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The search for healthy schools: A multilevel latent class analysis of schools and their students

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ABSTRACT

The objective of this study was to establish and investigate a taxonomy of school health among high school students in Ontario, Canada. Data analyzed were based on 3358 9th–12th graders attending 103 high schools who participated in the 2011 Ontario Student Drug Use and Health Survey. Based on 10 health-related indicators, multilevel latent class analysis was used to extract 4 student-level latent classes and 3 school-level latent classes. Unhealthy schools (19% of schools) had the lowest proportion of healthy students (39%) and the highest proportion of substance-using (31%) and unhealthy (18%) students. Healthy schools (66%) contained the highest proportion of healthy students (56%) and smaller proportions of substance-using (22%) and unhealthy students (8%). Distressed schools (15%) were similar to healthy schools in terms of the proportions of healthy and unhealthy students. Distressed schools, however, were characterized by having the largest proportion of distressed students (35%) and the lowest proportion of substance-using students (4%). Meaningful categories of schools with respect to healthy environments can be identified and these categories could be used for focusing interventions and evaluating school health programs.

1. Introduction

Schools provide environments that can influence student health and well-being. As such schools are well-positioned to provide health-enhancing policies and programs (Poland et al., 2000; Sawyer et al., 2012; Lee and Gortmaker, 2012), with evidence for the effectiveness of some school-based interventions (Dobbins et al., 2009; Dobbins et al., 2013; Kahn et al., 2002; Stewart-Brown, 2006). Yet, the school is also a setting where students are exposed to influences potentially detrimental to their health (Forrest et al., 2013).

Concepts such as “healthy schools” (Lee et al., 2010), “health promoting schools” (Stewart-Brown, 2006; Lee, 2009; World Health Organization, 1998), “comprehensive school health” (WHO Expert Committee on Comprehensive School Health Education and Promotion, 1995), and “coordinated school health” (Centers for Disease Control and Prevention, 2013) have gained prominence. These are intuitively appealing and compatible with broader principles of health promotion (World Health Organization, Health and Welfare Canada, Canadian Public Health Association, 1986; World Health Organization, 1997) and ecological models of health (Lee, 2009; McLeroy et al., 1988; Stokols, 1992; Sallis et al., 1999). The concept of healthy schools is endorsed by initiatives such as a coordinated framework developed through the School Health Policies Study (SHPPS) (Centers for Disease Control and Prevention, 2013). However, discussions about healthy schools are arguably more conceptual and prescriptive than evidence-based.

Although the generic concept of healthy schools is inherently positive, the features and composition of a healthy school remain largely uncharted. Which indicators comprise school health and how these are distributed are unclear. Also unclear is whether healthy schools are associated with, or result in, healthy students. Few studies have assessed the characteristics of healthy schools or their relationship to student health behaviours and well-being (Stewart-Brown, 2006), though a recent Cochrane review (Langford et al., 2014; Langford et al., 2011) assessed evidence from cluster randomized controlled trials on the effects of the WHO Health Promoting School Framework. The results indicated evidence of effectiveness for some interventions on particular health outcomes, but not others.

A more fundamental question is whether schools can be simply dichotomized as healthy or unhealthy, or whether a more complex

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taxonomy is necessary to describe them. Identifying a classification of school health would enhance our understanding of the meaning of healthy schools in addition to having potential implications for both public health and education policy and programs. To date, most previous research on health-related behaviours of adolescents has focused on students and schools using multilevel models based on single observed dependent variables, ignoring the interrelationships of multiple dependent measures constituting health, as well as the interrelationships of the multiple independent school characteristics defining healthy schools (Due et al., 2009; Goodman et al., 2003; Kairouz and Adlaf, 2003; Kristjansson et al., 2013; Leatherdale et al., 2005; Lee et al., 2013; Maes and Lievens, 2003; Rehm et al., 2005; Richmond et al., 2006; Richmond and Subramanian, 2008; Saab and Klinger, 2010). Other studies have restricted their investigations to single level, person centered mixture models such as latent class analysis (LCA), but ignoring the hierarchical structure of their student-school data (Chung et al., 2006; Connell et al., 2009; Conway et al., 2013; Jiang et al., 2010; Sullivan et al., 2010). In this paper we explore the question of whether there is a distinct taxonomy of school health by applying recently developed statistical techniques to examine health-related behaviours with data from a representative sample of high school students. In Canada, education is a provincial responsibility and students normally attend elementary (grades K–6), middle (7-8) and high school (9-12).

2. Methods

Our analysis is based on a sub-sample of 3358 students attending 103 high schools completing questionnaire items in our study. This sub-sample was derived from the 2011 Ontario Student Drug Use and Health Survey (OSDUHS), a biennially-repeated survey conducted by the Centre for Addiction and Mental Health (CAMH) and administered by York University's Institute for Social Research (ISR). This province-wide survey employs a stratified (region and school level), two-stage cluster (school, class) sampling design with unequal probability weighting and monitors substance use, mental and physical health, and risk behaviours among students in grades 7–12. The 2011 cycle comprised 9288 students attending 181 publicly funded elementary/middle and high schools in Ontario. Signed parental permission (for those aged under 18) and signed student assent were required for participants and students completed self-administered questionnaires during a regular class period. The school and student response rates were 71% and 63%, respectively. OSDUHS 2011 received approval from the Research Ethics Boards of CAMH, York University, and school boards requiring review (for details including questionnaires: http://www.camh.net/Research/osdus.html.)

2.1. Latent class indicators and covariates

We used 10 health-related indicators to extract student latent class membership, grounded in the Ontario Ministry of Education's (EDU) Foundations for a Healthy School Framework (http://www.edu.gov.on.ca/eng/healthyschools/foundations.html). Accordingly, health-related factors in domains such as healthy eating, physical activity, injury prevention, substance use, mental health, and healthy growth and development are the central curriculum-linked components of a healthy school (see Table 1 for indicators). Each indicator was binary coded with the value 1 depicting a healthy response. Definitions of the indicators are provided in the Supplemental materials (available online).

Student-level covariates included sex (female = 1, male = 0) and grade level (9th–12th), measured by three dummy variables, with the 9th grade set as the reference category. Both have been shown to be predictive of adolescent health behaviours (Centers for Disease Control and Prevention, 2012; Hibell et al., 2012; Leatherdale and Burkhalter, 2012; Paglia-Boak et al., 2012).

Table 1
Characteristics of high school students (n = 3358) from 103 schools in Ontario, Canada, 2011.

	Percent[a]	N[b]
Latent class indicators		
Consumed breakfast during past 5 school days	52.1	1746
Enrolled in physical education class	38.4	1281
Not exposed to bullying at school	74.2	2475
Did not ride in a vehicle with alcohol/drug using driver	65.7	2197
No cigarette smoking in the past 12 months	88.2	2957
No cannabis use in the past 12 months	69.3	2326
cNo binge drinking in the past 4 weeks	69.3	2320
Without elevated psychological distress	63.5	2128
No involvement in suicidal behaviours	88.8	2963
Healthy weight	74.7	2454
Student-level predictors of student-level latent class membership		
Sex		
Female	48.9	1815
Male	51.1	1543
Grade		
9	22.7	879
10	22.8	825
11	23.9	808
12	30.6	846
School-level predictors of school-level latent class membership		
School enrollment		
Small, ≤600 students	19.4	20
Not small, >600 students	80.6	83
Percentage of students in lower-income households, M (SD)	12.3	(7.5)

[a] Percentage is weighted.
[b] N is unweighted.

We obtained two school-level covariates for the 2011/2012 school year from the EDU website http://www.edu.gov.on.ca/eng/sift/glossary.asp: the percentage of students living in low income households and school enrolment. Following Leithwood & Jantzi (Leithwood and Jantzi, 2009), we contrasted smaller schools (≤600 students; coded 1) from larger schools (>600 students; coded 0). Low household income was represented by the percentage of households in the school area with census defined low incomes. Research has also linked school-level socioeconomic status (SES) disadvantage with levels of physical activity (Richmond et al., 2006), obesity (Lee et al., 2013; Richmond and Subramanian, 2008), emotional well-being (Saab and Klinger, 2010), depressive symptoms (Goodman et al., 2003), suicidality (Jablonska et al., 2014), and peer victimization (Due et al., 2009).

2.2. Statistical analyses

Multilevel latent class analysis (MLCA) (Asparouhov and Muthen, 2008; Henry and Muthen, 2010; Vermunt, 2008; Vermunt, 2003) was employed to empirically extract homogeneous latent classes of students based on their responses to 10 health-related indicators forming distinct latent classes of schools based on the distribution of student-level latent classes within schools. The MLCA model extends the traditional latent class (LC) framework to the multilevel context (in our example, the nesting of students in schools) by specifying categorical latent variables for *both* students (Level 1) and schools (Level 2) (Asparouhov and Muthen, 2008; Vermunt, 2003). In this model, student-level LCs are first extracted within clusters (schools), and then the random means from the student-level LC solution are used as indicators for a second LC model at the school-level. Furthermore, because our LC indicators were discrete, we employed nonparametric estimation not assuming normality (Henry and Muthen, 2010). Our rationale for using MLCA is that this approach allows us to explore more substantively meaningful Level 2 outcomes on the school level. The primary benefit of MCLA, then, is that not only are classes of students generated, as a traditional single-level LCA would produce, but also classes of schools based on the distribution of student-level classes.

To identify the best-fitting model, we used the four stage sequential modeling strategy (Henry and Muthen, 2010). In the first stage of the analyses, we ignored the multilevel structure of the data and estimated a series of traditional LC models to determine the number of latent classes at the student-level. In the second stage we estimated a series of MLCA models to account for the multilevel structure of the data. In these models, the number of student-level classes was based on the best fitting LC analysis model from the previous stage, and the LC model at the school-level was estimated to identify the number of school-level LCs. In the third stage of the analyses we determined whether the number of student-level classes changed with the specification of random effects at the school-level. This was accomplished by estimating a series of models in which the number of school-level classes was defined on the basis of results from the previous stage, and the LC model at the student-level was estimated to determine the number of student-level LCs. In the fourth stage, we extended the model to include a common factor on the student-level LC indicators and repeated the analyses completed in the second and third stages.

Model fit of the competing models was compared using the Bayesian Information Criterion (BIC) (Schwarz, 1978), where lower values indicate better model fit to the data. The BIC is the preferred measure for simultaneously deciding about the number of lower- and higher-level classes in multilevel mixture models (Henry and Muthen, 2010; Lukočienė et al., 2010). Classification quality of the competing models was assessed using entropy, (Ramaswamy et al., 1993) a measure that summarizes how well the latent classes can be distinguished. Entropy values range from 0 to 1, with higher values indicating clearer distinctions among the latent classes. Additionally, models were evaluated and compared according to interpretability of the obtained solutions.

As a final step, the best fitting model was expanded to include student-level covariates to predict membership in student-level latent classes and school-level covariates to predict school-level latent class membership. Covariate effects at each level were incorporated into the model via multinomial logistic regression. At each level, one class was specified as the reference class and all covariates were examined simultaneously. Covariates were included in the study to assess their differential impact across the latent classes as well as to evaluate whether the derived latent classes represented meaningful population heterogeneity.

To estimate our MLCA models, we used Mplus Version 7.0 (Muthén and Muthén, 1998–2012), using full-information maximum likelihood (FIML) estimation — which allows for dependent variable missing data under missing at random (MAR) assumptions (Little and Rubin, 2002; Graham, 2009) — with the robust maximum likelihood estimator (MLR) — which uses model-based methods to accommodate our complex survey data. In our data, 4.3% of students ($n = 144$) had missing data on one or more of the 10 dependent variables (none of the student or school covariates had missing data). Accordingly, the estimated models used all available data for the subsample under investigation (3358 high school students nested within 103 schools).

3. Results

3.1. Sample characteristics

Table 1 presents descriptive statistics for the study sample. Of the 3358 high school students, 48.9% were female and the mean age was 15.9 years (SD = 1.3). Not smoking cigarettes (88.2%) and not engaging in suicidal behaviours (88.8%) were the most frequently endorsed health-related behaviours reported by students. Enrolment in physical education classes (38.4%) and breakfast consumption (52.1%) were the least frequently endorsed. Of the 103 schools, 19.4% were small (≤600 students) and the school mean percentage of students residing in low-income households was 12.3% (SD = 7.5).

3.2. Traditional (fixed-effects) LCA

Table 2 reports key statistical parameters of the estimated models.

In the traditional LC analysis that ignored the nesting of students in schools, the lowest value of the BIC was for the 4-class solution (BIC = 35,632). The entropy for this model was 0.675, indicating a reasonable degree of class separation. The item profile plot for the four-class solution is depicted in Fig. 1. Class 1 and Class 4 had similar endorsement profiles for participation in physical education and healthy weight. However, the profiles for these two classes were distinguished by particularly large differences for all the other indicators. Accordingly, we designated Class 1 as unhealthy students and Class 4 as healthy students. Two qualitatively different classes were also identified. Class 2 (25.6%) and Class 3 (18.4%) had comparable endorsement probabilities for participation in physical education, healthy weight and breakfast consumption. But Class 2, designated as the distressed student, was characterized by indicators relating to elevated distress, suicidal behaviours and being bullied, while Class 3, designated the substance-using student, was characterized by the substance use indicators. In summary, we estimated a series of traditional LCA models to determine the number of latent classes at the student-level. Based on the BIC, entropy and interpretability, we selected the LCA model with four student-level latent classes as the best fitted.

Table 2
Fit criteria for different model specifications, 2011 Ontario Student Drug Use and Health Survey.

	Number of level 1 (student) classes				
	1 Class	2 Classes	3 Classes	4 Classes	5 Classes
Fixed effects LCA model					
No. of free parameters	10	21	32	43	54
Log-likelihood	−19,087	−17,923	−17,736	−17,642	−17,619
BIC	38,256	36,016	35,731	35,632	35,676
Entropy	1	0.802	0.693	0.675	0.689
Random effects nonparametric MLCA model					
2 Level 2 (school) classes					
No. of free parameters			35	47	59
Log-likelihood			−17,744	−17,637	−17,609
BIC			35,772	35,655	35,698
Entropy			0.803	0.793	0.801
3 Level 2 (school) classes					
No. of free parameters			38	51	64
Log-likelihood			−17,728	−17,621	−17,576
BIC			35,764	35,655	35,671
Entropy			0.825	0.815	0.807
4 Level 2 (school) classes					
No. of free parameters				55	
Log-likelihood				−17,614	
BIC				35,675	
Entropy				0.786	
Random effects nonparametric MLCA model with a continuous factor on Level 1 latent class indicators					
2 Level 2 (school) classes					
No. of free parameters			46	58	70
Log-likelihood			−17,658	−17,551	−17,518
BIC			35,690	35,573	35,604
Entropy			0.850	0.828	0.834
3 Level 2 (school) classes					
No. of free parameters			50	63	76
Log-likelihood			−17,642	−17,533	−17,508
BIC			35,691	35,577	35,633
Entropy			0.823	0.821	0.838
4 Level 2 (school) classes					
No. of free parameters				68	
Log-likelihood				−17,517	
BIC				35,587	
Entropy				0.853	

Note: BIC: Lower values indicate better model fit to the data. Entropy values range from 0 to 1, with higher values indicating clearer distinctions among the latent classes.

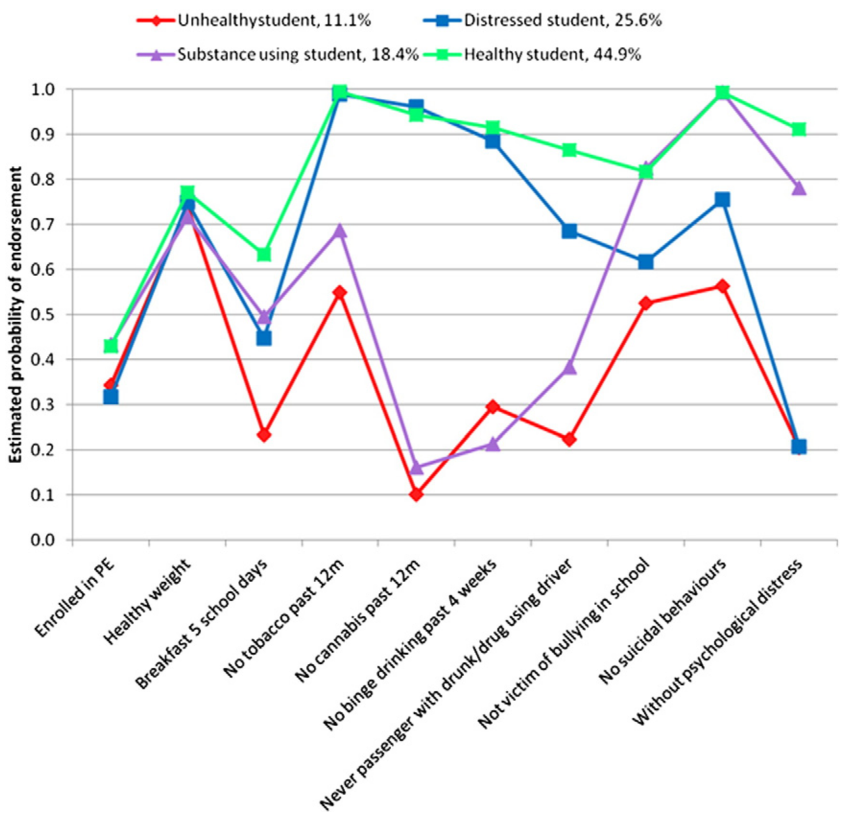

Fig. 1. Profile plot: Level 1, students: four-class solution.

3.3. Random effects nonparametric MLCA

Results of extending the four-class LCA model to include nonparametric random effects to account for the multilevel structure of the data are shown in Table 2. As indicated by the BIC, the models with a common factor provided a better fit to the data compared to the models without a common factor. This result suggests that schools have an impact on the student-level latent class indicators. Further, comparing values of the BIC between the models with a common factor and the fixed effects LCA models showed that the models with a common factor provided a better fit to the data. As such, we then compared models with and without a common factor on the Level 1 latent class indicators. Among these models, the one with the lowest BIC was the two-class model (BIC = 35,573), followed by the three-class model (BIC = 35,577). Because these two models had very close values on the BIC, we compared the results of the two solutions and found that the three-class model produced a third class that was substantively distinct from the two-class solution. Given the equivalent values of the BIC and greater interpretability, we selected the three-class model as the best fitting model. We also examined whether the number of student-level classes changed due to the inclusion of three school-level latent classes; the number of student-level classes remained unaltered (bottom of Table 2). In sum, the final model included four student-level latent classes, three school-level latent classes and a common factor on the Level 1 latent class indicators. Entropy for this model was 0.821, indicating good classification qualities.

Fig. 2 shows the final model and how the four student-level classes distribute among the three school-level classes.

Unhealthy schools belonging to Class 1 ($n = 20$; 19.4% of schools), had the lowest proportion of healthy students (38.6%) and the highest proportion of substance-using (30.7%) and unhealthy (17.6%) students. By contrast, healthy schools belonging to Class 3 ($n = 68$; 66.0%), contained the highest proportion of healthy students (56.3%) and a much smaller proportion of substance-using (22.0%) and unhealthy students (7.5%). Interestingly, healthy and unhealthy schools differed marginally in the proportion of distressed students they contained, 14.2% and 13.1%, respectively. Distressed schools belonging to Class 2 ($n = 15$; 14.6%), the class emerging between the 2 models with a similar BIC, were similar to the healthy schools in the proportions of healthy (53.8% vs. 56.3%) and unhealthy (7.6% vs. 7.5%) students. Distressed schools, however, were characterized by having the largest proportion of distressed students (34.5%) and the lowest proportion of substance-using students (3.7%).

3.4. Student-level and school-level covariate effects

Table 3 displays the results of the multinomial logistic regression part of the best fitting model that used student-level covariates to

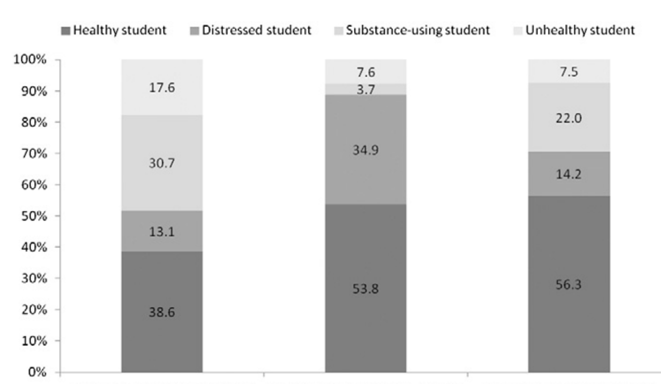

Fig. 2. Distribution of student-level latent classes ($n = 3358$ students) within school-level latent classes ($n = 103$ schools). 2011 Ontario Student Drug Use and Health Survey.

Table 3
Multinomial logistic regression results: covariate effects on level 1 and level 2 latent class membership, 2011 Ontario Student Drug Use and Health Survey.

	OR[a]	(95% CI[b])
Level 1 (student)		
Substance-using student vs. healthy student		
Sex		
Male	1.00	
Female	0.70	(0.45, 1.10)
Grade		
9	1.00	
10	4.64	(2.77, 7.75)
11	10.59	(5.68, 19.75)
12	15.44	(7.59, 31.39)
Distressed student vs. healthy student		
Sex		
Male	1.00	
Female	3.59	(2.56, 5.03)
Grade		
9	1.00	
10	1.40	(0.99, 1.97)
11	2.10	(1.33, 3.30)
12	2.25	(1.54, 3.30)
Unhealthy student vs. healthy student		
Sex		
Male	1.00	
Female	2.38	(1.47, 3.84)
Grade		
9	1.00	
10	2.60	(1.50, 4.49)
11	4.82	(2.52, 9.24)
12	5.72	(2.64, 12.38)
Level 2 (school)		
Unhealthy school vs. healthy school		
Percentage of students in low income households	1.05	(0.76, 1.45)
School enrollment size		
Not small, >600 enrolled	1.00	
Small, ≤600 students	9.69	(1.33, 70.56)
Distressed school vs. healthy school		
Percentage of students in low income households	1.20	(0.84, 1.73)
School enrolment size		
Not small, >600 enrolled	1.00	
Small, ≤600 students	3.99	(0.24, 65.17)
Distressed school vs. unhealthy school		
Percentage of students in low income households	1.14	(1.02, 1.29)
School enrolment size		
Not small, >600 enrolled	1.00	
Small, ≤600 students	0.41	(0.03, 5.55)

[a] OR = odds ratio.
[b] CI = confidence interval.

predict student-level class membership and school-level covariates to predict school-level class membership.

At the student-level, the healthy student class was the reference category. At the school-level, the odds ratios compare the odds of belonging to the distressed or unhealthy school classes versus the healthy school class. The odds of belonging to the distressed versus the unhealthy school class are also presented.

At the student-level, both sex and grade significantly predicted student-level latent class membership. More specifically, the odds of membership in the distressed student class compared to the healthy student class were 3.6 times higher for females than males. Similarly, females had 2.4-fold increased odds of membership in the unhealthy versus the healthy student class. However, comparing the substance-using student class to the healthy student class did not reveal a significant sex difference. Comparisons by grade showed that the odds of membership in the substance-using student class versus the healthy student class were 4.7–15.4 times higher among 10th, 11th and 12th graders than among 9th graders. The odds ratios comparing the distressed and unhealthy student classes with the healthy student class revealed a similar patterning of significant grade effects, with one exception. Ninth and tenth graders were equally likely to be in the distressed and healthy student classes.

At the school-level, school size predicted school-level latent class membership, but for only 1 of 3 contrasts. Specifically, the odds of belonging to the unhealthy school class as compared to the healthy school class were 9.7 times higher for small schools than larger schools. This difference was not observed when contrasting distressed versus healthy schools and distressed versus unhealthy schools. School-level SES inequality also predicted school-level latent class membership. For each percentage point increase in the percentage of students living in a lower-income household, the odds of belonging to the distressed school class relative to the unhealthy school class increased by 14%. Comparing the unhealthy school class to the healthy school class did not reveal this difference.

4. Discussion

Findings from our study provide insight into the question of whether schools can be categorized simply as healthy or unhealthy. While this dichotomy is implicit in existing concepts (Lee et al., 2010; Lee, 2009; World Health Organization, 1998; WHO Expert Committee on Comprehensive School Health Education and Promotion, 1995), we identified distressed schools as an additionally distinct type, characterized by a distribution of students with elevated psychological distress, victimization from bullying, and suicidality. Also important is that the distressed school was characterized by low student drug use compared to both other categories. Distressed schools also comprised similar proportions of healthy and unhealthy students as did the healthy school type. While distressed schools comprised <15% of schools in our sample, healthy schools made up 66% and unhealthy schools almost 20% of schools.

While our study could not identify underlying sources of distressed schools in relation to social structure, the process of schooling, or individual student characteristics, one covariate – lower household income – was related to higher odds of attending a distressed school as compared to an unhealthy school. Thus, SES appears to be related to school settings associated with distressed (and bullied) students, consistent with existing research (Due et al., 2009; Goodman et al., 2003; Saab and Klinger, 2010; Jablonska et al., 2014).

Additionally, smaller school size was associated with the distressed school type. Past research has identified a positive association between school size and bullying victimization among young children (Bowes et al., 2009). However, the mean school enrolment in our data was within our small category boundaries. We anticipate that there are several additional, unmeasured, factors associated with distressed schools (and with other school types) and with SES and school size, which need to be considered in future study.

Regarding the four student latent classes, we identified relationships between student type and sex, where females had increased odds of membership in the distressed and unhealthy groups versus the healthy group. Recent research has identified being female as related to power disadvantages and an increased likelihood of bullying victimization in some studies (Schumann et al., 2014). Our findings are also supported by research identifying females as more likely than males to experience low self-esteem, greater stress, and internalizing behaviour (Sieh et al., 2013). Research has also identified gender differences in physical activity and breakfast consumption among adolescents, with females less likely to be active or consuming breakfast compared to males (Iannotti and Wang, 2013; Kilani et al., 2013; Currie et al., n.d.).

Additionally, we identified relationships between student type and age, as represented by grade level. Students in higher grades had increased odds of being grouped in the substance-using, distressed, and unhealthy groups compared to the healthy group. These findings are supported by research indicating that adolescents face more problematic behaviour with increasing age (Sieh et al., 2013). Increasing age during adolescence has also been associated with substance use, such as cigarette smoking (Teevale et al., 2013), as well as a decreased likelihood of breakfast consumption (Iannotti and Wang, 2013), and a decline in physical activity (Allison et al., 2007).

This study is unique in its examination of the multilevel latent class structure of student-school health. Although multilevel models were largely developed with school system applications (Goldstein, 1987; Raudenbush and Bryk, 1986; Raudenbush and Willms, 1991) we did not locate published studies that have approached the investigation of student-school health through multilevel mixture models. We are fortunate to have our analyses built from a large population survey. The design with 103 geographically dispersed high schools ensures a heterogeneous sample of schools and students. Also, a sample of over 3000 high school students is sufficiently large to capture small or unique latent classes. Additionally, our LCA extraction and further modeling benefited from data collection with a wide scope.

4.1. Methodological limitations

Our study is not without limitations. First, our student data were self-reported; consequently, response and recall bias may exist. Second, only publicly-funded schools were included in the study, although 92% of the target population was represented (Paglia-Boak et al., 2012). Third, our school-level data were restricted to two covariates, limiting our predictors of latent class membership. Though consistent with an existing provincial healthy schools framework, the indicators used in the analysis represented health-related behaviours of students rather than additional components of such a framework (curriculum, physical and social environments) not measured in our data source. Also, the student-level indicators used were limited to items available in the 2011 OSDUHS. Regarding our analysis, we recognize the possibility that some neighbourhood effects may be misattributed to school-level effects. Another potential limitation of our analysis is that differing schools may have differing unmeasured exposures to community or school-level programming. Although the existence of local initiatives is possible, we contend that such factors would not likely alter our substantive conclusions.

4.2. Implications for policy and practice

Results from our study identify types of schools which, if modifiable, can be altered to strengthen their ability to enhance student wellbeing. A potential policy implication is that distressed schools may not be easily transformed into healthy schools simply by increasing healthy behaviours such as eating healthier foods or exercising, although there are links between such behaviours and mental health. Some of the characteristics associated with distressed schools may have social/structural roots or be influenced by wider school and community environmental or school climate factors, and thus are less amenable to curriculum or school-based micro-level organizational changes. Yet, despite recognition of the importance and meaning of the distressed schools, the finding that healthy schools were the most numerous school type in our study is encouraging.

In conclusion, we found evidence of meaningful subtypes of schools and associated student health-related behaviours that warrant further inquiry and development. Such classification poses benefits for the targeting and evaluation of school health policies and programs. In particular, school environment, climate and contextual factors need to be considered and addressed, as well as student-level behaviours.

Conflict of interest statement

The authors declare that there are no conflicts of interest.

Transparency document

The Transparency document related to this article can be found in the online version.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.pmedr.2016.06.016.

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