0.341	0.857	0.915	
Log-likelihood	4 school (level 2) latent classes				
BIC 85313 76963.2 76651.1 Entropy 0.606 0.84 0.866 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	Number of free parameters	7	15	23	
Entropy 0.606 0.84 0.866 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	Log-likelihood	-42621.8	-38407.3	-38211.6	
Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	BIC	85313	76963.2	76651.1	
continuous factor on level 1 latent class indicators 2 school (level 2) latent classes 15 21 Log-likelihood -38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	Entropy	0.606	0.84	0.866	
2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	Random effects nonparametric i	multilevel latent	class analysis n	nodels with a	
Number of free parameters 15 21 Log-likelihood -38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	continuous factor on level 1 later	nt class indicato	rs		
Number of free parameters 15 21 Log-likelihood -38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	2 school (level 2) latent classes				
Log-likelihood -38237.8 -38146.1 BIC 76624.3 76500.4 Entropy 0.82 0.714 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4			15	21	
Entropy 0.82 0.714 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	1		-38237.8	-38146.1	
3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	BIC		76624.3	76500.4	
Number of free parameters 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	Entropy		0.82	0.714	
Number of free parameters 17 24 Log-likelihood -38219.7 -38110.4 BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	3 school (level 2) latent classes				
BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4			17	24	
BIC 76607.9 76458.7 Entropy 0.85 0.707 4 school (level 2) latent classes 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	-		-38219.7	-38110.4	
4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	_		76607.9	76458.7	
4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	Entropy		0.85		
Log-likelihood -38211.4 -38085.4 BIC 76611.2 76438.4	4 school (level 2) latent classes				
BIC 76611.2 76438.4	Number of free parameters		19	27	
BIC 76611.2 76438.4	Log-likelihood		-38211.4	-38085.4	
Entropy 0.822 0.841	_		76611.2	76438.4	
	Entropy		0.822	0.841	

Supplementary Table 3 Fit statistics for the multilevel latent class analysis among female youth in 2014 participating in COMPASS from Ontario, Canada.

	Number of student (level 1) latent classes				
	1	2	3		
Fixed effects model					
Number of free parameters	4	9	14		
Log-likelihood	-31902.7	-29002.2	-28968.6		
BIC	63844.5	58092.7	58074.4		
Entropy	1	0.827	0.918		
Random effects nonparametric	multilevel late	ent class analysi	s models		
2 school (level 2) latent classes		v			
Number of free parameters	5	11	17		
Log-likelihood	-31902.7	-28931.5	-28847.3		
BIC	63854.4	57970.9	57861.4		
Entropy	0.043	0.801	0.798		
3 school (level 2) latent classes					
Number of free parameters	6	13	20		
Log-likelihood	-31902.7	-28905.3	-28780.9		
BIC	63864.2	57938.1	57758		
Entropy	0.907	0.83	0.818		
4 school (level 2) latent classes					
Number of free parameters	7	15	23		
Log-likelihood	-31902.7	-28901.8	-28737.9		
BIC	63873.9	57950.8	57701.3		
Entropy	0.068 0.853 0.814		0.814		
Random effects nonparametric	multilevel late	nt class analysis	models with a		
continuous factor on level 1 late					
2 school (level 2) latent classes					
Number of free parameters		15	21		
Log-likelihood		-28750.2	-28689		
BIC		57647.5	57583.9		
Entropy		0.827	0.837		
3 school (level 2) latent classes					
Number of free parameters		17	24		
Log-likelihood		-28731.2	-28660.3		
BIC		57629.1	57555.9		
Entropy		0.835	0.827		
4 school (level 2) latent classes					
Number of free parameters		19	27		
Log-likelihood		-28727.7	-28647.2		
BIC		57641.7	57559.1		
Entropy		0.857	0.826		

Supplementary Table 4 Fit statistics for the multilevel latent class analysis among male youth in 2014 participating in COMPASS from Ontario, Canada.

_	Number of student (level 1) latent classes			
	1	2	3	
Fixed effects model				
Number of free parameters	4	9	14	
Log-likelihood	-39148.5	-35105	-35030.3	
BIC	78336.4	70298.6	70198.4	
Entropy	1	0.8	0.859	
Random effects nonparametric	multilevel laten	t class analysis	models	
2 school (level 2) latent classes				
Number of free parameters	5	11	17	
Log-likelihood	-39148.5	-35022.6	-34889.7	
BIC	78346.3	70153.5	69946.8	
Entropy	0.03	0.811	0.835	
3 school (level 2) latent classes				
Number of free parameters	6	13	20	
Log-likelihood	-39148.5	-34980.7	-34813.1	
BIC	78356.1	70089.3	69823.1	
Entropy	0.015	0.862	0.932	
4 school (level 2) latent classes				
Number of free parameters	7	15	23	
Log-likelihood	-39148.5	-34977.2	-34790.4	
BIC	78365.9	70102.1	69807.2	
Entropy	0.606 0.827 0.918		0.918	
Random effects nonparametric	multilevel laten	t class analysis	models with a	
continuous factor on level 1 later	nt class indicate	ors		
2 school (level 2) latent classes				
Number of free parameters		15	21	
Log-likelihood		-34812.8	-34745.8	
BIC		69773.2	69698.3	
Entropy		0.763	0.85	
3 school (level 2) latent classes				
Number of free parameters		17	24	
Log-likelihood		-34800.8	-34710.2	
BIC		69768.9	69656.6	
Entropy		0.797	0.834	
4 school (level 2) latent classes				
Number of free parameters		19	27	
Log-likelihood		-34799.5	-34691.5	
BIC		69785.9	69648.9	
Entropy		0.792		

Supplementary Table 5 Fit statistics for the multilevel latent class analysis among female youth in 2015 participating in COMPASS from Ontario, Canada.

Fixed effects mode! I 2 3 Number of free parameters 4 9 14 Log-likelihood 57616.6 52167.6 52156.3 Entropy 1 0.832 0.544 Random effects nonparametric wultilevel latent classes Number of free parameters 5 11 17 Log-likelihood -28788.8 -25966.9 -25889.8 BIC 57626.4 52040.8 51944.9 Entropy 0.198 0.815 0.931 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -28788.8 -25942.8 -25844.3 BIC 57636.1 52012.2 51883.4 Entropy 0.221 0.825 0.938 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 <t< th=""><th></th><th colspan="4">Number of student (level 1) letent classes</th></t<>		Number of student (level 1) letent classes			
Fixed effects mode! Number of free parameters 4 9 14 Log-likelihood -28788.9 -26040 -26010 BIC 57616.6 52167.6 52156.3 Entropy 1 0.832 0.544 Random effects nonparametric tultilevel latert classus/steeds Number of free parameters 5 11 17 Log-likelihood -28788.8 -25966.9 -25889.8 BIC 57626.4 52040.8 51944.9 Entropy 0.198 0.815 0.931 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -28788.8 -25942.8 -25844.3 BIC 57636.1 52012.2 51883.4 Entropy 0.221 0.825 0.938 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3		Number of student (level 1) latent classes			
Number of free parameters 4 9 14 Log-likelihood -28788.9 -26040 -26010 BIC 57616.6 52167.6 52156.3 Entropy 1 0.832 0.544 Random effects nonparametric multilevel lateut class analysis models Sechoof (level 2) latent classes Number of free parameters 5 11 17 Log-likelihood -28788.8 -25966.9 -25889.8 BIC 57626.4 52040.8 51944.9 Entropy 0.198 0.815 0.931 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -28788.8 -25942.8 -25844.3 BIC 57636.1 52012.2 51883.4 Entropy 0.23 0.938 4 school (level 2) latent classes 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3	Fixed effects model	1	<i>–</i>	<u> </u>	
Log-likelihood -28788.9 -26040 -26010 BIC 57616.6 52167.6 52156.3 Entropy 1 0.832 0.544 Random effects nonparametri—tiltievel taves valves valves 2 school (level 2) latent classes Number of free parameters 5 11 17 Log-likelihood -28788.8 -25966.9 -25889.8 BIC 57626.4 52040.8 51944.9 Entropy 0.198 0.815 0.931 3 school (level 2) latent classes 13 20 Log-likelihood -28788.8 -25942.8 -25844.3 BIC 57636.1 52012.2 51883.4 Entropy 0.221 0.825 0.938 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 51749.9 51706.4 <td< td=""><td></td><td>4</td><td>9</td><td>14</td></td<>		4	9	14	
BIC 57616.6 52167.6 52156.3 Entropy 1 0.832 0.544 Random effects nonparametric wultilevel latent class sanalysis woels 2 school (level 2) latent classes Number of free parameters 5 11 17 Log-likelihood -28788.8 -25966.9 -25889.8 BIC 57626.4 52040.8 51944.9 Entropy 0.198 0.815 0.931 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -28788.8 -25942.8 -25844.3 BIC 57636.1 52012.2 51883.4 Entropy 0.221 0.825 0.938 4 school (level 2) latent classes 15 23 Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 <	-		-		
Entropy 1 0.832 0.544 Random effects nonparametric wultilevel latent class analysis worder Number of free parameters 5 11 17 Log-likelihood -28788.8 -25966.9 -25889.8 BIC 57626.4 52040.8 51944.9 Entropy 0.198 0.815 0.931 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -28788.8 -25942.8 -25844.3 BIC 57636.1 52012.2 51883.4 Entropy 0.221 0.825 0.938 4 school (level 2) latent classes 15 23 Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 Random effects nonparametric wultilevel latent classes Number of free param	_				
Random effects nonparametric bultilevel latent classes 2 school (level 2) latent classes 1 17 Number of free parameters 5 11 17 Log-likelihood -28788.8 -25966.9 -25889.8 BIC 57626.4 52040.8 51944.9 Entropy 0.198 0.815 0.931 3 school (level 2) latent classes -28788.8 -25942.8 -25844.3 BIC 57636.1 52012.2 51883.4 Entropy 0.221 0.825 0.938 4 school (level 2) latent classes -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 Random effects nonparametric bultilevel latent classes Number of free parameters 15 2 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.796 -25731.1		1			
Number of free parameters	**	multilevel late			
Number of free parameters 5 11 17 Log-likelihood -28788.8 -25966.9 -25889.8 BIC 57626.4 52040.8 51944.9 Entropy 0.198 0.815 0.931 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -28788.8 -25942.8 -25844.3 BIC 57636.1 52012.2 51883.4 Entropy 0.221 0.825 0.938 4 school (level 2) latent classes 15 23 Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 Random effects nonparametric multilevel latent classes substituted by a substituted latent classes Number of free parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51			iii class allalysis	inoucis .	
Deg-likelihood -28788.8 -25966.9 -25889.8 BIC 57626.4 52040.8 51944.9 Entropy 0.198 0.815 0.931 0.93	•	5	11	17	
BIC 57626.4 52040.8 51944.9 Entropy 0.198 0.815 0.931 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -28788.8 -25942.8 -25844.3 BIC 57636.1 52012.2 51883.4 Entropy 0.221 0.825 0.938 4 school (level 2) latent classes 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 Random effects nonparametric multilevel latent class analysis multilevel swith a continuous factor on level 1 latent class indicates Number of free parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.706 3 3 school (level 2) latent classes 17 24 Log-likelihood -25796.6 -25731.1 </td <td>-</td> <td>_</td> <td></td> <td></td>	-	_			
Entropy 0.198 0.815 0.931 3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -28788.8 -25942.8 -25844.3 BIC 57636.1 52012.2 51883.4 Entropy 0.221 0.825 0.938 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 Random effects nonparametric multilevel latent class analysis with a continuous factor on level 1 latent class indicaters Parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 51796.6 -25731.1 BIC 51758.5 51695.6 Entropy -25796.6 -25731.1 BIC 51758.5	_				
3 school (level 2) latent classes Number of free parameters 6 13 20 Log-likelihood -28788.8 -25942.8 -25844.3 BIC 57636.1 52012.2 51883.4 Entropy 0.221 0.825 0.938 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 Random effects nonparametric trustillevel latent class indicates indicat					
Number of free parameters 6 13 20 Log-likelihood -28788.8 -25942.8 -25844.3 BIC 57636.1 52012.2 51883.4 Entropy 0.221 0.825 0.938 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 Random effects nonparametric wultilevel latent class analysis with a continuous factor on level 1 latent class indicators Number of free parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 51796.6 -25731.1 BIC likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.641 -25795.6 Entropy 0.641 -25793.6 -25713.4 <td< td=""><td></td><td></td><td>- · · · · -</td><td></td></td<>			- · · · · -		
Log-likelihood -28788.8 -25942.8 -25844.3 BIC 57636.1 52012.2 51883.4 Entropy 0.221 0.825 0.938 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 15 21 Log-likelihood (level 2) latent classes -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19<	` '	6	13	20	
BIC 57636.1 52012.2 51883.4 Entropy 0.221 0.825 0.938 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9<	-				
Entropy 0.221 0.825 0.938 4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 <td< td=""><td>_</td><td></td><td></td><td></td></td<>	_				
4 school (level 2) latent classes Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4					
Number of free parameters 7 15 23 Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	• •				
Log-likelihood -28788.9 -25931.2 -25818.3 BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	` '	7	15	23	
BIC 57645.8 52008.2 51860.3 Entropy 0.068 0.83 0.937 Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	-	-28788.9	-25931.2	-25818.3	
Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	9	57645.8	52008.2	51860.3	
Random effects nonparametric multilevel latent class analysis models with a continuous factor on level 1 latent class indicators 2 school (level 2) latent classes Number of free parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	Entropy	0.068	0.83	0.937	
continuous factor on level 1 latent class indicators 2 school (level 2) latent classes 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4		multilevel late	nt class analysis	models with a	
Number of free parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4					
Number of free parameters 15 21 Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	2 school (level 2) latent classes				
Log-likelihood -25802 -25751.1 BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4			15	21	
BIC 51749.9 51706.4 Entropy 0.784 0.706 3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	-		-25802	-25751.1	
3 school (level 2) latent classes Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	0		51749.9	51706.4	
Number of free parameters 17 24 Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	Entropy		0.784	0.706	
Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	3 school (level 2) latent classes				
Log-likelihood -25796.6 -25731.1 BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	Number of free parameters		17	24	
BIC 51758.5 51695.6 Entropy 0.726 0.641 4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	-		-25796.6	-25731.1	
4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	_		51758.5	51695.6	
4 school (level 2) latent classes Number of free parameters 19 27 Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4	Entropy		0.726	0.641	
Log-likelihood -25793.6 -25713.4 BIC 51771.9 51689.4					
BIC 51771.9 51689.4	Number of free parameters		19	27	
BIC 51771.9 51689.4	-		-25793.6	-25713.4	
Entropy 0.797 0.693	9		51771.9	51689.4	
	Entropy		0.797		

Supplementary Table 6 Fit statistics for the multilevel latent class analysis among male youth in 2015 participating in COMPASS from Ontario, Canada.

	Number of student (level 1) latent classes			
	1	2	3	
Fixed effects model				
Number of free parameters	4	9	14	
Log-likelihood	-37414.3	-33262.3	-33219.1	
BIC	74867.8	66612.9	66575.7	
Entropy		0.82	0.841	
Random effects nonparametric	multilevel late	nt class analysis	models	
2 school (level 2) latent classes		-		
Number of free parameters	5	11	17	
Log-likelihood	-37414.3	-33144.3	-33023.7	
BIC	74877.6	66396.4	66214.2	
Entropy	0.039	0.841	0.937	
3 school (level 2) latent classes				
Number of free parameters	6	13	20	
Log-likelihood	-37414.3	-33104.6	-32963.3	
BIC	74887.4	66336.8	66122.8	
Entropy	0.357	0.881	0.955	
4 school (level 2) latent classes				
Number of free parameters	7	15	23	
Log-likelihood	-37414.3	-33101.6	-32934.6	
BIC	74897.2	66350.3	66094.9	
Entropy	0.02	0.799	0.843	
Random effects nonparametric			models with a	
continuous factor on level 1 late	ent class indica	tors		
2 school (level 2) latent classes				
Number of free parameters		15	21	
Log-likelihood		-32947.7	-32899.5	
BIC			66005.1	
Entropy		0.8	0.676	
3 school (level 2) latent classes				
Number of free parameters		17	24	
Log-likelihood		-32926.8	-32859.4	
BIC		66020.4	65954.2	
Entropy		0.86	0.726	
4 school (level 2) latent classes				
Number of free parameters		19	27	
Log-likelihood		-32926.4	-32835	
BIC		66039.4	65934.9	
Entropy		0.759	0.75	

Appendix D Supplementary Material for Chapter 6

Supplementary Table 7 Cross-tables showing Body Mass Index (BMI) status (categorical) transitions [%(n)] across gender in Waves 1 and 2 and Waves 2 and 3.

			Wave 2		
		Normal	Overweight	Obese	Chi-square
			Females		
	Normal	92.8 (1688)	6.7 (121)	0.50 (9)	1361.7***
	Overweight	28.5 (87)	59.0 (180)	12.5 (38)	
e 1	Obese	9.7 (7)	26.4 (19)	63.9 (46)	
Wave	·		Males		
-	Normal	89.5 (1321)	9.3 (137)	1.2 (18)	1439.9***
	Overweight	27.9 (126)	60.6 (274)	11.5 (52)	
	Obese	5.6 (10)	30.5 (54)	63.8 (113)	
			Wave 3		
		Normal	Overweight	Obese	
			Females		
	Normal	95.0 (1565)	4.6 (76)	0.40 (6)	1482.1***
	Overweight	25.8 (73)	62.5 (177)	11.7 (33)	
e 2	Obese	5.4 (4)	32.4 (24)	62.2 (46)	
Wave 2					
F 1	Normal	90.3 (1205)	9.1 (122)	0.50(7)	1470.0***
	Overweight	28.2 (118)	62.9 (263)	8.8 (37)	
	Obese	6.9 (11)	26.9 (43)	66.2 (106)	
	***p<0.0001				