A gender-stratified, multilevel latent class assessment of chronic disease risk behaviours' association with Body Mass Index among youth in the COMPASS study

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ABSTRACT

This paper sought to examine chronic disease risk behaviour latent classes and their association with Body Mass Index (BMI), assessing for gender differences. 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. 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 a 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. 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.

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 and 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 and 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 and 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 and 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*[1] relative to their *health conscious*[2] 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).

2. Methods

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

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 = 41,734), 78.4% in 2014 (n = 39,013) and 79.9% from 2015 (n = 37,106); the primary reason for non-participation was absence from school.

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.

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[1] This class has the lowest PA and moderate sedentary time relative to their peers.

[2] 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.

2.4. Measures

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 and Laxer, 2013).

This study used BMI as a continuous variable as well as a binary variable (*normal* versus *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/m^2, our analyses included youth with BMI values between 15.6 and 37.6 kg/m^2.

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.

2.4.2. Chronic disease risk behaviours (predictor 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).

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 et al., 2014b).

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 60 min of moderate-to-hard activity daily, were considered to meet PA guidelines; otherwise they did not (Tremblay et al., 2016).

2.4.2.2. Substance use behaviours.

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 and 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 and Burkhalter, 2012).

2.5. Statistical analyses

2.5.1. Descriptive analyses

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

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 and 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 and 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 interpretability of the classes, as recommended by previous research (Henry and Muthén, 2010; Lanza et al., 2007). MLCA was conducted in Mplus (Muthén and Muthén, 2018), while the SAS 9.4 (SAS Institute Inc., 2013) was used for all regression analyses with significance level of 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.

3. Results

3.1. Participant characteristics

Table 1 presents descriptive summary statistics of the participant's behaviours and characteristics. Of the 41,103 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 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%).

3.2. Gender differences

Results from our analyses indicate that there are differences in CDRB engagement across gender. Fig. 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

Table 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	$n = 41{,}103$	$n = 38{,}440$	$n = 36{,}543$
Schools	$n = 79$	$n = 78$	$n = 72$
Gender			
Female	49.1 (19,176)	49.1 (17,866)	48.0 (16,516)
Male	50.9 (19,898)	50.9 (18,546)	52.0 (17,911)
Grade			
Grade 9	27.0 (11,056)	27.3 (10,425)	27.5 (9981)
Grade 10	25.7 (10,507)	26.8 (10,240)	25.8 (9385)
Grade 11	24.7 (10,085)	24.4 (9353)	24.9 (9030)
Grade 12	22.6 (9243)	21.5 (8217)	21.8 (7914)
Ethnicity			
White	74.6 (30,390)	73.6 (28,056)	71.5 (25,918)
Non-white	25.4 (10,358)	26.4 (10,044)	28.5 (10,325)
Weight status [categorized Body Mass Index (BMI)]			
Normal	57.4 (23,591)	55.0 (21,163)	54.0 (19,714)
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 (12,330)	30.0 (11,489)	30.2 (10,988)
Does not meet PA guidelines	69.9 (28,631)	70.0 (26,818)	69.8 (25,412)
Currently a binge drinker			
No	76.4 (31,289)	77.9 (29,820)	79.2 (28,809)
Yes	23.6 (9661)	22.1 (8480)	20.8 (7586)
Currently a marijuana user			
No	83.3 (33,390)	83.4 (31,338)	83.9 (29,888)
Yes	16.7 (6703)	16.6 (6228)	16.1 (5750)
Currently a smoker			
No	88.1 (36,216)	88.5 (34,004)	87.9 (31,724)
Yes	11.9 (4887)	11.5 (4436)	12.1 (4353)

females. Pearson's χ^2 tests showed that these gender differences are significant ($p < 0.0001$) as presented in Supplementary Table 1. As such, the remaining analyses were gender-stratified.

3.3. Multilevel latent class analysis (MLCA)

3.3.1. MLCA fit statistics

Table 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 Supplementary Tables 1–5. 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).

3.3.2. MLCA findings

Fig. 2 shows the distribution of female and male youth in their respective (multilevel) latent classes across 2013–2015. The left panel, (Fig. 2a, c, e) shows latent classes for females and the right panel (Fig. 2b, d, f) for males for 2013–2015, respectively. The final models
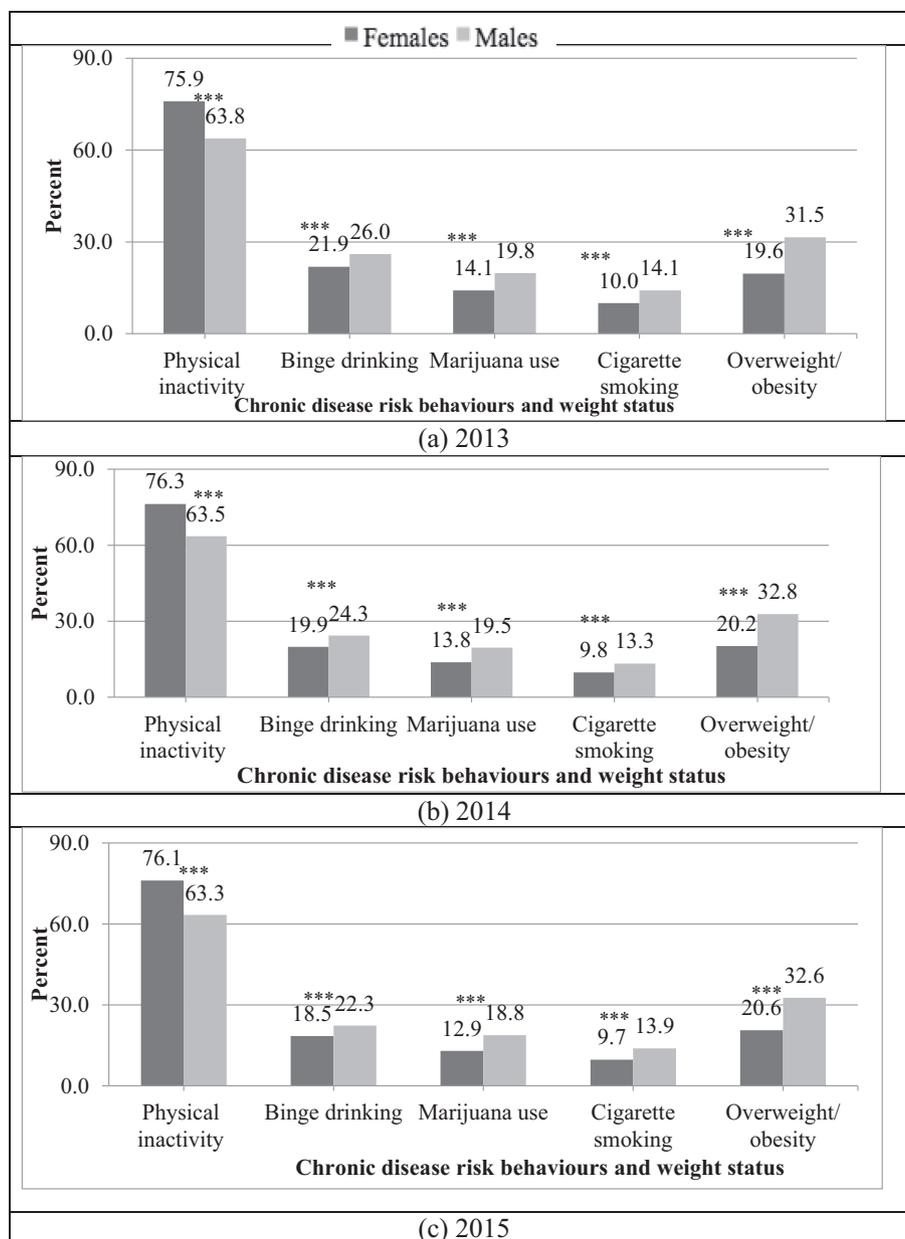
Fig. 1. The chronic disease risk behaviours and weight status of female and male youth (in percentages) who participated in COMPASS across years 2013-2015 in Ontario, Canada.
Pearson's χ^2 tests *** $p < 0.0001$.

had either two or three student latent classes, and three or four school latent classes, as is evident in Fig. 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.

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.

3.4. Association between latent classes of chronic disease risk behaviours and BMI

Table 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

Table 2
Fit statistics for the multilevel latent class analysis among female youth in 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	−35,118.9	−32,082.1	−32,054.5
BIC	70,277.4	64,253.1	64,247.4
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	−35,118.9	−31,993.1	−31,892.6
BIC	70,287.2	64,094.9	63,953.2
Entropy	0.937	0.811	0.776
3 school (level 2) latent classes			
Number of free parameters	6	13	20
Log-likelihood	−35,118.9	−31,973.8	−31,833.3
BIC	70,297.1	64,076.1	63,864.1
Entropy	0.024	0.833	0.81
4 school (level 2) latent classes			
Number of free parameters	7	15	23
Log-likelihood	−35,118.9	−31,971.3	−31,807
BIC	70,307	64,090.8	63,841.2
Entropy	0.027	0.788	0.816
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		−31,780.7	−31,751.5
BIC		63,709.5	63,710.4
Entropy		0.816	0.761
3 school (level 2) latent classes			
Number of free parameters		17	24
Log-likelihood		−31,763.4	−31,721
BIC		63,694.8	63,680.8
Entropy		0.840	0.697
4 school (level 2) latent classes			
Number of free parameters		19	27
Log-likelihood		−31,760.6	−31,704.8
BIC		63,708.9	63,676.4
Entropy		0.833	0.699

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 $0.50 \, \text{kg/m}^2$ (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 a lower odds of overweight/obesity by 15% (for binary BMI) and a lower (continuous) BMI by $0.50 \, \text{kg/m}^2$ 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 $0.25 \, \text{kg/m}^2$ (CI = 0.04, 0.45) higher (continuous) BMI than their ACE peers (Model 6).

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 et al., 2013; Kritsotakis et al., 2016; Silva et al., 2014; Simen-Kapeu and 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 et al., 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 et al., 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.

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
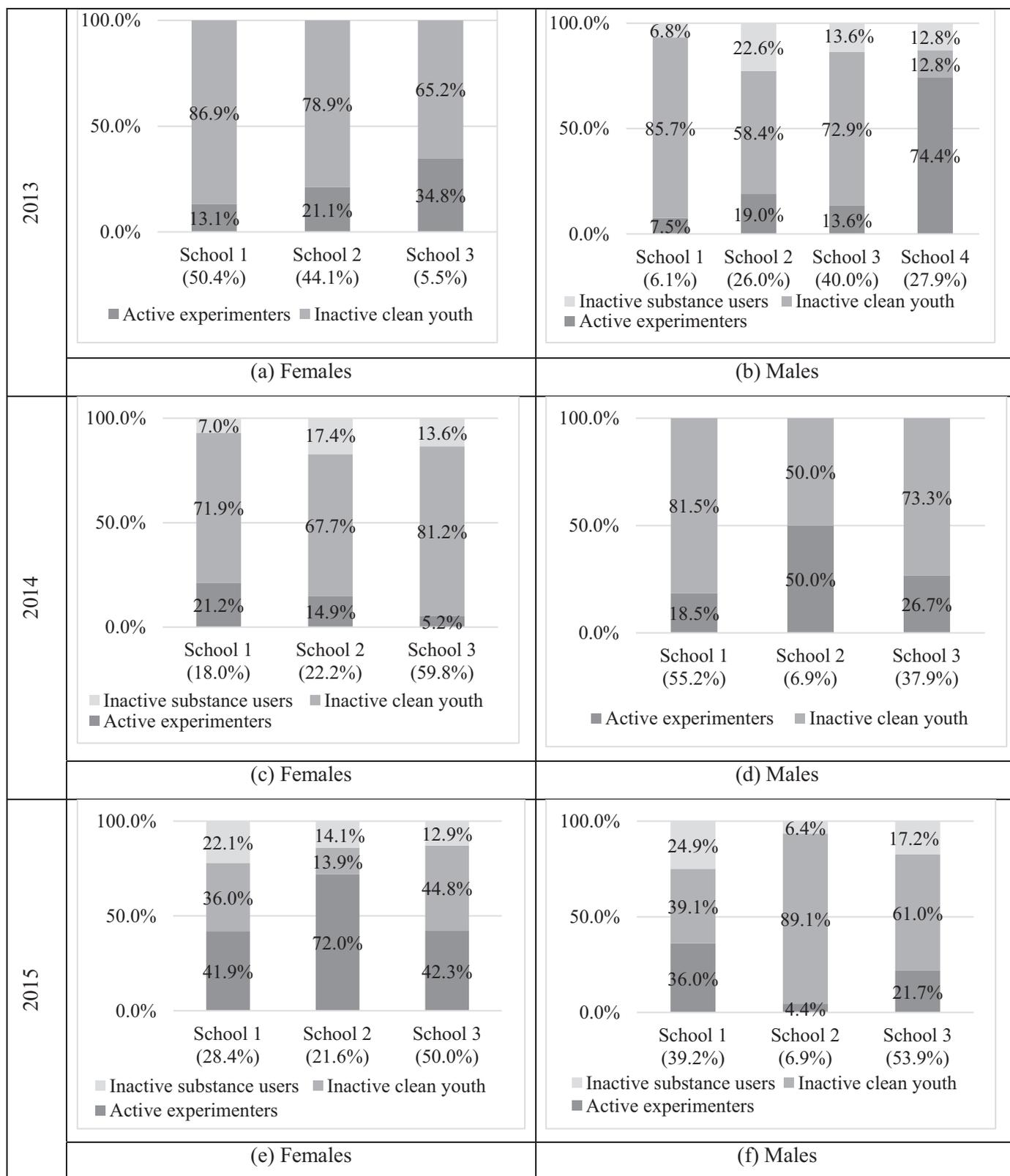
Fig. 2. Distribution of youth latent classes in school latent classes from the multilevel latent class analysis models for females and males, participating in COMPASS across the years 2013–2015.

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

Table 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]			β coefficients from the linear regression, with continuous BMI as an outcome		
	2013	2014	2015	2013	2014	2015
	Females					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ACE (ref.)						
INC	0.75*** (0.67, 0.84)	0.98 (0.84, 1.1)	1.2** (1.1, 1.3)	−0.46*** (−0.62, −0.31)	−0.20 (−0.42, 0.02)	0.12 (−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)

	Odds ratios from the logistic regression, with weight status (binary BMI) as an outcome[a]			β coefficients from the linear regression, with continuous BMI as an outcome		
	2013	2014	2015	2013	2014	2015
	Males					
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
ACE (ref.)						
INC	0.85** (0.78, 0.93)	0.85** (0.78, 0.94)	0.91 (0.82, 1.0)	−0.51*** (−0.68, −0.35)	−0.50*** (−0.67, 0.32)	−0.50*** (−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)

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.
[a] The category 'normal BMI' served as the reference category for the binary BMI outcome.

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 et al., 2014a); 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 et al., 2007). In contrast with previous research (Sherry et al., 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 and 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.

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 and Sussman, 2003). Such successful substance use prevention models can be used for obesity prevention programs (Sakuma et al., 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 et al., 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.

Author contributions

STL conceived of the COMPASS study and wrote the funding proposal, developed the tools, and is leading study implementation and coordination.

NH conceived this study, designed the analysis plan, and drafted the manuscript. AC provided statistical consultations (analysis and interpretation of results) throughout. STL, AC, and PB provided ideas and thoughts for discussion. All authors supported NH in the study design and analysis, as well as critically revised and approved the final manuscript.

Acknowledgements

Declaration of Competing Interest

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ypmed.2019.105758.

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