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RESEARCH ARTICLE

Early substance use and the school environment: A multilevel latent class analysis

Jillian Halladay RN PhD[1,2]; James MacKillop PhD[2,3]; Samuel Acuff PhD[4]; Michael Amlung PhD[5]; Catharine Munn MSc MD FRCP(C)[3,6]; Katholiki Georgiades PhD[3,6,7]

Abstract

Background: Early substance use is associated with increased risks for mental health and substance use problems which are compounded when using several substances (i.e., polysubstance use). A notable increase in substance use occurs when adolescents transition from elementary to secondary schooling. **Objective:** This study seeks to characterize student and school classes of substance use. **Methods**: A cross-sectional multilevel latent class analysis and regression was conducted on a representative sample of 19,130 grade 6-8 students from 180 elementary schools in Ontario, Canada to: 1) identify distinct classes of student substance use; 2) identify classes of schools based on student classes; and 3) explore correlates of these classes, including mental health, school climate, belonging, safety, and extracurricular participation. **Results**: Two student and two school classes were identified. 4.1% of students were assigned to the high probability of early polysubstance use class while the remaining 95.9% were in the low probability class. Students experiencing depressive and externalizing symptoms had higher odds of being in the early polysubstance use class (Odds Ratio [OR]s=1.1-1.25). At the school level, 19% of schools had higher proportions of students endorsing polysubstance use. Perceptions of positive school climate, belonging, and safety increased the odds of students being in the low probability of early polysubstance use student-level class (ORs=0.85-0.93) and lower probability of early polysubstance use school-level class. Associations related to extracurricular participation were largely not statistically significant. **Conclusions**: Student and school substance use classes may serve as targets for tailored prevention and early interventions. Results support examining school-based interventions targeting school climate, belonging, and safety.

***Key Words**: adolescent, substance use, mental health, school, elementary*

Résumé

Contexte: L'utilisation précoce de substances est associée à des risques accrus pour la santé mentale et les problèmes liés à l'utilisation de substances qui sont aggravés lorsque plusieurs substances sont utilisées (c.-à-d. utilisation de

[1]The Matilda Centre for Research in Mental Health and Substance Use, University of Sydney, Camperdown NSW, Australia
[2]Peter Boris Centre for Addictions Research, McMaster University/St. Joseph's Healthcare Hamilton, Hamilton, Ontario
[3]Department of Psychiatry and Behavioural Neurosciences, McMaster University, Hamilton, Ontario
[4]Recovery Research Institute, Massachusetts General Hospital and Harvard Medical School, Boston, Massachusetts, United States
[5]Cofrin Logan Center for Addiction Research and Treatment, The University of Kansas, Lawrence, Kansas, United States
[6]Department of Health Research Methods, Evidence, and Impact, McMaster University, Hamilton, Ontario
[7]Offord Centre for Child Studies, McMaster University, Ron Joyce Children's Health Centre, Hamilton, Ontario

Corresponding Email: jillian.halladay@sydney.edu.au / halladje@mcmaster.ca

polysubstances). Une augmentation notable de l'utilisation de substances se produit quand les adolescents passent du cours primaire au cours secondaire. **Objectif:** La présente étude cherche à caractériser l'utilisation de substances chez les classes d'élèves et d'écoles. **Méthodes**: Une analyse transversale et une régression des classes latentes multi-niveaux ont été menées sur un échantillon représentatif de 19 130 élèves de la 6e à la 8e année de 180 écoles primaires de l'Ontario, Canada, pour: 1) identifier les classes d'élèves distinctes utilisant des substances; 2) identifier les classes d'écoles d'après les classes d'élèves; et 3) explorer les corrélats de ces classes, notamment la santé mentale, le climat scolaire, l'appartenance, la sécurité, et la participation extrascolaire. **Résultats**: Deux classes d'élèves et deux classes d'écoles ont été identifiées. Des élèves au nombre de 4,1 % ont été assignés à la classe probabilité élevée d'une utilisation précoce de polysubstances alors que les 95,9 % restants étaient dans la classe probabilité faible. Les élèves souffrant de dépression et de symptômes externalisants avaient des probabilités plus élevées d'être dans la classe utilisation précoce de polysubstances (Rapport de cotes [RC] = 1,1-1,25). Au niveau des écoles, 19 % d'entre elles avaient des proportions plus élevées d'élèves approuvant l'utilisation de polysubstances. Les perceptions positives du climat scolaire, de l'appartenance et de la sécurité accroissaient les probabilités d'élèves étant dans la classe d'élèves faible probabilité d'utilisation précoce de polysubstances (RC = 0,85-0,93) et une probabilité plus faible de la classe d'écoles ayant une utilisation précoce de polysubstances. Les associations liées à une participation extrascolaire étaient largement non significatives statistiquement. **Conclusions**: Les classes d'utilisation de substances d'élèves et d'écoles peuvent servir de cibles pour une prévention adaptée et des interventions précoces. Les résultats soutiennent l'examen des interventions en milieu scolaire qui ciblent le climat scolaire, l'appartenance et la sécurité.

***Mots clés**: adolescent, utilisation de substances, santé mentale, école primaire*

Introduction

A notable increase in adolescent substance use occurs around age 14, corresponding to the transition from elementary (i.e., up to grade 8 in Canada) to secondary (i.e., grades 9-12) schooling (1). Among grade 8 students (13-14 years of age) across Ontario, Canada in 2019, 15.8%, 4.7%, and 0.7% reported past year alcohol, cannabis, and cigarette use respectively, all of which approximately doubled in prevalence by grade 9 (1). Earlier age of substance use initiation, particularly by age 14 (subsequently referred to as early use), has been associated with greater risks of experiencing substance use disorders (SUD) and physical, psychological, and social problems later in life (2-9). Thus, late childhood to early adolescence is a critical period for substance use prevention.

Early alcohol use has also been associated with an increased likelihood of risky use, such as heavy episodic drinking (HED) in later adolescence (10), and higher odds of suicidality compared to later initiation (3). In particular, early HED has been associated with other substance use, SUDs, injuries, fighting, and academic impairment later in adolescence (11, 12). Early onset of cannabis has been associated with anxiety and depression in young adulthood (13) and suicidal behaviours (14). Further, early smoking has been strongly associated with later morbidity and mortality (15), drinking and driving (12), and shorter time to onset of other psychiatric disorders (5).

Adolescents may endorse using more than one substance in a period of weeks to months, also known as multiple (>=2) or poly (>=3) substance use (16). In comparison to single substance use, multiple use further increases the risk of transitioning from use to SUD (9) and experiencing other negative mental health, educational, and social problems (17-21). For cannabis, though early initiation is related to increased transitions to cannabis use disorder, this association may be explained by co-occurring use of other substances and mental health symptoms (9). Adolescents who use multiple substances may have a higher biopsychosocial liability to initiate substance use and experience problems from use (22), and therefore, early initiation of multiple substances (rather than single substances) and co-occurring mental health symptoms are important to consider. Cluster-based methods, such as latent class analysis (LCA), are increasingly being used to identify these patterns of co-occurrence including patterns differing in the: a) number, types, and frequencies of substance use, and b) presence and severity of co-occurring emotional or behavioural symptoms (16). Previous work has found these patterns to differ by gender, with some suggesting girls are more likely to be in classes lower in substance use and higher in emotional symptoms (16, 23). Adolescent substance use has, more broadly, been shown to increase with age (1, 16), be higher among youth in rural areas (23, 24), and have nuanced and inconsistent associations based on race (23, 25) and socioeconomic status (23, 26, 27). However, few existing cluster-based studies have focused on early adolescents, substantially limiting our understanding of patterns and correlates of early initiation.

Importance of School Context

Schools have been found to account for up to 20% of the variability in student substance use, depending on the substance and frequency pattern being measured (28, 29). Accordingly, the Public Health Agency of Canada (30) recently proposed the Blueprint for Action: Preventing Substance Related Harms Among Youth Through a Comprehensive School Health Approach, suggesting upstream prevention efforts focused on the school environment similar to the internationally recognized Icelandic Prevention Model (31). These models focus on schools—seen as a hub for youth and their communities—to prevent or delay substance use. Several targets map onto universal, malleable aspects of a school's environment including: school climate encompassing interpersonal relationships, social and emotional support, and culture; school belonging or connectedness and commitment to community values; and school safety (32, 33). Existing studies examining these domains of a school's social environment have demonstrated positive associations with student mental health (34, 35) and negative associations with substance use initiation or frequency (23, 33, 36). These prevention models also seek to increase involvement in substance-free prosocial activities, such as involvement in extracurriculars like sports or clubs (30, 31). Extracurricular participation is hypothesized to be protective based on evidence from behavioural economic approaches for substance use that aim to reduce substance-related reinforcement while maximizing substance-free reinforcements (37). Some evidence suggests that these school characteristics may be more protective for female students, compared to males (23, 38).

School contextual factors related to patterns of co-occurrence among early adolescents remain a largely uninvestigated, and potentially powerful, component to understanding and preventing this phenomenon. Patterns derived from cluster-based analyses of student substance use and mental health symptoms can be used as: 1) outcomes of intervention studies, and 2) targets for school interventions by identifying groups of students and/or types of schools that require more support. Multilevel cluster-based methods are increasingly being applied to characterize both student and school substance use patterns, due to the known strong clustering of substance use within schools (39, 40). However, most of the existing studies are conducted with older adolescents (16, 23, 39, 40), leaving important gaps in the literature given that the early initiation of substance use is associated with salient risks (1, 41).

Objectives

The primary objectives of this study were to: 1) identify distinct classes of co-occurring substance use and mental health symptoms among elementary students (grades 6-8; ~11-14 years); 2) identify classes of schools based on these student classes; and 3) explore school correlates of student and school classes, including school climate, belonging, and safety and student involvement in school-based extracurriculars. The secondary objective was to examine, at the student-level, whether the structure of co-occurring of multiple substance use and mental health symptoms and related school-level correlates differed across gender. It was hypothesized that students belonging to classes with higher probabilities of polysubstance use would also endorse higher negative mental health symptoms, and that this co-occurrence would be related to poorer perceptions of positive school climate, belongingness, and safety, and less engagement with extracurriculars. We hypothesized that co-occurring mental health symptoms would be more common and that school-level correlates would yield larger associations for girls.

Methods

Sample

This study is a secondary analysis of grade 6-8 students included in the 2014-2015 cross-sectional School Mental Health Surveys (SMHS) in Ontario, Canada. The SMHS study was designed to examine associations between school and classroom contexts, and student mental health and psychosocial outcomes. All SMHS procedures were approved by the Hamilton Integrated Research Ethics Board at McMaster University and the Research Ethics Committees of the School Boards involved in the study. Schools were selected based on the sampling design of a companion study—the Ontario Child Health Study (OCHS; 42)—resulting in a representative sample of schools (excluding First Nations reserves). Among the 359 selected elementary (up to grade 8) and secondary (grades 9-12) schools, 248 (69%) agreed to participate with no notable differences between participating versus non-participating schools on key school characteristics including school type (public/separate), language (English/French), region, enrolment, proportion of English Language Learners, standardized achievement levels, and socio-economic and demographic characteristics (data available from the author). Within elementary schools, anonymous surveys were administered to all students in grade 6-8 classrooms. Survey data used for this analysis includes data from 19,130 elementary school students (response rate=62.3%) from 180 schools.

Variables

Substance Use

Substance use questions were adapted from the National Longitudinal Survey of Children and Youth (43). Heavy episodic drinking (HED) was measured by asking students if they had 5 or more drinks of alcohol on the same occasion at any point within the past 4 weeks from never to 5 or more times [0-5]. For cannabis use, students were asked about their experience using cannabis with response options [0-4]: I have never tried marijuana; I have tried marijuana, but only once or twice; I used to smoke marijuana once a week, but have not done so in the last month; I smoke sometimes, but not every week; and I usually smoke marijuana at least once a week. For cigarettes, students were asked about their experience with smoking cigarettes with response options [0-4]: I have never tried smoking, not even a few puffs; I have tried smoking, but only once or twice; I used to smoke every day, but have not smoked a cigarette in the last month; I smoke sometimes, but not every day; and I usually smoke at least 1 cigarette a day. All substances were dichotomized into separate indicators of never [0] or any use [1].

Mental Health Symptoms

Mental health symptoms were assessed using a modified subset of the OCHS Emotional and Behavioural Scales (44) to measure the frequency of symptoms over the preceding 6 months on a scale from never/not true to often/very true [0-2] for: Generalized Anxiety Disorder (GAD; 4 items; Cronbach's alpha [a]=0.87), Major Depressive Episode (MDE; 5 items; a=0.82), Oppositional Defiant Disorder (ODD; 5 items; a=0.80), and Attention Deficit Hyperactivity Disorder (ADHD; 4 items; a=0.76). Items within subscales were summed, where higher scores reflect more symptoms.

School Environment

School climate was measured by summing 20 items related to relationships, fairness, academic pressure and expectations, positive behavioural support, and social and emotional learning (45). Response options were scored from disagree a lot to agree a lot [0-3; a=0.91]. School belonging was measured by summing 3 items related to feeling close to people at school, feeling like they belong at school, and being happy to be at school rated from strongly disagree to strongly agree [0-4; a=0.83] (46). School safety was measured by summing 5 items scored from not safe to very safe [0-3; a=0.84], asking about safety in and around the school (47). Regarding extracurriculars, students were asked "How often do you participate in the following activities at school, but not in class: 1) Played sports on a team, and/or taken part in physical activities (e.g., dance, karate, gymnastics), with a coach or instructor, other than in gym class? [Sports]; 2) Taken part in art, drama or music groups, outside of class? [Art]; or 3) Taken part in a school club or group such as yearbook club, photography club or student council? [Clubs]." Response options included [0-4]: almost never, about once a month, about once a week, a few times a week, and most days.

Covariates

Student-level covariates included gender ("Are you…. Female [1]? Male [0]?"), age in years, family assets (z-score; based on the number of vehicles, computers, cellphones, and electronic tablets their family owns), family structure (1=2 parents, 0=1 or no parents), parental education (1=post-secondary education, 0=high school or less), and race and ethnicity. Students were asked about their race and cultural group. Race and ethnicity in this analysis included: White; East Asian/Southeast Asian/South Asian (ESA); Black African/Caribbean/Canadian/American (Black); Other (West Asian/Arab, Latin American/Central, American/South American, Aboriginal/Native, Other); and Multiple races and/or ethnicities (~77% White + another racial or ethnic group[s], ~23% non-White racial or ethnic groups). School-level covariates included median family income in the neighbourhoods of attending students, school enrolment, and rural or urban status based on the school's postal code.

Analyses

First, student-level substance use and mental health symptom patterns were explored through latent class mixture modelling using Mplus (version 7) including binary indicators for substance use [HED, CAN, TOB] and continuous indicators for mental health symptoms [GAD, MDE, ADHD, ODD]. Random split halves were generated for sample cross-validation, with the final model re-estimated in the full sample (48). Models were estimated for 1-k profiles when the model no longer converged or when Bayesian Information Criterion (BIC) began to increase (48). Solutions were compared based on class enumeration and separation diagnostics, indicator specific class homogeneity and separation statistics, and theoretical clinical relevance. For binary indicators, high class homogeneity was defined as probabilities >0.7 or <0.3 (48). Bivariate residuals were examined to evaluate tenability of the local independence assumption (48). Unanticipated modeling issues arose when mental health indicators were included in latent class mixture models (continuous or binary) including violation of modelling assumptions, poor separation between classes on substance use indicators (all probabilities<0.3), and/or poor separation between classes on mental health indicators (probabilities~0.5). Due to these unanticipated issues, post hoc analyses were explored whereby only substance use indicators were included. To determine whether subsequent analyses should be stratified by gender, measurement invariance was examined by: 1) stratifying the sample and assessing qualitative differences, and 2) using multi-group function where groups were i) constrained to have equal parameters and ii) freed parameters and then compared using model fit and class separation diagnostics (48).

Second, multilevel latent class analysis (MLCA) models were used to estimate the distribution and structure of substance use at the school-level (49). MLCA examines whether school classes can be identified based on proportions of student classes within them. Models were compared based on similar criteria as above, with BIC being the primary criterion for the basis of model selection. Each student and school were assigned an adjusted probability of being in each class. These posterior probabilities and the most likely class memberships (i.e., the class with the highest probability) from the final MLCA were used for subsequent modeling.

Third, descriptive statistics and logistic regression analyses using the identified student and school classes were conducted in SAS ® Enterprise Guide 7.1. Descriptive statistics were estimated across all student and school classes pooled across imputations (described below). For school class descriptives, school climate, belonging, safety, and extracurriculars were averaged across all students within a school. Next, a series of random intercept multilevel (students, classes, schools) logistic regression models using student-level class membership as the outcome were conducted using the residual pseudo-likelihood method and applying the Satterthwaite adjustment. Logistic regressions were estimated by imputation, pooling estimates and standard errors for final results. Models were run separately for school climate, belonging, safety, and extracurriculars and all models were adjusted for socio-demographics. Differential gender effects were explored through interaction terms. Correlates of class membership at the school-level were explored using single-level (school-level) univariable regressions. A conservative p-value to account for the large sample size of <0.005 was used to denote statistical significance.

Regarding missing data, within-person mean substitution (i.e., proration) was used within summative scale variables for those with <=30% missingness (50). Overall, 65% of students had complete responses on all variables with 96% and 95% having complete responses for mental health and substance use variables, respectively. Remaining missingness was addressed using Full Information Maximum Likelihood in cluster analyses and Multilevel Multiple Imputation using BLIMP (51) in regression models. See Supplementary Material for extended missing data (SM.1), student-level (SM.2), and school-level (SM.3) analysis information.

Results

Student-Level Classes

When exploring clusters with substance use indicators only, the 2-class model fit best as per significant likelihood ratio tests, cross-replication, and convergence; it was also highly homogenous with well separated classes, no assumption violations, and the model held across genders. Thus, a 2-class substance-use only model was selected as the final model (Fig.1), which had an entropy of 0.95 (indicating high classification certainty), with a low probability of polysubstance use class (n=17,878, 96.5%) and high probability of polysubstance use class (n=650, 3.5%). See SM.2 for detailed results including BIC and other model fit and class diagnostics.

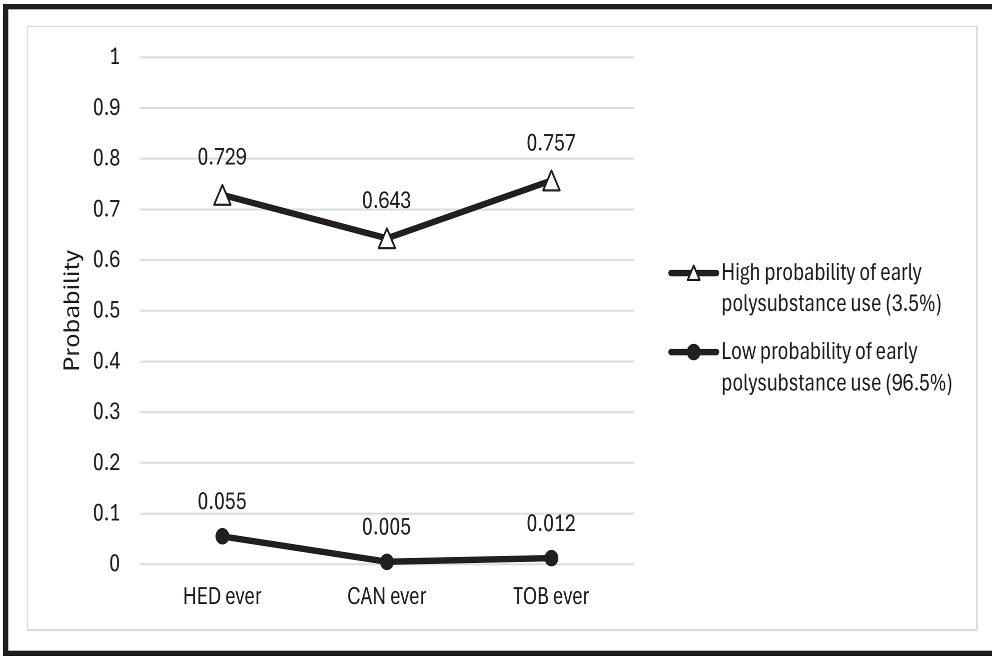
School-Level Classes

At the school-level, a 2-class model was selected (Fig.2) with an overall entropy of 0.893 which identified schools where students had a low probability of polysubstance use (Low; n=145 schools; 80.6%) and schools where students had a higher probability of polysubstance use (High; n=35 schools; 19.4%) with all average posterior probabilities >0.8. Adjusting for school clustering slightly increased the proportion of the student polysubstance use class (3.5% to 4.1% prior to multiple imputation). See SM.3 for detailed results.

Characterizing Student Classes

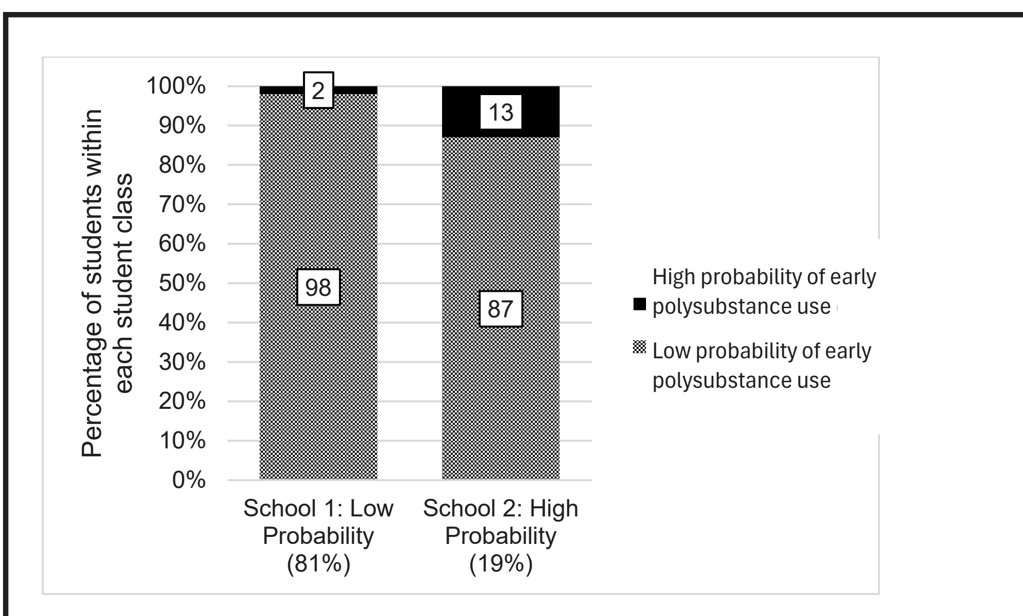
See Table 1 for descriptives and Table 2 for logistic regression results. In the adjusted socio-demographic only model, student-level covariates were significantly related to student substance use class membership. There were no significant gender differences. Compared to younger students, older students had greater odds of being in the high probability of

Figure 1. Student-Level 2-Class Substance Use Model (single level analysis, n=18,528)[a]



[a]HED = Heavy episodic drinking; CAN = Cannabis involvement; TOB = Tobacco smoking involvement

Figure 2. School-level 2-Class Model



early polysubstance use class. Compared to White students, Black students had greater odds, and ESA students lower odds, of being in the high probability of early polysubstance use class. Students with two-parents, parents with post-secondary education, and those endorsing greater family assets had lower odds of being in the high probability of early polysubstance use class.

Given mental health indicators were removed from the classification of students, they were included as covariates in a logistic regression model. MDE, ADHD, and ODD symptoms were positively related to being in the high probability of early polysubstance use class while GAD was not (OR_{MDE}=1.1 [95% CI 1.05-1.15]; OR_{ADHD}=1.13 [1.08-1.18]; OR_{ODD}=1.25 [1.21-1.3]). Students reporting higher

Table 1. Student-Level Descriptives[a]

	Total	Student Profiles	
		Low probability of early polysubstance use class (95.8%)	High probability of early polysubstance use class (4.2%)
Female	52%	52%	48%
Age	12.2 (1.1)	12.2 (1.0)	13.0 (1.8)
White Race and/or Ethnicity	54.2%	54.1%	56.9%
Black Race and/or Ethnicity	5.3%	5.1%	9.4%
ESA Race and/or Ethnicity	19.9%	20.4%	8.1%
Other Race and/or Ethnicity	10.2%	10.1%	12.5%
Multiple Races and/or Ethnicities	10.3%	10.2%	13.0%
Family Structure: 2 parents	78.7%	79.5%	61.0%
Parents PS	85.2%	86.2%	62.0%
Family Assets	-0.05 (1.1)	-0.04 (1.0)	-0.39 (1.5)
GAD	2.1 (2.3)	2.0 (2.3)	3.4 (2.9)
MDE	2.3 (2.4)	2.2 (2.3)	4.4 (3.2)
ADHD	2.5 (2.1)	2.4 (2.0)	4.2 (2.3)
ODD	2.1 (2.3)	2.0 (2.2)	4.6 (3.1)
Sports	2.1 (1.6)	2.1 (1.6)	2.1 (1.7)
Arts	1.0 (1.4)	1.0 (1.4)	0.8 (1.4)
Clubs	1.2 (1.5)	1.2 (1.5)	1.1 (1.5)
Climate	40.7 (8.5)	41.1 (8.2)	33.0 (11.7)
Belonging	8.5 (2.7)	8.6 (2.7)	6.6 (3.5)
Safety	11.1 (3.2)	11.1 (3.2)	9.4 (4.3)
Heavy Drinking[b]	8.4%	5.7%	72.2%
Cannabis[b]	3.2%	0.4%	69.9%
Tobacco[b]	4.4%	1.1%	81.4%

[a]Descriptives run using the Bayesian imputed dataset from the substance use class model presented as pooled percentages or pooled mean and standard deviations

[b]Substance use indicators not imputed, so descriptive statistics based on complete cases

Abbreviations: ESA=East Asian/Southeast Asian/South Asian; Parents PS=Parental Post-secondary Education; GAD=Generalized Anxiety Disorder symptoms; MDE=Major Depressive Episode symptoms; ADHD=Attention Deficit Hyperactivity Disorder symptoms; ODD=Oppositional Defiant Disorder symptoms

school climate, belonging, and safety had lower odds of being in the high probability of early polysubstance use class ($OR_{climate}$=0.93 [0.92-0.94]; OR_{belong}=0.85 [0.83-0.87]; OR_{safe}=0.89 [0.87-0.91]). Frequency of participation in extracurriculars was not significantly related to class membership, regardless of the type[1]. No significant gender differences emerged. See SM.4 for gender interaction models. See SM.5 for models separated by substance.

Characterizing School Classes

Based on ecological correlations[2], schools with higher proportions of students endorsing higher probabilities of polysubstance use were smaller in size, had lower median family income, lower average arts-based extracurricular participation, and lower average school climate, belonging, and safety scores than schools with lower proportions. See Table 3.

1. A series of post hoc analyses explored interactions between each extracurricular activity and: (1) family assets, (2) parental education, (3) family structure, and (4) rurality. No interactions were statistically significant. See SM.6.

2. To note, these ecological correlations are looking at associations between school classes and the entire student body within a school. Thus, these correlations do not infer student-level processes (i.e., correlation of the group of students is not a property of the individual student).

Table 2. Multilevel Logistic Regressions with Student Profile Membership[a]

	High probability of early polysubstance use class (ref=low probability)
ICC (Empty Model)	mean (min, max)
School	0.153 (0.145, 0.157)
Class	0.108 (0.104, 0.114)
Demographic Model	OR (95%CI); p-value
Female	0.84 (0.72-0.99); 0.0355
Age	**1.73 (1.6-1.86); <.0001**
Black	**1.65 (1.2-2.27); 0.0021**
ESA	**0.56 (0.41-0.77); 0.0004**
Other	1.12 (0.87-1.45); 0.3791
Multiple	1.31 (1.01-1.68); 0.038
Family Structure: 2 parents	**0.55 (0.47-0.66); <.0001**
Parents PS	**0.41 (0.34-0.49); <.0001**
Family assets	0.94 (0.87-1.01); 0.0907
Median Income (increments of $10,000)	0.93 (0.87-1); 0.04
School Size (increments of 200)	0.8 (0.67-0.94); 0.0082
Rural	1.23 (0.8-1.9); 0.3479
Mental Health Model (adjusted for demographics)	OR (95%CI); p-value
GAD	0.99 (0.95-1.04); 0.7337
MDE	**1.1 (1.05-1.15); <.0001**
ADHD	**1.13 (1.08-1.18); <.0001**
ODD	**1.25 (1.21-1.3); <.0001**
Extracurricular Model (adjusted for demographics)	OR (95%CI); p-value
Sports	0.99 (0.94-1.04); 0.7911
Art	0.95 (0.89-1.01); 0.0947
Clubs	1.05 (0.98-1.11); 0.1512
School Environment Models (adjusted for demographics)	OR (95%CI); p-value
Climate	**0.93 (0.92-0.94); <.0001**
Belonging	**0.85 (0.83-0.87); <.0001**
Safety	**0.89 (0.87-0.91); <.0001**

Bolded significant p<0.005

[a]Reported as pooled Odds Ratios (95% Confidence Interval); p-value. All models are adjusted for all demographics except the ICC model.

Abbreviations: ESA=East Asian/Southeast Asian/South Asian; Parents PS=Parental Post-secondary Education; GAD=Generalized Anxiety Disorder symptoms; MDE=Major Depressive Episode symptoms; ADHD=Attention Deficit Hyperactivity Disorder symptoms; ODD=Oppositional Defiant Disorder symptoms

Table 3. School-Level Characteristics				
	Total (n=180)	Low (n=145)	High (n=35)	p-value[a]
School Size mean (SD)	482 (185)	508 (185)	375 (147)	**<0.001**
Median Family Income, mean (SD)	84,481 (23,300)	87,199 (22,145)	73,223 (24,887)	**0.002**
Rural, n (%)	23 (13%)	16 (11%)	7 (20%)	0.16
Climate, mean (SD)	40.8 (2.6)	41.2 (2.4)	39.1 (2.9)	**<0.001**
Belonging, mean (SD)	8.5 (0.7)	8.6 (0.6)	7.9 (0.7)	**<0.001**
Safety, mean (SD)	11.0 (0.9)	11.2 (0.8)	10.5 (0.9)	**<0.001**
Sports, mean (SD)	2.2 (0.3)	2.2 (0.3)	2.3 (0.3)	0.16
Arts, mean (SD)	1.0 (0.3)	1.1 (0.3)	0.9 (0.2)	**0.002**
Clubs, mean (SD)	1.2 (0.3)	1.2 (0.3)	1.1 (0.3)	0.10

[a]p-values based on pooled univariable logistic regressions.

Discussion

In a sample of 19,130 students attending 180 schools, two student-level substance use classes and two school-level substance use classes were identified. Among students, 4.1% were assigned to the high probability of early polysubstance use class, and thus represent an at-risk group, while the remaining 95.9% were in the low probability class. Students reporting higher levels of MDE, ADHD, and ODD symptoms had a greater odds of being in the high probability of early polysubstance use class, though inclusion of mental health indicators directly into the cluster model did not yield statistically or theoretically useful classes. At the school-level, 19% of schools had higher proportions of students with a high probability of early polysubstance use (i.e., 13% vs. 2% high probability students). Perceptions of positive school climate, belonging, and safety increased the odds of students being in the low probability of early polysubstance use class and lower risk schools. Thus, school climate, belonging, and safety may provide promising targets for future universal school-based efforts to prevent early substance use.

The low and high probability student-level early polysubstance use classes reflect two of the four common substance use patterns found in a recent systematic review (16). The review was heavily based on analyses of older adolescents with the few studies focused on early adolescents reporting more limited cluster solutions similar to the present findings. For example, a study of grade 7 students in Texas found a similar 2-class model with 77.5% in a “no risk” class and the remaining in a “tobacco susceptible class” with high probabilities of cigarette and e-cigarette use or susceptibility to use in the future (52). Additionally, the analysis in the current paper did not retain mental health symptoms in the final cluster model, however, higher symptoms of MDE, ADHD, and ODD did increase the odds of students being in the polysubstance use class, consistent with prior work (16). GAD symptoms were not related to use, which is not surprising given the inconsistencies in existing evidence regarding the significance, direction, magnitude, and possible non-linear nature of associations between anxiety and substance use (53). Overall, the classes suggest that: 1) targeting multiple substances may be critical for preventing early substance use, and 2) though mental health symptoms are associated with early use, given symptoms were not retained in the final cluster-based models, this co-occurrence may not increase the differentiation of younger adolescents given substance use, symptoms, and their co-occurrence have lower prevalence and frequency until later in adolescence (23).

The proportion of students assigned to the two substance use classes significantly varied across schools, corresponding with prior work demonstrating between school differences in student substance use (28, 29). Similar to the previous findings using secondary school data from the SMHS (23), average school climate scores were significantly higher in schools with lower proportions of students endorsing polysubstance use. The present study further found average school belonging, safety, and arts participation to be higher in schools with lower proportions of students using substances. Unlike other MLCAs, the current study found median family income was lower in schools with higher proportions of student polysubstance use and rurality was not related (23, 39, 40). Overall, these findings indicate that early polysubstance use is, in part, influenced by school environments and that some schools may require more resources and supports to prevent and address early initiation.

Although directionality cannot be inferred, these findings imply that improving school climate, belonging, and safety may help schools prevent early substance use among young adolescents. Aligned with prior work, positive student perceptions of climate, belonging, and safety increased the odds of students being in the low probability of substance use class (33, 36). We did not find the effects of these school environmental factors to differ between males and females, suggesting that gender differences in schools' impact on substance use may not arise until middle to late adolescence (23, 38). Collectively, these results support the Public Health Agency of Canada's Blueprint for Action which suggests taking an expansive school-based health promotion approach (30), including building social and emotional skills, improving interpersonal relationships, increasing school belonging, and promoting school safety. More longitudinal and intervention research is needed to pinpoint the most important protective school characteristics and to identify sustainable ways to amplify these factors.

Surprisingly, frequency of extracurricular participation was not significantly related to early polysubstance use at the student-level, and only arts-activities differed at the school level. Prior studies have found that alternative substance-free activities may play a larger role in reducing the escalation of substance use, rather than preventing initiation (37). Therefore, extracurricular activities may yield protective effects in later adolescent years when substance use becomes more prevalent and frequent (1).

Consistent with other research, adolescents in the current study who reported indicators reflective of higher socioeconomic status (e.g., higher parental education, family assets, living with two parents) had lower odds of being in the high probability of early polysubstance use class (16, 37). Prior work suggests that diminished alternative reinforcement may mediate the associations between socioeconomic disparities and adolescent substance use (37, 54). Thus, extracurriculars may be particularly important among adolescents experiencing socioeconomic disparities by providing opportunities for rewarding and pleasurable activities without substances. However, extracurricular activities can be heavily driven by socioeconomic factors, whereby those with more socioeconomic advantages are more likely to participate (55); therefore, school-based extracurricular activities that increase access to alternative activities for all students are important to consider. While there was no evidence of differential effects of extracurricular participation based on indicators of socioeconomic status in the current study, future longitudinal work is merited.

Significant racial and ethnic differences also emerged between lower and higher probabilities of polysubstance use. Consistent with prior work, youth who identified as East Asian, Southeast Asian, or South Asian had a lower odds of being in the high probability class in comparison to White youth (23, 25, 56). Lower rates of substance use among Asian youth are often attributed to parenting style and disapproval of substance use, though levels of substance use tend to vary by immigrant background (25, 57). On the other hand, Black youth had higher odds of polysubstance use. In the prior review—heavily based on US samples—Black youth tended to have lower odds of polysubstance use (16). Evidence from Canada is mixed, with some finding increased odds of polysubstance use among Black youth (56) while others have found no differences (23, 25). Recent work among Black individuals in Canada aged 15-40 has found racial discrimination to be positively associated with substance use (58). More research is needed to understand these racial and ethnic disparities in early adolescent substance use, including identifying key cultural, familial, and discrimination-based correlates.

Strengths of this work include a large, representative sample of both early adolescents and elementary schools. With regard to limitations, first, causality cannot be inferred as the data are cross-sectional. Though many student and school-level confounders were included, it is possible that this does not include all relevant confounders (e.g., community activities). Related to measurement: 1) only heavy episodic drinking was assessed, not capturing students who had initiated alcohol use at lower levels; 2) substance use and mental health symptom questions had differing timeframes; 3) students were not explicitly asked about gender or sex and only offered binary options— some students were likely misclassified and there is a risk that sex and gender were conflated; and 4) despite strong psychometric properties, self-reported mental health symptom measures should be interpreted as indicators, rather than diagnoses. It is also important to acknowledge that this data was collected in 2014-2015; over the past decade, tobacco use among youth has declined but e-cigarette use has increased (1). As such, this exploration should be replicated in a more contemporary sample to identify consistent and emerging risk and protective factors over time. Lastly, 87% of the sample were from urban schools and schools in Indigenous settings were not included, constraining generalizability.

In a large representative sample of grade 6 to 8 students, this study identified two distinct classes of individuals characterized by low and high probabilities of early polysubstance use, and subsequently likewise identified two distinct classes of elementary schools, characterized by greater or lesser distributions of these student classes. The early polysubstance use class can serve as a target for the development and evaluation of prevention and early intervention efforts. The results suggest schools are important contexts for substance use interventions and improving school climate, belonging, and safety may be key mechanisms to address with future interventions.

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Contributors

JH conceived of and designed the secondary analysis. JH led the data cleaning, data analyses, interpretation of results, and writing. JM, SA, CM, MA, and KG provided methodological and substantive support throughout the design, interpretation, and manuscript process. JH drafted the first version of the manuscript and was responsible for editing, submitting, and responding to reviewers. All authors approved the final version of the article.

Conflict of Interest

No authors have conflicts of interest except JM, who is a Principal in BEAM Diagnostics, Inc and Consultant to Clairvoyant Therapeutics.

References

1. Boak A, Elton-Marshall, T., Mann, RE, & Hamilton, HA. Drug use among Ontario students, 1977-2019: Detailed Findings from the Ontario Student Drug Use and Health Survey (OSDUHS). Toronto, ON: Centre for Addiction and Mental Health; 2020.
2. Gobbi G, Atkin T, Zytynski T, Wang S, Askari S, Boruff J, et al. Association of cannabis use in adolescence and risk of depression, anxiety, and suicidality in young adulthood: A systematic review and meta-analysis. JAMA Psychiatry. 2019;76(4):426-34. 10.1001/jamapsychiatry.2018.4500
3. Ahuja M, Awasthi M, Records K, Lamichhane RR. Early age of alcohol initiation and its association with suicidal behaviors. Subst Use Misuse. 2021:1-7. doi: 10.1080/10826084.2021.1922452
4. Moss HB, Chen CM, Yi H. Early adolescent patterns of alcohol, cigarettes, and marijuana polysubstance use and young adult substance use outcomes in a nationally representative sample. Drug Alcohol Depend. 2014;136:51-62. doi: 10.1016/j.drugalcdep.2013.12.011
5. Jamal M, Does AJ, Penninx BW, Cuijpers P. Age at smoking onset and the onset of depression and anxiety disorders. Nicotine Tob Res. 2011;13(9):809-19. doi: 10.1093/ntr/ntr077
6. Jordan CJ, Andersen SL. Sensitive periods of substance abuse: Early risk for the transition to dependence. Dev Cogn Neurosci. 2017;25:29-44. doi: 10.1016/j.dcn.2016.10.004
7. Behrendt S, Wittchen H-U, Höfler M, Lieb R, Beesdo K. Transitions from first substance use to substance use disorders in adolescence: is early onset associated with a rapid escalation? Drug Alcohol Depend. 2009;99(1-3):68-78. doi: 10.1016/j.drugalcdep.2008.06.014
8. Rioux C, Castellanos-Ryan N, Parent S, Vitaro F, Tremblay RE, Séguin JR. Age of cannabis use onset and adult drug abuse symptoms: A prospective study of common risk factors and indirect effects. Can J Psychiatry. 2018;63(7):457-64. doi: 10.1177/0706743718760289
9. Lopez-Quintero C, de los Cobos JP, Hasin DS, Okuda M, Wang S, Grant BF, et al. Probability and predictors of transition from first use to dependence on nicotine, alcohol, cannabis, and cocaine: Results of the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC). Drug Alcohol Depend. 2011;115(1-2):120-30. doi: 10.1016/j.drugalcdep.2010.11.004
10. Aiken A, Clare PJ, Wadolowski M, Hutchinson D, Najman JM, Slade T, et al. Age of alcohol initiation and progression to binge drinking in adolescence: A prospective cohort study. Alcohol Clin Exp Res. 2018;42(1):100-10. doi: 10.1111/acer.13525
11. Kuntsche E, Rossow I, Simons?Morton B, Bogt TT, Kokkevi A, Godeau E. Not early drinking but early drunkenness is a risk factor for problem behaviors among adolescents from 38 European and North American countries. Alcohol Clin Exp Res. 2013;37(2):308-14. doi: 10.1111/j.1530-0277.2012.01895.x
12. Riala K, Hakko H, Isohanni M, Järvelin M-R, Räsänen P. Teenage smoking and substance use as predictors of severe alcohol problems in late adolescence and in young adulthood. J Adolesc Health. 2004;35(3):245-54. doi: 10.1016/j.jadohealth.2003.08.016
13. Hayatbakhsh MR, Najman JM, Jamrozik K, Mamun AA, Alati R, Bor W. Cannabis and anxiety and depression in young adults: A large prospective study. J Am Acad Child Adolesc Psychiatry. 2007;46(3):408-17. doi: 10.1097/chi.0b013e31802dc54d
14. Fergusson DM, Horwood LJ, Swain?Campbell N. Cannabis use and psychosocial adjustment in adolescence and

young adulthood. Addiction. 2002;97(9):1123-35. doi: 10.1046/j.1360-0443.2002.00103.x

15. Choi SH, Stommel M. Impact of age at smoking initiation on smoking-related morbidity and all-cause mortality. Am J Prev Med. 2017;53(1):33-41. doi: 10.1016/j.amepre.2016.12.009
16. Halladay J, Woock R, El-Khechen H, Munn C, MacKillop J, Amlung M, et al. Patterns of substance use among adolescents: a systematic review. Drug Alcohol Depend. 2020:108222. doi: 10.1016/j.drugalcdep.2020.108222
17. Banks DE, Rowe AT, Mpofu P, Zapolski TCB. Trends in typologies of concurrent alcohol, marijuana, and cigarette use among US adolescents: An ecological examination by sex and race/ethnicity. Drug Alcohol Depend. 2017;179:71-7. https://doi.org/10.1016/j.drugalcdep.2017.06.026
18. Connor JP, Gullo MJ, White A, Kelly AB. Polysubstance use: Diagnostic challenges, patterns of use and health. Curr Opin Psychiatry. 2014;27(4):269-75. https://doi.org/10.1097/yco.0000000000000069
19. Yurasek AM, Aston ER, Metrik J. Co-use of alcohol and cannabis: A review. Curr Addict Rep. 2017;4(2):184-93. doi: 10.1007/s40429-017-0149-8
20. Kokkevi A, Kanavou E, Richardson C, Fotiou A, Papadopoulou S, Monshouwer K, et al. Polydrug use by European adolescents in the context of other problem behaviours. Nord Stud Alcohol Drugs. 2014;31(4):323-42. https://doi.org/10.2478/nsad-2014-0026
21. Kelly AB, Evans-Whipp TJ, Smith R, Chan GCK, Toumbourou JW, Patton GC, et al. A longitudinal study of the association of adolescent polydrug use, alcohol use and high school non-completion. Addiction. 2015;110(4):627-35. https://doi.org/https://doi.org/10.1111/add.12829
22. Vanyukov MM, Ridenour TA. Common liability to drug addictions: Theory, research, practice. Drug Alcohol Depend. 2012;123(0 1):S1. doi: 10.1016/j.drugalcdep.2012.01.005
23. Halladay J, MacKillop J, Munn C, Amlung M, Georgiades K. Individual-and school-level patterns of substance use and mental health symptoms in a population-based sample of secondary students: A multilevel latent profile analysis. Drug Alcohol Depend. 2022;240:109647. doi: 10.1016/j.drugalcdep.2022.109647
24. McInnis OA, Young MM, Saewyc E, Jahrig J, Adlaf E, Lemaire J, et al. Urban and Rural Student Substance Use. Ottawa, Ont: Canadian Centre on Substance Abuse; 2015
25. Hamilton HA, Owusu-Bempah A, Boak A, Mann RE. Ethnoracial differences in cannabis use among native-born and foreign-born high school students in Ontario. J Ethn Subst Abuse. 2018;17(2):123-34. doi: 10.1080/15332640.2017.1312655
26. Lee JO, Cho J, Yoon Y, Bello MS, Khoddam R, Leventhal AM. Developmental pathways from parental socioeconomic status to adolescent substance use: Alternative and complementary reinforcement. J Youth Adolesc. 2018;47(2):334-48. doi: 10.1007/s10964-017-0790-5
27. Hoffmann JP. Family structure and adolescent substance use: an international perspective. Subst Use Misuse. 2017;52(13):1667-83. doi: 10.1080/10826084.2017.1305413
28. Hale DR, Patalay P, Fitzgerald-Yau N, Hargreaves DS, Bond L, Gorzig A, et al. School-level variation in health outcomes in adolescence: analysis of three longitudinal studies in England. Prev Sci. 2014;15(4):600-10. doi: 10.1007/s11121-013-0414-6
29. Shackleton N, Hale D, Bonell C, Viner RM. Intraclass correlation values for adolescent health outcomes in secondary schools in 21 European countries. SSM Popul Health. 2016;2:217-25. doi: 10.1016/j.ssmph.2016.03.005
30. Public Health Agency of Canada. Blueprint for action: Preventing substance-related harms among youth through a comprehensive school health approach. Ottawa, ON; 2021.
31. Kristjansson AL, Mann MJ, Sigfusson J, Thorisdottir IE, Allegrante JP, Sigfusdottir ID. Development and guiding principles of the Icelandic model for preventing adolescent substance use. Health Promot Pract. 2020;21(1):62-9. doi: 10.1177/1524839919849032
32. Aldridge JM, McChesney K. The relationships between school climate and adolescent mental health and wellbeing: A systematic literature review. Int J Educ Res. 2018;88:121-45. https://doi.org/10.1016/j.ijer.2018.01.012
33. Daily SM, Mann MJ, Lilly CL, Bias TK, Smith ML, Kristjansson AL. School climate as a universal intervention to prevent substance use initiation in early adolescence: A longitudinal study. Health Educ Behav. 2020;47(3):402-11. doi: 10.1177/1090198120914250
34. Ford T, Degli Esposti M, Crane C, Taylor L, Montero-Marín J, Blakemore S-J, et al. The role of schools in early adolescents' mental health: Findings from the MYRIAD study. J Am Acad Child Adolesc Psychiatry. 2021. doi: 10.1016/j.jaac.2021.02.016
35. Bear GG, Yang C, Pell M, Gaskins C. Validation of a brief measure of teachers' perceptions of school climate: Relations to student achievement and suspensions. Learn Environ Res. 2014;17(3):339-54. https://doi.org/10.1007/s10984-014-9162-1
36. Fletcher A, Bonell C, Hargreaves J. School effects on young people's drug use: A systematic review of intervention and observational studies. J Adolesc Health. 2008;42(3):209-20. doi: 10.1016/j.jadohealth.2007.09.020
37. Leventhal AM, Bello MS, Unger JB, Strong DR, Kirkpatrick MG, Audrain-McGovern J. Diminished alternative reinforcement as a mechanism underlying socioeconomic disparities in adolescent substance use. Prev Med. 2015;80:75-81. doi: 10.1016/j.ypmed.2015.05.021.
38. Langille DB, Asbridge M, Cragg A, Rasic D. Associations of school connectedness with adolescent suicidality: Gender differences and the role of risk of depression. Can J Psychiatry. 2015;60(6):258-67. doi: 10.1177/070674371506000604
39. Lee Y, Kim Y, Leatherdale ST, Chung H. Multilevel latent class profile analysis: An application to stage-sequential patterns of alcohol use in a sample of Canadian youth. Eval Health Prof. 2021;44(1):50-60. doi: 10.1177/0163278721989547
40. Gohari MR, Cook RJ, Dubin JA, Leatherdale ST. Identifying patterns of alcohol use among secondary school students in Canada: A multilevel latent class analysis. Addict Behav. 2020;100:106120. doi: 10.1016/j.addbeh.2019.106120.
41. Solmi M, Radua J, Olivola M, Croce E, Soardo L, de Pablo GS, et al. Age at onset of mental disorders worldwide: Large-scale

meta-analysis of 192 epidemiological studies. Mol Psychiatry. 2021:1-15. doi: 10.1038/s41380-021-01161-7

42. Boyle MH, Georgiades K, Duncan L, Comeau J, Wang L, OCHS Team. The 2014 Ontario Child Health Study—methodology. Can J Psychiatry. 2019;64(4):237-45. doi: 10.1177/0706743719833675
43. Statistics Canada. National Longitudinal Survey of Children and Youth: Cycle 8 Survey Instruments 2008/2009 Book 2 - Youth Questionnaires. Ottawa, ON: Statistics Canada; 2009.
44. Duncan L, Georgiades K, Wang L, Comeau J, Ferro MA, Van Lieshout RJ, et al. The 2014 Ontario Child Health Study Emotional Behavioural Scales (OCHS-EBS) Part I: A checklist for dimensional measurement of selected DSM-5 disorders. Can J Psychiatry. 2018:0706743718808250. doi: 10.1177/0706743718808250
45. Bear G, Yang C, Mantz L, Pasipanodya E, Hearn S, Boyer D. Technical manual for Delaware school survey: Scales of school climate, bullying, victimization, student engagement, positive, punitive, and social emotional learning techniques. 2014.
46. National Longitudinal Study of Adolescent to Adult Health (Add Health), 1994-2008 [Public Use] [Internet]. Carolina Population Center, University of North Carolina-Chapel Hill. 2001. Available from: http://www.icpsr.umich.edu/icpsrweb/DSDR/studies/21600.
47. Consortium on Chicago School Research. Survey of Chicago Public Schools Elementary School Student Edition Chicago, IL: Consortium on Chicago School Research, Urban Education Institute, University of Chicago; 2009.
48. Masyn KE. 25 latent class analysis and finite mixture modeling. The Oxford Handbook of Quantitative Methods. 2013:551.
49. Mäkikangas A, Tolvanen A, Aunola K, Feldt T, Mauno S, Kinnunen U. Multilevel latent profile analysis with covariates: Identifying job characteristics profiles in hierarchical data as an example. Organ Res Methods. 2018;21(4):931-54. https://doi.org/10.1177/109442811876069
50. Graham JW. Missing data analysis: Making it work in the real world. Annu Rev Psych. 2009;60:549-76. doi: 10.1146/annurev.psych.58.110405.085530
51. Keller BT, Enders CK. Blimp user's guide (Version 3). Los Angeles, CA2021.
52. Delk J, Carey FR, Case KR, Creamer MR, Wilkinson AV, Perry CL, et al. Adolescent tobacco uptake and other substance use: A latent class analysis. Am J Health Behav. 2019;43(1):3-14. doi: 10.5993/AJHB.43.1.1
53. Cerdá M, Sagdeo A, Galea S. Comorbid forms of psychopathology: Key patterns and future research directions. Epidemiol Rev. 2008;30(1):155-77. doi: 10.1093/epirev/mxn003
54. Andrabi N, Khoddam R, Leventhal AM. Socioeconomic disparities in adolescent substance use: Role of enjoyable alternative substance-free activities. Soc Sci Med. 2017;176:175-82. doi: 10.1016/j.socscimed.2016.12.032.
55. Guèvremont A, Findlay L, Kohen D. Organized extracurricular activities of Canadian children and youth. Health Rep. 2008;19(3):65. PMID: 18847147
56. Zuckermann AME, Williams GC, Battista K, Jiang Y, de Groh M, Leatherdale ST. Prevalence and correlates of youth poly-substance use in the COMPASS study. Addict Behav. 2020;107:106400. doi: 10.1016/j.addbeh.2020.106400
57. Lee MH, Kim-Godwin YS, Hur H. Race/ethnicity differences in risk and protective factors for marijuana use among U.S. adolescents. BMC Public Health. 2021;21(1):1167. https://doi.org/10.1186/s12889-021-11159-z
58. Cénat JM, Dromer É, Auguste E, Dalexis RD, Darius WP, Kogan CS, et al. Frequency and factors related to substance use among Black individuals aged 15–40 years old in Canada: The role of everyday racial discrimination. Psychol Addict Behav. 2023. doi: 10.1037/adb0000913

SUPPLEMENTAL MATERIAL

1. Detailed missing data
2. Detailed mixture modeling results for elementary students
3. Detailed school level MLCA results
4. Gender interaction results
5. Separate regression models for use of each substance
6. Post-hoc extracurricular and socioeconomic disadvantage interactions

1. Detailed missing data

Prior to examining missingness, mean substitution was used within summative scale variables for those with <=30% missingness. There were 386 missing data patterns where about 64.7% were complete cases (See table 1.1 for detailed results). Specifically, 96.2% had complete mental health related data and 95.1% had complete substance use responses. Missingness was addressed using Full Information Maximum Likelihood (FIML) in cluster analyses. However, 31.6% of the sample had at least one demographic variable missing, with the highest missing on parental education (28.4%) followed by family assets (6.1%), family structure (4.9%), then race/ethnicity (1.9%).

To explore differences in students with and without missing data, a series of multilevel (students, classes, schools) logistic regressions were performed to evaluate missingness for any variable. Any missing was coded as a 1 and those with complete data were coded as 0. Missingness was significantly more likely among students who were male, younger, Black, 'other' racial minority, and came from families with lower family assets and <2 parents (other demographics not significant). Substance use was not significantly related to missing. Regarding predictor variables of interest, higher ADHD, ODD, and depression symptoms, and lower school belonging, safety, and extracurricular participation were related to missingness. Further, clustering in classes and schools accounted for about 4.6% and 2.5% of the variability in missing respectively. See Table 1.2 for detailed results.

Thus, MMI was conducted using a fully Bayesian model-based imputation approach with the full conditional Metroplis sampler, latent cluster means, and non-informative priors (20 imputations); a logit function was applied to the dependent variable (substance use profile membership), categorical predictors were specified, and all predictor associations were left unspecified (full details available here: Blimp 3.0).

Table 1.1 Percentage of variable missingness

	Missing n (%)
HED	693 (3.62%)
Cannabis	824 (4.31%)
Smoking	751 (3.93%)
Female	96 (0.5%)
Age	72 (0.32%)
Race and/or Ethnicity	366 (1.91%)
2 parents	941 (4.92%)
Parents PS	5425 (28.36%)
Assets	1171 (6.12%)
Anxiety	671 (3.51%)
Depression	578 (3.02%)
ADHD	519 (2.71%)
ODD	542 (2.83%)
Sports	335 (1.75%)
Arts	468 (2.45%)
Clubs	417 (2.18%)
Climate	160 (0.84%)
Belonging	271 (1.42%)
Safety	187 (0.98%)
Median family Income	0%
Enrolment	0%
Rural*	0%
All Complete	12381 (64.72%)
Missing only 1	4713 (24.64%)
Complete Mental health	18401 (96.19%)
Complete Substance Use	18187 (95.07%)
Complete Predictors	18316 (95.74%)
Complete Covariates	18316 (68.41%)

*note: where rural/urban designation was missing based on postal code [k=5 schools, n=656 students], the primary sampling unit designation was used [all urban]

1.2 Multilevel logistic regressions predicting missingness

Any substance or mental health missing	Missing OR (95% CI) p-value
Female	0.82 (0.77-0.87); <.0001
Age	0.77 (0.75-0.8); <.0001
Family Assets	0.83 (0.8-0.86); <.0001
2 parents	0.77 (0.71-0.83); <.0001
Parents PS	0.86 (0.73-1.01); 0.0658
ESA	0.96 (0.86-1.06); 0.3689
Black	0.82 (0.77-0.87); <.0001
Other	1.37 (1.23-1.52); <.0001
Multiracial	1.02 (0.92-1.14); 0.6643
School Size	<1.00 (1.00-1.00); <.0001
Median Income	<1.00 (1.00-1.00); <.0001
Rural	1.11 (0.93-1.34); 0.2488
Heavy Drinking	0.96 (0.86-1.08); 0.5165
Cannabis	1.04 (0.87-1.25); 0.6695
Tobacco	1.16 (0.99-1.35); 0.062
Anxiety	1.01 (1-1.03); 0.0534
Depression	1.03 (1.01-1.04); 0.0002
ADHD	1.09 (1.08-1.11); <.0001
ODD	1.04 (1.03-1.06); <.0001
Climate	1 (1-1); 0.5911
Belonging	0.97 (0.96-0.98); <.0001
Safety	0.96 (0.95-0.97); <.0001
Sports	0.93 (0.91-0.94); <.0001
Art	0.91 (0.89-0.93); <.0001
Clubs	0.95 (0.93-0.97); <.0001

2. Student Level Mixture Model Elementary students

Detailed Methods

Substance use and mental health patterns were identified through mixture modelling using Mplus (version 7) including indicators for substance use (HED, CAN, TOB) and indicators for mental health symptomatology (GAD, MDE, ADHD, ODD). Random split halves were generated for split sample cross-validation (51). Bivariate residuals were examined to evaluate tenability of the local independence assumption (TECH10, whereby a residual >=1.96 was significant) (52). Due to unanticipated issues with models combining substance use and mental health indicators in one cluster model, post hoc analyses were explored whereby: 1) mental health symptom indicators were coded as binary indicators with adolescents scoring >=1SD on the summative scores coded as a 1, and 2) only substance use indicators were included. Using the first split half, models were estimated for 1 profile up until k profiles when the model no longer converged with up to 500 random starts or when BIC began to increase (51-53). The following class enumeration diagnostics were compared across models: convergence, BIC and Corrected Akaike's Information Criterion (CAIC; both assessing for smaller scores and elbow on a line graph of estimates), Approximate Weight of Evidence Criterion (AWE), Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT), bootstrapped likelihood ratio test (BLRT), and Relative Improvement (RI) (51, 52). Models were also compared quantitatively and qualitatively based on clinical relevance of latent class separation, with quantitative class separation diagnostics including: posterior class probability (p), model class assignment proportion (mcaP), average posterior probability (AgePP >0.9), odds of correct classification (OCC>5), and overall entropy (>0.9) for the k-profile model (51, 52). Lastly, indicator specific class homogeneity and separation were also explored. Class homogeneity was explored for binary indicators using indicator probabilities, whereby high homogeneity was defined as probabilities >0.7 or <0.3, and for continuous indicators within class indicator variance was compared to overall sample variance whereby ratios of >0.9 indicate low homogeneity and <0.6 indicate high homogeneity (52). Class indicator separation as examined using odds ratios (ORs) for binary indicators whereby ORs > 5 or <0.2 indicated high separation, and standardized mean differences (SMDs) for continuous indicators whereby SMDs >2 indicated high separation and <0.85 reflect low separation (52). Using the second split half, the best model was replicated by fixing parameter estimates based on the first split half estimates (51). The same K-class models but with freed parameters were also estimated and compared using the same diagnostics as above. As the sample sizes were large, nested likelihood ratio tests to compare fit were not examined. Subsequently, all models explained for split half 1 were re-estimated in split half two to see if all model estimates converged on the same final model selection. The best fitting model was re-estimated in the full sample. Full Information Maximum Likelihood (FIML) was used in all cluster analyses. Measurement invariance across gender was then examined by: 1) stratifying the sample into males and females and re-estimating best fitting models, and 2) using multi-group functioning where groups were i) constrained to have equal parameter estimates versus ii) freed parameter estimates (8, 10). Models were compared based on BIC and CAIC, AWE. Models were also compared quantitatively and qualitatively based on clinical relevance of latent class separation.

Table 2.1 Model enumeration fit statistics

k-classes	LL	Npar	BIC	CAIC	AWE	LMR-LRT p-value	BLRT p-value	Relative Improvement
Random Split Half 1 (n=9348)								
Substance use (dichotomous) and mental health (continuous) indicators								
1	-88454.673	11	176931.347	176964.024	176969.524	n/a	n/a	n/a
2	-82874.699	19	165923.113	165843.842	165853.342	0.0000	0.0000	n/a
3	-81199.517	27	162645.893	162533.243	162546.743	0.0000	0.0000	0.30021323
4	-80356.806	35	161033.615	160887.587	160905.087	0.0313	0.0324	0.15102418
5	-79792.649	43	159978.444	159799.039	159820.539	0.0047	0.0050	0.10110388
6	-78829.855	51	158125.998	157913.217	157938.717	0.0000	0.0000	0.17254453
7	-78484.169	59	157507.77	157261.61	157291.11	0.0000	0.0000	0.06195118
Substance use (dichotomous) and mental health (dichotomous) indicators								
1	-21807.669	7	43679.339	43650.133	43653.633	n/a	n/a	n/a
2	-19668.399	15	39473.941	39411.3588	39418.8588	0.0000	0.0000	
3	-19207.922	23	38626.271	38530.1705	38541.6705	0.0000	Not repl.	0.21524959
4	Convergence issues							
Substance use only indicators								
1	-5717.438	3	11462.28	11449.7882	11451.2882	n/a	n/a	n/a
2	-4837.681	7	9739.302	9710.15703	9713.65703	0.0000	0.0000	n/a
3	parameters had to be fixed for the purpose of estimation, entropy was 0.440							
Random Split Half 2 (n=9364)								
Substance use and mental health indicators								
1	-88259.666	11	176619.924	176574.018	176579.518	n/a	n/a	n/a
2	-82603.541	19	165380.83	165301.54	165311.04	0.0000	0.0000	n/a
3	-81135.985	27	162518.876	162406.199	162419.699	0.0000	0.0000	0.25946315
4	-80204.499	35	160729.06	160582.999	160600.499	0.0000	0.0000	0.16468625
5	-79691.763	43	159776.745	159597.299	159618.799	0.0005	0.0006	0.09065146
6	-78734.939	51	157936.253	157723.423	157748.923	0.0000	0.0000	0.16916599
7	-78434.58	59	157408.694	157162.476	157191.976	0.4952	0.4986	0.05310332
Substance use only indicators								
1	-5479.383	3	10986.165	10973.6804	10975.1804	n/a	n/a	n/a
2 - freed	-4622.809	7	9309.553	9280.41823	9283.91823	0.0000	0.0000	n/a
2 - fixed	-4634.36	1	9277.853	9273.69146	9274.19146	0.0000	0.0000	n/a
3	parameters had to be fixed for the purpose of estimation							
Full Sample (n=18528)								
Substance use indicators								
2	-9466.421	7	19001.631	18969.7168	18973.2168	0.0000	0.0000	n/a

continued

k-classes	LL	Npar	BIC	CAIC	AWE	LMR-LRT p-value	BLRT p-value	Relative Improvement
Table 2.1 continued								
Gender Invariance (n=18528)								
Substance use indicators								
2 - fixed	-22136.405	9	44361.208	44320.201	44324.701			
2 - free	-22111.269	15	44369.868	44301.523	44309.023			
M - 1	-5795.461	3	9990.587	11632.9909	11634.4909			
M - 2	-4963.514	7	9990.587	9961.63108	9965.13108	0.0000	0.0000	n/a
M -3	Did not converge							
F -1	-5277.856	3	10583.238	10570.6669	10572.1669			
F - 2	-4390.095	7	8844.42	8815.08484	8818.58484	0.0000	0.0000	n/a
F - 3	Did not converge							

Figure 2.1 Elbow plots of model fit indices for combined substance use and mental health models - random split half models

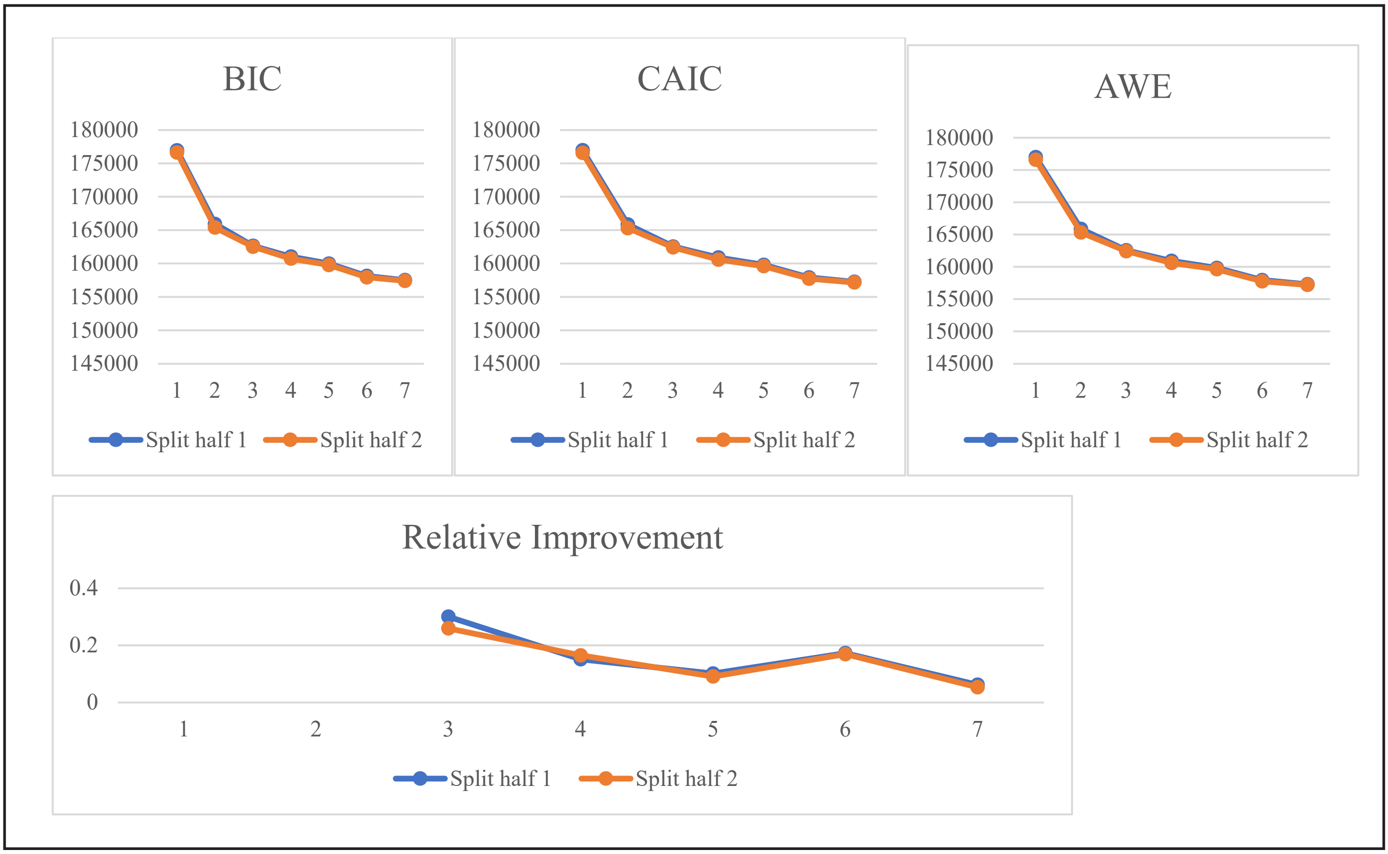


Table 2.2 Class Diagnostics

	n assigned	Posterior class probability (90% CI)	mcalPK (90% CI)	AvePPK	OCCK	Entropy
Random Split Half 1 (n=9348)						
2 cluster mixture model (combined)						
1	7088	0.753 (0.744, 0.763)	0.758	0.97	10.6	0.863
2	2260	0.247 (0.237, 0.256)	0.242	0.927	38.8	
3 cluster mixture model (combined)						
1	6054	0.640 (0.631, 0.651)	0.648	0.958	12.8	0.876
2	2663	0.291 (0.281, 0.300)	0.285	0.911	25.0	
3	631	0.069 (0.063, 0.074)	0.068	0.938	205.6	
2 cluster LCA (substance use only)						
1	8939	0.957 (0.952, 0.961)	0.965	0.991	5.0	0.951
2	329	0.043 (0.039, 0.048)	0.036	0.97	715.6	
Random Split Half 2 (n=9364)						
2 cluster mixture model (combined)						
1	7155	0.759 (0.750, 0.769)	0.764	0.972	11.0	0.866
2	2209	0.240 (0.231, 0.250)	0.236	0.928	40.7	
3 cluster mixture model (combined)						
1	664	0.073 (0.067, 0.079)	0.071	0.929	166.2	0.865
2	6058	0.640 (0.630, 0.651)	0.647	0.966	16.0	
3	2642	0.287 (0.277, 0.296)	0.282	0.885	19.1	
2 cluster LCA (substance use only) - freed						
1	8934	0.957 (0.953, 0.961)	0.965	0.991	4.9	0.951
2	326	0.043 (0.039, 0.047)	0.035	0.963	580.1	
2 cluster LCA (substance use only) - fixed						
1	8940	0.958 (0.952, 0.962)	0.965	0.999	44.0	0.952
2	320	0.042 (0.038, 0.046)	0.035	0.792	86.5	
Full Sample (n=18528)						
2 cluster mixture model (substance use)						
1	650	0.043 (0.039, 0.047)	0.035	0.97	717.3	0.95
2	17878	0.957 (0.953, 0.961)	0.965	0.991	5.0	

continued

Table 2.2 continued

	n assigned	Posterior class probability (90% CI)	mcalPK (90% CI)	AvePPK	OCCK	Entropy
Fixed Gender Invariant Model (n=18436)						
2 cluster mixture model (substance use)						
1 - Male	330	0.021 (0.018, 0.024)	0.018	0.958	1051.1	0.975
2 - Male	8446	0.455 (0.444, 0.465)	0.458	0.991	132.0	
1 - Female	314	0.022 (0.019, 0.025)	0.017	0.981	2317.9	
2 - Female	9346	0.502 (0.491, 0.513)	0.507	0.99	98.1	
Free Gender Model (n=18436)						
2 cluster mixture model (substance use)						
1	8439	0.452 (0.443, 0.463)	0.458	0.987	0.987	0.974
2	337	0.024 (0.020, 0.027)	0.018	0.967	0.967	
1	9347	0.504 (0.493, 0.514)	0.507	0.993	0.993	
2	313	0.020 (0.017, 0.023)	0.017	0.969	0.969	

3. Detailed Elementary School level MLCA results

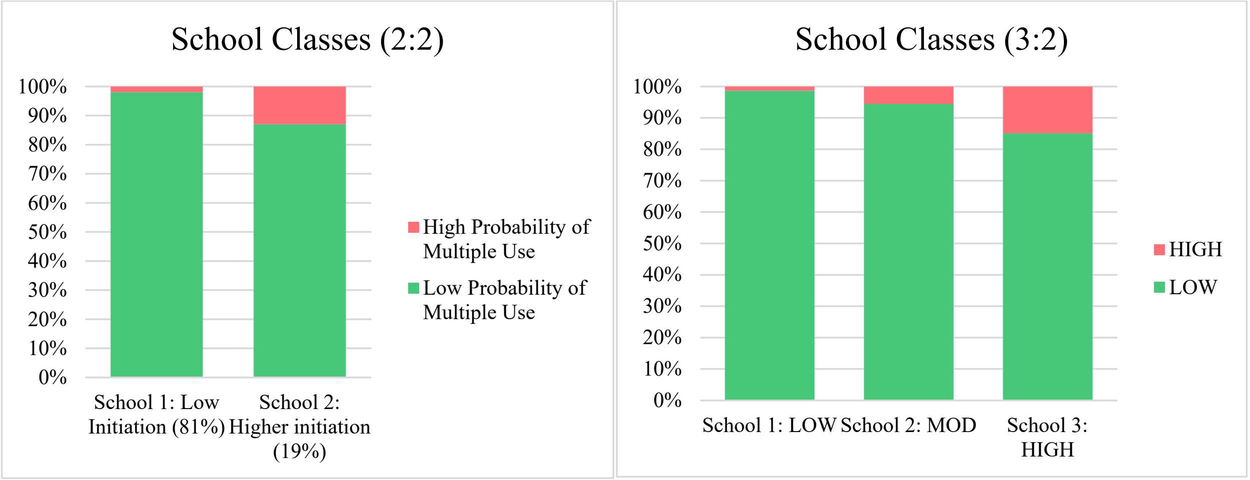
Table 3.1 Model enumeration fit statistics (n=18528)

k-classes	LL	Npar	BIC	CAIC	AWE	Entropy
school 1	-9466.421	7	19001.631	18969.7168	18973.2168	0.95
school 2	-9360.186	9	18808.815	18767.7825	18772.2825	0.893
school 3	-9346.998	11	18802.093	18751.9421	18757.4421	0.774
school 4	-9341.619	13	18810.99	18751.7198	18758.2198	0.773

Table 3.2 Class Diagnostics

	n assigned	Posterior class probability (90% CI)	mcalPK	AvePPK	OCCK	Entropy
2-School class model						
School 1- HIGH	410 (12.8%)	0.024 (0.020, 0.027)	0.022	0.833	207.088	0.893
School 1 - LOW	2798 (87.2%)	0.162 (0.154, 0.170)	0.151	0.884	39.487	
School 2 - HIGH	349 (2.3%)	0.024 (0.021, 0.027)	0.019	0.895	347.079	
School 2 - LOW	14971 (97.7%)	0.791 (0.782, 0.799)	0.808	0.959	6.190	
3-School class model						
School 1 - HIGH	144 (1.4%)	0.011(0.009, 0.013)	0.008	0.777	320.336	0.774
School 1- HIGH	10490 (98.6%)	0.543 (0.532, 0.553)	0.566	0.870	5.642	
School 2 - LOW	331 (5.5%)	0.021 (0.018, 0.024)	0.018	0.751	139.520	
School 2 - HIGH	5659 (94.5%)	0.320 (0.310, 0.330)	0.305	0.770	7.103	
School 3 - LOW	284 (14.9%)	0.015 (0.013, 0.018)	0.019	0.787	237.325	
School 3- HIGH	1620 (85.1%)	0.087 (0.081, 0.093)	0.080	0.806	43.360	

Figure 3.1. Visual representation of the proportion of student classes within school classes



4. Gender interaction results

Table 4.1. Multilevel Logistic Regressions with Student Profiles Membership, Gender Interactions

	Early Polysubstance Use Class (ref=Non-Use Class)
Mental Health Model (adjusted for demographics)	OR (95%CI); p-value
GAD	0.97 (0.9-1.03); 0.2979
GAD*Female	1.05 (0.96-1.15); 0.3231
MDE	1.05 (0.98-1.12); 0.1355
MDE*Female	1.08 (0.99-1.18); 0.0885
ADHD	1.08 (1.01-1.15); 0.0242
ADHD*Female	1.1 (1.01-1.21); 0.0318
ODD	1.28 (1.22-1.35); <.0001
ODD*Female	0.96 (0.9-1.03); 0.2908
Extracurricular Model (adjusted for demographics)	OR (95%CI); p-value
Sports	1.01 (0.95-1.09); 0.6804
Sports*Female	0.96 (0.87-1.06); 0.3885
Art	1 (0.91-1.1); 0.9468
Art*Female	0.9 (0.79-1.02); 0.0966
Clubs	1.11 (1.02-1.21); 0.0169
Clubs*Female	0.89 (0.79-1); 0.052
School Environment Models (adjusted for demographics)	OR (95%CI); p-value
Climate	0.93 (0.92-0.94); <.0001
Climate*Female	0.99 (0.97-1); 0.1615
Belonging	0.88 (0.84-0.91); <.0001
Belonging*Female	0.95 (0.9-0.99); 0.0299
Safety	0.9 (0.88-0.93); <.0001
Safety*Female	0.97 (0.93-1.01); 0.1862

Bolded significant p<0.005

[a]Reported as pooled Odds Ratios (95% Confidence Interval); p-value. All models are adjusted for all demographics.

5. Separate regression models for use of each substance

Table 5.1. Multilevel Logistic Regressions Predicting Student Profile Membership for use of each substance separately

	Substance Use Class *focus of manuscript (ref=Non-Use Class)	Any Heavy Drinking (ref=None)	Any Cannabis Initiation (ref=None)	Any Smoking Initiation (ref=None)
	mean (min, max)	mean (min, max)	mean (min, max)	mean (min, max)
ICC (Empty Model)				
School	0.153 (0.145, 1.57)	0.052 (0.050, 0.054)	0.092 (0.084, 0.097)	0.080 (0.074, 0.086)
Class	0.108 (0.104, 0.114)	0.074 (0.068, 0.080)	0.135 (0.127, 0.144)	0.087 (0.082, 0.091)
	OR (95%CI); p-value	OR (95%CI); p-value	OR (95%CI); p-value	OR (95%CI); p-value
Demographic Model				
Female	0.84 (0.72-0.99); 0.0355*	**0.72 (0.65-0.81); <.0001**	**0.77 (0.65-0.92); 0.0046**	**0.78 (0.68-0.91); 0.0011**
Age	**1.73 (1.6-1.86); <.0001**	**1.53 (1.45-1.62); <.0001**	**1.78 (1.64-1.94); <.0001**	**1.59 (1.49-1.71); <.0001**
Black	**1.65 (1.2-2.27); 0.0021**	1.29 (1.02-1.63); 0.0349*	**1.86 (1.35-2.58); 0.0002**	1.45 (1.07-1.96); 0.0151*
ESA	**0.56 (0.41-0.77); 0.0004**	**0.56 (0.46-0.69); <.0001**	**0.48 (0.33-0.68); <.0001**	0.7 (0.54-0.92); 0.0108*
Other	1.12 (0.87-1.45); 0.3791	1.09 (0.91-1.31); 0.3406	0.94 (0.69-1.27); 0.6769	1.33 (1.05-1.69); 0.0195*
Multiple	1.31 (1.01-1.68); 0.038*	1.12 (0.94-1.35); 0.2023	1.19 (0.9-1.58); 0.2129	1.31 (1.03-1.68); 0.0294*
2 parents	**0.55 (0.47-0.66); <.0001**	**0.68 (0.6-0.77); <.0001**	**0.58 (0.48-0.71); <.0001**	**0.53 (0.45-0.63); <.0001**
Parents PS	**0.41 (0.34-0.49); <.0001**	**0.56 (0.48-0.65); <.0001**	**0.39 (0.31-0.48); <.0001**	**0.46 (0.37-0.56); <.0001**
Family assets	0.94 (0.87-1.01); 0.0907	1.02 (0.96-1.08); 0.4995	0.89 (0.82-0.97); 0.005*	0.99 (0.92-1.06); 0.7956
Median Income (increments of $10,000)	0.93 (0.87-1); 0.04*	1 (0.97-1.04); 0.8461	0.92 (0.87-0.98); 0.0058*	0.93 (0.88-0.98); 0.005*
School Size (increments of 200)	**0.8 (0.67-0.94); 0.0082**	0.9 (0.81-0.99); 0.0359	0.86 (0.75-1); 0.0523	0.86 (0.76-0.98); 0.0198
Rural	1.23 (0.8-1.9); 0.3479	1.29 (1-1.66); 0.0478	1.04 (0.71-1.53); 0.8247	1.2 (0.87-1.66); 0.2742
Mental Health Model (adjusted for demographics)				
GAD	0.99 (0.95-1.04); 0.7337	**0.96 (0.93-0.99); 0.0091**	0.99 (0.94-1.04); 0.5748	0.97 (0.93-1.01); 0.1123
MDE	**1.1 (1.05-1.15); <.0001**	**1.1 (1.07-1.14); <.0001**	**1.13 (1.07-1.19); <.0001**	**1.13 (1.09-1.18); <.0001**
ADHD	**1.13 (1.08-1.18); <.0001**	**1.11 (1.08-1.15); <.0001**	**1.09 (1.04-1.15); 0.0004**	**1.12 (1.08-1.17); <.0001**
ODD	**1.25 (1.21-1.3); <.0001**	**1.19 (1.16-1.22); <.0001**	**1.23 (1.18-1.28); <.0001**	**1.24 (1.2-1.29); <.0001**
Extracurricular Model (adjusted for demographics)				
Sports	0.99 (0.94-1.04); 0.7911	**1.1 (1.06-1.14); <.0001**	1 (0.95-1.06); 0.9905	0.96 (0.92-1.01); 0.1427
Art	0.95 (0.89-1.01); 0.0947	**0.94 (0.9-0.98); 0.0031**	0.92 (0.85-0.99); 0.0201*	0.92 (0.87-0.98); 0.0103*
Clubs	1.05 (0.98-1.11); 0.1512	**1.06 (1.02-1.1); 0.0072**	1.02 (0.95-1.09); 0.6424	1.04 (0.98-1.1); 0.2012
School Environment Models (adjusted for demographics)				
Climate	**0.93 (0.92-0.94); <.0001**	**0.94 (0.94-0.95); <.0001**	**0.92 (0.92-0.93); <.0001**	**0.93 (0.93-0.94); <.0001**
Belonging	**0.85 (0.83-0.87); <.0001**	**0.88 (0.87-0.9); <.0001**	**0.85 (0.83-0.87); <.0001**	**0.85 (0.83-0.87); <.0001**
Safety	**0.89 (0.87-0.91); <.0001**	**0.89 (0.88-0.91); <.0001**	**0.89 (0.86-0.91); <.0001**	**0.89 (0.87-0.91); <.0001**

Bolded significant p<0.005; * p<0.05

Note. Reported as pooled Odds Ratios (95% Confidence Interval); p-value. All models are adjusted for all demographics except the ICC model.

6. Post-hoc extracurricular and socioeconomic disadvantage interactions

Table 6. Separate regression models for use of each substance	Early Polysubstance Use Class (ref=Non-Use Class) OR (95%CI); p-value
Extracurricular Model (adjusted for demographics)	
Sports	1 (0.95-1.05); 0.9938
Sports*Family Assets	1.03 (0.98-1.07); 0.2643
Art	0.95 (0.89-1.01); 0.1266
Art*Family Assets	1.02 (0.96-1.08); 0.5856
Clubs	1.04 (0.98-1.1); 0.23
Clubs*Family Assets	0.97 (0.93-1.03); 0.3225
Extracurricular Model (adjusted for demographics)	
Sports	1.02 (0.93-1.13); 0.6071
Sports*Parental Education	0.95 (0.85-1.07); 0.4164
Art	0.98 (0.88-1.1); 0.7572
Art*Parental Education	0.95 (0.82-1.09); 0.4702
Clubs	1.09 (0.98-1.22); 0.1265
Clubs*Parental Education	0.94 (0.82-1.08); 0.3911
Extracurricular Model (adjusted for demographics)	
Sports	0.98 (0.9-1.06); 0.5843
Sports*Family Structure	1.02 (0.92-1.14); 0.649
Art	0.9 (0.8-1.01); 0.0668
Art*Family Structure	1.08 (0.94-1.25); 0.2726
Clubs	1.12 (1.02-1.24); 0.0239
Clubs*Family Structure	0.89 (0.79-1.01); 0.0808
Extracurricular Model (adjusted for demographics)	
Sports	0.99 (0.93-1.04); 0.6155
Sports*Rural	1.05 (0.91-1.2); 0.5113
Art	0.93 (0.87-1); 0.0576
Art*Rural	1.09 (0.91-1.3); 0.3351
Clubs	1.05 (0.99-1.12); 0.1252
Clubs*Rural	0.95 (0.81-1.11); 0.532

Bolded significant p<0.005

[a]Reported as pooled Odds Ratios (95% Confidence Interval); p-value. All models are adjusted for all demographics.