Using Decision Trees to Examine the Influence of the School Environment on Youth Mental Health

by

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Author’s Declaration

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

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

Statement of Contributions

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

Chapter 5: Battista K, Diao L, Patte KA, Dubin JA, Leatherdale ST. (In Press). Examining the use of decision trees in population health surveillance research: an application to youth mental health survey data in the COMPASS study. *Health Promotion and Chronic Disease Prevention in Canada.* 43(2)

Chapter 6: Battista K, Patte KA, Diao L, Dubin JA, Leatherdale ST. (2022). Using decision trees to examine environmental and behavioural factors associated with youth anxiety, depression, and flourishing. *International Journal of Environmental Research and Public Health*. 19 10873. doi:10.3390/ijerph191719873

Chapter 7: Battista K, Patte KA, Diao L, Dubin JA, Leatherdale ST. (Under Review) Examining changes in school mental health practices over time and associations to youth depression, anxiety, and psychosocial wellbeing.

As lead author of these three chapters, I was responsible for developing the research questions, conducting literature research, leading the study designs, conducting the statistical analyses, interpreting the results, and writing the initial drafts of the manuscripts. My co-authors provided guidance during each step of the research and provided feedback on draft manuscripts. Dr. Leatherdale and Dr. Dubin provided significant direction throughout. Under Dr. Leatherdale's and Dr. Dubin's co-supervision, I also prepared the remaining chapters of this thesis, which were not written for publication.

Abstract

Youth mental health is a current public health priority in Canada, with nearly one in four young people living with a mental illness. The contextual school environment can be particularly influential given the considerable amount of time that youth spend in school. Schools are seen as ideal settings for prevention and early intervention initiatives. While a myriad of practices and programs are being implemented across schools to address student mental health, there is limited and contradictory evidence on their effectiveness. Most available research has been conducted using statistical techniques that have limited ability to account for the complex interactions between co-occurring environmental influences. While machine learning techniques such as decision trees are well suited for this type of analysis, they are relatively underused in public health research.

The overall objective of this dissertation was to use decision tree analysis to further our understanding of the influence of the school contextual environment on youth depression, anxiety, and psychosocial wellbeing. Specific objectives were to (1) compare the performance of decision trees to traditional regression models in the context of health survey data, (2) determine which environmental and behavioural factors are most influential on mental health outcomes, and (3) determine which, if any, combinations of school mental health practices are associated with better student mental health. These objectives were addressed through three manuscripts using student- and school-level data from the 2017-18 and 2018-19 waves of the COMPASS study.

The first manuscript provided a methodological overview and application of two decision tree techniques: classification and regression trees and conditional inference trees. Decision tree model performance was compared to traditional linear and logistic regression. All techniques showed general agreement in the identification of key differentiating factors across five outcomes. Tree models had slightly lower prediction accuracy than regression models but were more parsimonious. Unlike traditional regression methods, decision trees allowed for the identification of non-linear associations and differential impacts among high-risk subgroups.

The second manuscript used cross-sectional student-level data to examine associations of various environmental and behavioural risk factors with youth anxiety, depression, and flourishing levels. Having a happy home life and sense of school connection were identified as key protective factors, while behavioural factors such as diet, movement, and substance use did not emerge as important differentiators. Females lacking both happy home life and sense of connection to school were at

greatest risk for higher anxiety and depression levels. These results highlighted the importance of the home and school environments and suggested that a sense of connection to school may help to mitigate the negative influence of a poor home environment.

The third manuscript used longitudinal student- and school-level data to examine variation in school mental health practices as well as associations between changes in these practices and youth anxiety, depression, and flourishing levels. Decision trees were used to comprehensively examine whether any combination of practice and service changes were associated with mental health outcomes. While substantial variability was seen in the mental health practices and services offered between schools and across years, decision tree analysis found no combinations of changes that meaningfully contributed to better student mental health outcomes. These results suggested that incremental practice changes were not effective and highlighted the need for more comprehensive school mental health approaches.

This dissertation used a novel decision tree approach to expand our knowledge of the influence of the school contextual environment on youth depression, anxiety, and psychosocial wellbeing. These findings have important implications for practice, as they suggest that schools can enhance student mental health through initiatives that foster a supportive school environment and sense of connection. These findings further support calls for comprehensive school health programming by showing that current tactics of incremental and sporadic practices changes at the individual school level are ineffective. This dissertation also provides a framework for future research, as the decision tree approach used here can be applied to other public health domains to examine complex interactions and identify high-risk subgroups. Further, the ability to comprehensively examine permutations of simultaneously changing factors makes decision trees a compelling tool for natural experiment evaluation. In addition to answering important research questions regarding the influence of school context on youth mental health, this dissertation work highlights the potential power in combining machine learning methods with large population health surveillance data.

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Lastly, a big, big thank you to my bae, Jason. I literally wouldn't have made it through this without you. I'm so, so, so happy that we are no longer 18,000km apart and can finally stare up at the same moon.

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Chapter 1
General Introduction

Mental health has been identified as a public health priority both nationally(1,2) and globally(3,4). Within Canada, nearly 1 in 4 young people are living with a mental illness(5) and youth have been identified as a priority group for mental health prevention and intervention initiatives(1,2,5). In 2018, 4.6% of Canadian youth (5.8% of females and 3.4% of males) reported having a diagnosed mood disorder, representing over 100,000 youth(6). While the prevalence of mood disorders among youth has been relatively stable in recent years(6), perceived mental health has worsened. In 2018, 6.7% of Canadian youth aged 12 to 17 reported fair or poor perceived mental health and 13.8% reported high life stress, compared to 4.1% and 12.1% respectively in 2015(6). Youth are an important target group for mental health interventions because nearly 70% of all mental illness occurs before age 18(7). Youth also have higher rates of mood disorders than any other age group(8), and youth who have experienced a mental illness are at higher risk of experiencing a mental illness as adults(5).

Positive mental health is associated with better physical health(9) and increased life expectancy(10) while poor mental health and the existence of mental health disorders are associated with chronic physical illness(11), substance use(12), and decreased life expectancy(13). Additionally, youth with untreated mental illness are more likely to miss educational and employment opportunities(1). From a public health perspective, primary prevention of mental illness can be just as important as clinical intervention. It is important for prevention efforts to focus both on promotion of positive mental health and prevention of poor mental health and mental health disorders(14).

The causes of mental illness are complex and are not only related to internal/intrinsic factors but also ecological factors(15) such as relationships with family and friends(16) and the built environment(17). In the case of youth, schools are a particularly important contextual environment to consider since youth spend a considerable amount of time at school (approx. 25 hours per week). More than any other age group, youth are particularly influenced by their friends and social circle(18), with schools serving as a key location for social interaction. Additionally, within the school setting, youth interact with authority figures who can shape their attitudes. Schools also provide mental health support providers with access to youth from a variety of backgrounds and socioeconomic circumstances who may otherwise be difficult to reach. As such, schools are considered an ideal context in which to address mental health(5,19).

While it is recognized that the school contextual environment has the potential to influence youth mental health, there is limited and often conflicting evidence of the impact of school practices. Many mental health practices and programs in place in Canadian schools have not been evaluated for effectiveness, while effectiveness research on school-based interventions has been primarily limited to small trials with inconclusive results. There is a dearth of large-scale natural experiment evidence addressing the effect of school mental health practices and most past research has been conducted using statistical techniques that have limited ability to account for the complex interactions between co-occurring environmental influences. This dissertation research addressed this knowledge gap with respect to the influence of the school contextual environment and school practices on student mental health in Canada. Specifically, this dissertation research used a novel application of decision tree methods to investigate the relative importance of school context and whether specific combinations of school practices are associated with better youth mental health outcomes.

Chapter 2
Background and Literature Review

2.1 Measures of Mental Health

The concept of mental health is broad and encompasses both positive constructs such as resilience and flourishing, and negative constructs such as depression and anxiety. Generally, mental health refers to a person's level of psychological and emotional wellbeing. Mental health is often defined as a positive concept: the World Health Organization defines mental health as “a state of wellbeing in which the individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community”(20). In contrast, mental illness, also referred to as mental disorder, is broadly defined as a “set of symptoms or behaviour associated in most cases with distress and interference with personal functions”(21). Assessment and measurement of mental health or mental illness is often done using validated scales of concepts. This thesis uses the term “mental health” to refer to the umbrella concept of both positive mental wellbeing and absence of mental illness, and examined mental health using measures of depression, anxiety, and flourishing.

2.1.1 Depression

Unipolar depression is a set of mood disorders (including Major Depressive Disorder and Major Depressive Episodes) characterized by feelings of sadness, hopelessness, and despondency. Major Depressive Disorder (commonly referred to as simply “depression”) can be clinically diagnosed using criteria from the Diagnostic and Statistical Manual of Mental Disorders (DSM-V)(22). Key diagnostic criteria for clinical depression include sustained depressed mood, anhedonia (diminished pleasure or interest in activities), fatigue, feelings of worthlessness or guilt, diminished concentration, or suicidal ideation(22). While sadness is a common symptom of depression, depression differs from sadness in terms of the duration of these feelings and other symptoms experienced, with anhedonia being a key differentiating factor. Aside from clinical diagnosis, several scales have been developed to measure depression, including the Center for Epidemiologic Studies Depression Scale (CESD)(23). The CESD-10, a shortened version of the CESD, has shown factorial validity and internal consistency within adolescent populations(24), and is often used to measure depression in population studies. The CESD-10 scale assesses constructs of positive affect (e.g., happiness, hopefulness), depressive affect (e.g., loneliness, fear, irritability) and somatic symptoms (e.g. trouble concentrating, restless sleep)(24) by measuring the frequency of various symptoms.

2.1.2 Anxiety

Generalized anxiety disorder is a mood disorder characterized by persistent worry and tension. Like depression, generalized anxiety can be clinically diagnosed using criteria from the DSM-V(22) based on physical and emotional symptoms. Anxiety can also be measured using self-report scales, the most widely used being the Generalized Anxiety Disorder - 7 Scale (GAD-7)(25). The GAD-7 has shown validity for use in assessing anxiety symptoms in adolescents and in distinguishing between mild and moderate generalized anxiety disorder(26). The scale assesses frequency of anxiety symptoms such as worry, nervousness and irritability.

2.1.3 Flourishing

Flourishing is a state of positive wellbeing, characterized by positive emotional, psychological, and social functioning. Unlike anxiety and depression, which are constructs related to mental illness, flourishing is a construct related to positive mental health. While the concept of flourishing is relatively new, it is increasingly being examined in mental health research. Flourishing can be measured using Diener's Flourishing Scale (FS)(27), which has been shown to have strong internal consistency and criterion validity across a range of age groups(28,29). The scale assesses overall psychosocial wellbeing by asking respondents to indicate level of agreement with self-perceived success in areas of relationships, self-esteem, life purpose and optimism.

2.1.4 Sex Differences in Mental Health Measures

Prevalence of mental illnesses such as anxiety and depression in adolescent populations tends to be higher for females than males(30). These differences are commonly attributed to sociocultural gender norms rather than biological sex differences(30). In general, females are more likely than males to exhibit internalizing symptoms, which are captured within the depression (CESD-10) and anxiety (GAD-7) scales(31). Previous research has found the CESD-10 and GAD-7 scales to have measurement invariance by sex within an adolescent sample in COMPASS(32), suggesting that differences seen in these scales reflect true differences in depression and anxiety levels between females and males.

2.2 The School Environment

The contextual school environment encompasses the physical setting, population composition, and cultural context of the school, and can be particularly influential on youth health behaviours given the considerable amount of time that youth spend in school. Beyond the influence of the physical built environment, the school also serves as a setting for complex social interaction. The social-ecological model of health, originally developed by Bronfenbrenner(33), suggests that an individual's health behaviours are influenced by a hierarchical network of internal and environmental factors, and the interaction between these factors. More specifically, health is influenced by factors at the individual, interpersonal, organizational, community and public policy levels(34). In the context of the school environment, youth may be influenced at the interpersonal level by peer and teacher relationships and at the organizational level by school policies, procedures, culture, and built environment. Following the social-ecological framework, any interventions to address health need to account for these multiple levels of influence on youth(33). The school may influence youth mental health both directly through explicit practices and intervention programs, and indirectly through its policies, culture, and composition.

2.2.1 School-level Differences and Intraclass Correlation

It is important to understand the extent to and the ways in which school environments differ to understand the potential influences that various contextual factors have on youth mental health. A common measure of school heterogeneity is the intraclass correlation coefficient (ICC). In the context of this dissertation work, the ICC represents the amount of variability between student mental health outcomes that is attributable to differences between the schools they attend. While there is no defined cut-off for what is considered a meaningful or significant ICC, from a statistical perspective an ICC of 5% is considered moderate(35,36). A systematic review of the effect of the school environment on emotional health found estimated ICCs between 0.4% and 6%(37). Additional studies examining various measures of mental health found relatively low estimated ICCs between 0% and 3%(35,38), while another study examining various aspects of school climate found more meaningful estimated ICCs between 2% and 6%(39), suggesting that in the domain of youth mental health the school ICC is sensitive to the specific outcome under study. In the context of school-level interventions, higher ICCs could suggest that school-level interventions have potential to be effective in modifying health behaviours(36). However, the heterogeneity of the school environment may make application of interventions across locations more challenging(40).

2.2.2 School Compositional and Structural Factors

Past research into the influence on youth mental health of school-level compositional factors such as socioeconomic status (SES), urbanicity, and enrolment size has shown mixed results. SES is the most examined factor, and some studies have found lower school SES to be significantly associated with depression, anxiety, and wellbeing symptoms(38,41), while a Canadian study found that neighbourhood income explained most between-school difference in depressed mood(42). Additionally, a recent review of school contextual impacts on health inequalities found evidence that low school-level SES worsened mental health inequalities(43). However, other studies have found no association between school-level SES and depression(44–46). School urbanicity is less often examined, though one study found that students in urban schools had higher odds of suicidal behaviour but not depression symptoms(45), while another found students in urban schools had poorer mental health(38). No association has been found between school size or ethnic composition and depression symptoms after controlling for other environmental and socio-educational factors(44,45,47,48).

Research on the relationship between mental health and the structural (i.e., physical, built) school environment is limited; however, a recent systematic review found some evidence of a positive effect of green spaces and designated "healthy spaces" on mental wellbeing(49). The same review found mixed evidence on the effect of school start times(49), while associations have been found between difficulties in transportation to school and anxiety and depression(50). Two studies on other structural factors such as coeducational vs. same-sex schools, public vs. private schools, and elements of the staff work environment found no significant associations to depression symptoms or wellbeing(38,45). Overall, while studies have found a significant school effect in terms of ICC, there is limited evidence that this effect is due to the composition or built structure of the school environment.

2.2.3 School Climate and Connectedness

More research has focused on cultural aspects of the school environment, which are generally considered modifiable. School climate, broadly defined as the quality and character of school life, is most examined. Several studies have found associations between aspects of positive school climate and better depression(38,47,51) and mental wellbeing(38,52–54) outcomes, though the strength of association varies by study and exact measure. Additionally, being surrounded by peers with positive attitudes toward school has been associated with a lower likelihood of negative emotions such as anxiety and self-destructive thoughts(55). Other studies have found mixed results or no association between school climate, but some evidence of a protective association between school safety and depressive symptoms(56,57). When examining staff reports on various aspects of school climate separately, Virtanen et al.(58) found that low perceptions of trust and participation were associated with student depression and psychological symptoms but found no association for other aspects such as support for innovation, orientation towards high-quality work, or accepted and clear goals. Overall, the inconsistent definition of school climate complicates inference on its association to mental health outcomes.

Closely related to and often intertwined with the contextual-level concept of school climate is individual-level student sense of school connectedness. The definition of school connectedness varies throughout past research but is commonly measured using multi-item school connection scales. School connectedness has been associated with depression(59–61), anxiety(59), emotional/mental distress(62,63), and mental wellbeing(53) outcomes. A systematic review of the effect of the school environment found no beneficial effect of environmental factors at the school level but did find that perceptions of connectedness and support affect emotional health(37). However, while school connectedness is measured at the individual level and often considered an individual-level characteristic, a study by Prati et al.(54) examining both school-level and student-level sense of community argued that it should be considered a school-level characteristic. Overall, available evidence suggests a protective influence of positive school climate and sense of school connection on student mental health.

2.3 School Mental Health in Canada

As mentioned previously, youth mental health is a public health priority in Canada(1,2,5) and schools have been identified as an ideal context in which to address mental health(5,19). Federal organizations, provincial governments and organizations, school districts, and individual schools all play a role in developing mental health strategies and implementing policies, practices, and program interventions.

2.3.1 National Mental Health Strategies

The Mental Health Commission of Canada (MHCC) is a federally funded organization tasked with developing tools and programs to support the mental health of Canadians and providing recommendations to governments and community stakeholders(64). The MHCC published the Mental Health Strategy for Canada in 2012(5), which calls for an increase in comprehensive school-based mental health programs. The strategy recommends the implementation of initiatives that promote mental health for all students in combination with targeted prevention efforts for at-risk students. While specific program suggestions are not provided in the recommendations, the MHCC has also released a school-based activities toolkit focused on mental health stigma with specific practice recommendations such as poster campaigns and assemblies(65).

The Joint Consortium for School Health (JCSH) is another national group comprised of representatives from provincial health and education ministries and the Public Health Agency of Canada (PHAC) and tasked with bringing together health and education systems to improve the health and wellbeing of Canadian children and youth using a comprehensive school health approach(66). While the organization's focus is not specific to mental health, the JCSH published a better practices report focusing on the promotion of positive mental health within schools in 2013(19). The report provides specific better practices for school health stakeholders related to the social and physical environment, teaching and learning, partnerships and services, and healthy school policy.

2.3.2 Provincial Mental Health Strategies

Education and healthcare fall within provincial jurisdiction and as such various provincial governmental organizations have developed various mental health strategies. These strategies often include strategic priorities for school-based mental health, but most do not provide specific practice or program recommendations(67–77). In Ontario, the Ministry of Health and Long-Term Care published a Comprehensive Mental Health and Addictions Strategy(67), which includes a focus on building school-based capacity. The strategy suggests implementing training and programs to support early identification of mental health issues but does not provide specific program recommendations. Additionally, the Ontario Ministry of Education released Ontario's Well-Being Strategy for Education in 2016(78), which focuses on promoting positive mental health and wellbeing but did not recommend specific policies or practices. Most mental health promotion initiatives in Ontario focus on improving mental health knowledge as mandated in the Health and Physical Education curriculum(79).

In British Columbia, the Ministry of Mental Health and Addictions created a mental health roadmap in 2019(68) that includes strategic direction on mental health in schools, and has allocated funding for school-based mental health programs with a focus on staff training and student workshops aimed at promoting mental health literacy and social and emotional learning(80) In Alberta, the governmental Mental Health Review Committee released a Valuing Mental Health report(69) in 2015 with a strategic priority of enhancing school-based mental health programs. In Quebec, the Institut National de Santé Publique du Quebec released a synthesis of recommendations(70) for school-based practices aimed at improving mental health and addressing mental health issues.

2.3.3 School and School District Initiatives

While broad mental health strategies are prescribed federally and provincially, it is primarily the responsibility of individual school districts and schools to create and implement actionable mental health practices and programs. A 2019 survey of Ontario principals found that schools are increasingly concerned with the mental health challenges of their students and are implementing a host of policies and programs to address these concerns(81). Along with embedding mental health education throughout the curriculum, a patchwork of school-specific initiatives and student-led activities have been implemented. According to the 2019 survey, initiatives generally focus on positive school-wide mental health and range from specific programming to broader environmental changes(81). Schools are also working to adapt the broader environment through creating a school climate focused on open dialogue and changing the physical environment by creating safe spaces for self-regulation and meditation(81). However, schools are often heavily reliant on community and other third-party supports for assistance with program implementation. For example, School Mental Health Ontario is an implementation support team that works with school districts to implement best practices, with a focus on a tiered intervention model(82). Overall, while many mental health initiatives have been implemented across schools, no comprehensive universal programming has been applied provincially or nationally.

2.4 Effectiveness of School Mental Health Initiatives

While a multitude of initiatives related to youth mental health have been implemented in schools across Canada, there is limited evidence on their effectiveness. The MHCC has reported that less than half of mental health programs in schools have been evaluated(7). Additionally, most initiatives being implemented are not based on past evidence of effectiveness. In Ontario, less than half of public health initiatives focused on youth mental health are considered evidence-based(83). While the body of evidence is growing, most information on the effectiveness of programs and practices comes from studies based outside of Canada, such as in the United States and Europe. A review of the literature on associations between school mental health policies, practices, and programs and student anxiety, depression, and flourishing outcomes shows a multitude of studies of one-time intervention trials, but limited evidence related to ongoing policies and practices.

2.4.1 Ongoing School Policies and Practices

Literature on the influence of school policies and practices primarily focuses on teaching and disciplinary styles, as well as the relative benefit of in-school mental health services provided by professional mental health staff compared to existing school staff. Regarding teaching styles, there is some evidence that a supportive teaching style is associated with positive mental health and protective against mental health problems. Perceived teacher support has been associated with higher odds of positive health(84) and lower rates of depression(85,86), anxiety(86), and psychosomatic problems(87). Conversely, passive teaching styles(88) and poor student-teacher relationships(89) have been associated with emotional and behavioural problems and lower subjective wellbeing. Regarding disciplinary styles, one study found that authoritative school environments characterized by high structure and high support have been associated with better social-emotional health(90), while another study found that permissive disciplinary style characterized by low structure and high support is associated with increased odds of depressive symptoms(91), suggesting that a lack of structure may limit the benefits of teacher support.

Literature on school-based mental health services notes several benefits. On-site school mental health services often provide a first step in addressing concerns, serve as a guide to out-of-school supports, and are often used by high-risk students(92). Additionally, schools that provide early identification and screening programs have seen an increase in service use by youth with mild to moderate mental and behavioural disorders(93) and increased referral to external providers(94). Few studies have examined the impacts of in-school mental health services and student anxiety, depression, and flourishing outcomes; however, one past longitudinal study found that increases to the availability of mental health services led to decreases in depressive symptoms(44). However, while schools are seen as an ideal setting to provide mental health services, many schools do not have the resources or expertise to provide these services independently(95). Additionally, from the student perspective, teachers may not be the preferred source of emotional wellbeing support due to concerns around confidentiality(96) whereas students generally prefer adults in clear mentorship roles(96,97). Thus, while availability of mental health services is associated with improved student mental health, trained mental health professionals may be needed to ensure effectiveness.

2.4.2 School-based Intervention Programs

In contrast to the limited research available for ongoing school policies and practices, far more research exists evaluating the effectiveness of school program interventions, mostly through small intervention trials. Most studies are conducted in the United States and Europe, with limited Canadian evidence available. Several review articles have examined overall effectiveness in relation to anxiety, depression, and wellbeing outcomes. While results are inconsistent, interventions that are long-term, whole-school approaches that focus on both universal and targeted populations and are delivered by trained staff show the most promise(98). However, a general lack of rigor and high risk of bias have limited the ability to draw conclusions on the effectiveness of individual programs.

Regarding interventions focused on mental illness prevention, a 2017 review examining a wide range of school-based anxiety and depression prevention programs found that externally delivered, targeted interventions were more effective at prevention of depression than universal programs (i.e., those delivered to the entire study body) or those administered by school staff, though the same effects were not seen for anxiety(99). While many of the programs reviewed showed small positive effects, the authors noted that 80 of 81 studies showed some degree of bias. Another review of randomized controlled trials for anxiety and depression prevention programs found that the majority of interventions studied were effective for both depression (65%) and anxiety (73%), though the overall mean effect size was considered very small(100). In contrast to the 2017 review, two other reviews of similar interventions found universal programs to be more effective than targeted programs(100,101). Despite this, targeted interventions have been found to perform better for certain types of programs: CBT-based interventions delivered to targeted populations showed greatest reductions to depression(102), and the positive effects of yoga interventions for anxiety reduction were strongest for targeted, longer-duration programs(103). However, both reviews warned against drawing firm conclusions of program effectiveness due to methodological issues and small sample sizes.

In contrast to programs focusing on mental illness, resilience-focused and holistic wellbeing interventions that concentrate on positive mental health have shown limited effectiveness. A 2017 review of universal resilience interventions found no effect on anxiety, depression, or general psychological distress, though some improvement was seen for internalizing problems(104). Most studies reviewed had a high risk of bias. Reviews of the Penn Resiliency Program, a widely adopted 12-session program focused on cognitive restructuring, showed no overall evidence of effectiveness(105), with high variability in results depending on the target group and specific implementation(106). A positive wellbeing-focused intervention, The World Health Organization Health Promoting Schools Framework, is a holistic approach focusing on curriculum and environment changes that has been widely implemented globally and supported in Canada by the JCSH; however, studies examining the impact of this intervention on depression found no effect(107). A broader review of mindfulness-based programs found that while all studies reported positive results, none included age-appropriate measures(108). Thus, the lack of positive evidence found to date may be due to poor study design or measurement rather than ineffective interventions.

2.4.3 Gaps between Evidence and Practice

A meta-review of mental health promotion and problem prevention programs found that, while effect sizes were small to moderate in statistical terms, the real-world impact can be particularly meaningful for high-risk students(98). However, the effects associated with specific interventions were variable and could not always be relied upon. In general, whole-school, long-term approaches to the promotion of mental health appear to be more effective than brief class-based programs(98,109). Brief interventions that focus only on individual skills in the absence of environmental change are insufficient to produce lasting effects(40,110). Despite this, in practice most school-based interventions tend to be short-term(109). Additionally, evidence shows that school-based interventions are only effective when completely and accurately implemented(98), though in practice interventions are often poorly implemented due to inconsistent and poorly trained implementers(109,111), insufficient funding, and misalignment with intended and actual outcomes(111). This gap between evidence and practice may reflect systemic issues in knowledge translation, insufficient time and resources, and inadequate support. A lack of good quality evidence on the effectiveness of specific available programs may also hamper implementation.

2.5 Use of Decision Trees in Public Health Research

Decision tree learning is a machine learning technique that is increasingly being used in health research as an alternative to traditional regression methods. Decision trees are statistical models that examine an outcome of interest by segmenting the sample into distinct subgroups based on similar combinations of predictor variables. The subgroups are determined by hierarchically partitioning the data using a series of splits. This hierarchical partitioning is represented by a tree structure. The predicted value of the outcome for each subgroup is determined by averaging the outcome over all members of the subgroup. Several decision tree techniques have been developed over the last 50 years(112), including classification and regression trees (CART) and conditional inference trees (CI).

Decision trees have the benefit of being easy to interpret visually and mimicking the human decision-making process. While linear and logistic regression models have traditionally been used in public health research to examine relationships between outcomes and a set of predictor variables, their ability to handle interaction effects between predictors is limited(113). Decision trees are better suited to account for complex interactions among variables(114,115). Additionally, since decision trees are non-parametric, they do not rely on the same model assumptions as regression models and can be used to examine non-linear relationships between variables(113). Unlike decision trees, regression models also typically examine average effects and therefore interventions based on regression model results are geared toward the average member of the population as opposed to accounting for the needs of high-risk subgroups(116). Decision trees may also have improved prediction accuracy over regression models when underlying associations are non-linear(115), though evidence of relative accuracy appears to be situation dependent. Despite these benefits, decision trees are relatively underutilized in public health research. In the examination of contextual effects specifically, given the complexity of the school environment with multiple interacting factors and combinations of policies and programs being implemented, decision tree analysis may be preferable to regression methods in examining the influence of these policies and programs on youth health behaviours.

2.6 Summary and Knowledge Gaps

With nearly 1 in 4 young people living with a mental illness(5), youth mental health is a current public health concern in Canada(1,2). The school environment can have a meaningful impact on the mental health of students and can serve as an ideal context for prevention and intervention initiatives(5,19). Cultural aspects of the school environment such as school climate and student connectedness have been associated with depression(38,47,51,59–61), anxiety(59), emotional/mental distress(62,63), and mental wellbeing(38,52–54). Several strategies have been developed nationally and provincially to address mental health within school settings. Individual schools and boards have also responded to increasing concerns around student mental health with the implementation of a multitude of practices and program interventions(81). However, there is limited and contradictory evidence on the effectiveness of many school-based mental health initiatives currently being implemented. While school teaching and disciplinary styles(88,90,91) and school-based mental health services(44) have been associated with positive student mental health outcomes, there is very limited evidence within the Canadian context. Additionally, while many school-based interventions have been evaluated internationally, insufficient sample size and poor study quality limit inference on the effectiveness of individual programs. In general, universal long-term approaches have shown the most promise(98), though there is a disconnect in Canada between best available evidence and actual practice.

While school-based mental health initiatives are being implemented across the country, there is little evidence to guide administrators and other staff on the effective implementation of policies, practices, and programs. Very few interventions have been evaluated in the Canadian context, and reviews of interventions globally have assessed the quality of evidence as poor(99,109). While randomized controlled trials are often considered the gold standard for evaluation, small sample sizes, artificial study environments, and the absence of real-world influences can limit the external validity of results. Additionally, since many studies do not sufficiently report on setting components, the ability to translate results from a controlled trial to a real-world setting can be difficult(117). Reviews have noted a need for large-scale natural experiments of the school environment that account for the impact of real-world factors on variations in program implementation(37,100). Decision tree analysis is a relatively underutilized technique within the field of public health that is well-suited to the examination of complex environmental factors and identification of high-risk groups. The overall goal of this thesis was therefore to use decision trees to better understand the influence of the school contextual environment on youth depression, anxiety, and psychosocial wellbeing.

Chapter 3
Study Rationale and Research Questions

This research used decision tree analysis to further our understanding of the influence of the school environment on youth mental health through three studies. The specific aims of this research were to (1) compare the performance of decision trees to traditional regression models in the context of health survey data, (2) determine which contextual and behaviour factors are most influential on mental health outcomes, and (3) determine which, if any, combinations of school mental health practices are associated with better student mental health.

3.1 Study 1 – Comparing the Performance of Decision Trees to Traditional Regression Methods

Decision trees are a machine learning technique that are increasingly being used in health research. Decision trees can account for complex and non-linear relationships between variables (113–115), making them well suited for use in research on school environments, which are characterized by complex interactions between multiple factors. Decision trees may have improved prediction accuracy over regression methods in cases where restrictive assumptions on the functional form of the data are not met (115); however, past evidence appears to be mixed and domain dependent. The use of decision tree techniques has the potential to improve analysis of complex environmental data in the domain of youth health.

3.1.1 Study 1 Research Questions

The objective of Study 1 was to examine two types of decision tree techniques: classification and regression trees (CART) and conditional inference trees (CI). This study aimed to compare the performance of these decision tree techniques to logistic regression and linear regression in predicting youth mental health outcomes in a large, multi-school observational survey study. Specifically, this study answered the following research questions:

1. Do CART and CI have better prediction accuracy than logistic and linear regression, as measured by area under the receiver operating characteristic curve (AUC) and average mean square prediction error (MSPE)?
2. Is relative variable importance, measured as the relative improvement to model fit, consistent across different classification and regression techniques?

3. Qualitatively, how does model interpretability compare across different classification and regression techniques?

3.1.2 Study 1 Hypotheses

I expected the following results for each research question:

1. Based on previous research in other health domains, I expected classification and regression trees to have better prediction accuracy than regression techniques for depression, anxiety, and flourishing outcomes in this context.
2. I expected relative variable importance to vary between regression and tree techniques, but that the most important variables would be consistently identified.
3. I expected tree methods to have more direct interpretations than regression models when interaction terms were considered.

3.2 Study 2 – Examining Environmental and Behavioural Factors Associated with Youth Mental Health Outcomes

Following the social-ecological model(33), youth mental health can be influenced by a hierarchy of behavioural, interpersonal, and contextual factors. From a public health perspective, environmental risk and protective factors are important to examine given that many are considered modifiable. The school environment can be a particularly influential context given the amount of time youth spend at school. School connectedness has been associated with lower depression(59–61), lower anxiety(59), and better mental wellbeing(53). However, past research has generally examined various behavioural and contextual influences in isolation. Additionally, the primarily regression-based analytic techniques used have focused on quantifying average population effects rather than examining differential impacts on high-risk groups. An exploratory examination using decision tree techniques could help to better understand the complex interactions between a wide array of behavioural and environmental influences on youth mental health.

3.2.1 Study 2 Research Questions

The objective of Study 2 was to use an exploratory decision tree analysis to determine which contextual and behaviour factors are most influential on youth mental health outcomes. Specifically, this study aimed to use decision trees to examine interacting associations between behavioural (diet, physical activity, sedentary behaviour, sleep, substance use) and interpersonal/contextual (family relationships, peer relationships, school connectedness) factors and youth depression, anxiety, and flourishing levels. This study answered the following research questions:

1. Which behavioural (diet, physical activity, sedentary behaviour, sleep, substance use) and interpersonal/contextual (family relationships, peer relationships, school connectedness) factors emerge as differentiators of youth depression, anxiety, and flourishing levels?
2. Does school connectedness have a protective association to youth depression, anxiety, and flourishing levels, and how does this association vary by other behavioural and interpersonal factors?
3. Are there differential associations between behavioural and interpersonal factors and depression, anxiety, and flourishing levels across certain demographic subgroups of students?

3.2.2 Study 2 Hypotheses

I expected the following results for each research question:

1. Because of lack of previous research, I did not have an a priori hypothesis for the relative importance of and interaction between various behavioural and environmental factors.
2. I expected school connectedness to emerge as an important differentiator of student depression, anxiety, and flourishing levels.
3. Based on previous research, I expected sex to emerge as an important differentiator of depression, anxiety, and flourishing levels, and expected females to have worse mental health levels than males.

3.3 Study 3 – Examining the Impact of School Mental Health Practices on Youth Mental Health Outcomes

While schools have been identified as ideal contexts in which to address youth mental health in Canada(7,19), most mental health initiatives in place in Canadian schools are not evidence-based(7,83). A lack of evidence exists on the effectiveness of ongoing school practices, and while there have been many studies evaluating one-time program interventions, small sample sizes and poor study designs have led to limited and contradictory evidence(99). There is a need for large-scale natural experimental evidence that accounts for the impact of co-occurring changes(113). Identifying specific combinations of practices associated with better student mental health can help to inform the evidence base for school mental health best practices.

3.3.1 Study 3 Research Questions

The objective of Study 3 was to determine which, if any, combinations of school mental health practices are associated with better student mental health. Specifically, this study aimed to examine changes in mental health practices and youth depression, anxiety, and flourishing levels to answer the following research questions:

1. Is there an effect of school-level contextual differences on youth depression, anxiety, and flourishing levels, as measured by the intraclass correlation coefficient (ICC)?
2. What school mental health practices are in place across a large sample of Canadian high schools, and is there variation in these practices across schools or over time?
3. Are certain combinations of practice changes associated with lower levels of depression and anxiety, or higher levels of flourishing in youth?

3.3.2 Study 3 Hypotheses

I expected the following results for each research question:

1. Based on previous research, I expected moderate yet meaningful ICCs of approximately 2-6% for depression, anxiety, and flourishing outcomes.
2. I expected schools to vary substantially in the availability of mental health services, levels of staff training, and coordination with external organizations.
3. Based on previous research, I expected the availability of full-time mental health professionals and on-site counselling services to be associated with lower levels of depression and anxiety. I expected staff training on mental health awareness to be associated with higher levels of flourishing.

Chapter 4
Methodology

This chapter describes the general methodology used to answer the previously described research questions. All research questions were answered using data from The COMPASS Study (COMPASS). This chapter describes the COMPASS study design, samples, survey measures, and statistical analysis techniques used throughout this thesis.

4.1 The COMPASS Study

The COMPASS Study (COMPASS) is an ongoing prospective cohort study (2012-2027) designed to collect hierarchical data from Canadian secondary schools in Ontario, Alberta, British Columbia, and Quebec, and the students who attend these schools(118). The purpose of COMPASS is to evaluate how changes in the school environment - including the built environment, policies, practices, and programs - influence youth health behaviours. COMPASS collects student- and school-level data related to healthy eating, physical activity, sedentary behaviour, substance use, mental health, bullying, school connectedness, and academic achievement. COMPASS uses a quasi-experimental design to evaluate natural experiments that can inform school-based prevention programming. COMPASS has received ethics clearance from the University of Waterloo Research Ethics Board (ORE 30118). Additional details about the COMPASS host study are available online (https://uwaterloo.ca/compass-system).

4.1.1 Sampling and Recruitment

COMPASS uses purposeful sampling to recruit schools based on their use of active-information, passive-consent parental permission protocols. Passive-consent protocols are required to ensure higher participation rates and to reduce selection bias(119). School-level sampling occurs in two stages. First, the COMPASS research coordinator recruits school districts/boards that use passive-consent protocols and receives district/board approval and ethics clearance. Next, the COMPASS research coordinator recruits individual schools within the district/board. Additional details on school board and school recruitment are available(120–122).

COMPASS uses whole-school sampling, meaning that all grade 9 to 12 students (secondary I-V in Quebec) within a participating school are eligible and invited to participate. Active-information, passive-consent parental permission protocols are used. Parents/guardians are informed of the study a minimum of two weeks in advance of the data collection date and may contact the COMPASS research coordinator should they choose to withdraw their child(ren) from the study. Students may choose to decline participation at any time on the day of the data collection(123).

Schools are surveyed annually throughout the course of the study. To follow students over time, COMPASS uses an anonymous linking process to generate a longitudinal cohort sub-sample. As part of the student questionnaire, students answer a series of questions related to their name, sex, and month of birth that are used to create self-generated identification codes. These self-generated codes are matched across years to follow students over time while keeping their identities anonymous. Additional details on data linkage are available(124).

The research questions in this thesis were answered using data from the 2017-18 (Year 6) and 2018-19 (Year 7) data collection years. The 2017-18 sample consisted of 66,434 students from 122 schools in Ontario (61 schools), Alberta (8 schools), British Columbia (16 schools) and Quebec (37 schools). The participation rate for 2017-18 was 81.9%. The 2018-19 sample consisted of 74,501 students from 136 schools in Ontario (61 schools), Alberta (8 schools), British Columbia (15 schools) and Quebec (52 schools). The participation rate for 2018-19 was 84.2%. Between 2017-18 and 2018-19, data from 28,567 students from 116 schools were successfully linked, allowing for a two-year longitudinal sample.

4.2 Data Sources and Measures

The research questions in this thesis were answered using student-level data from the COMPASS student questionnaire and school-level data from the COMPASS School Policies and Practices questionnaire, as well as supplemental census data from Statistics Canada.

4.2.1 Student Questionnaire

The COMPASS student questionnaire is a 16-page paper-based questionnaire completed by students during class time on the day of the data collection. The questionnaire is self-administered and anonymous and takes approximately 40 minutes to complete. Detailed procedures for the questionnaire administration are available(123). The student questionnaire is available in English and French. Students in Quebec primarily complete the questionnaire in French, while students in all other provinces complete the questionnaire in English. The questionnaire includes measures on student demographics, healthy eating, physical activity, sedentary behaviour, substance use, mental health, bullying, school connectedness, and academic achievement(125). A complete copy of the student questionnaire used in 2017-18 and 2018-19 is provided in Appendix A. This thesis used outcome measures of student depression, anxiety, and flourishing scales as well as 23 core predictor measures.

4.2.1.1 Mental Health Scales

Depression was measured using the Centre of Epidemiologic Studies Depression Scale - 10 (CESD-10)(23,126). The scale assesses symptoms of depression by asking respondents to indicate the frequency of various symptoms (e.g., sadness, loneliness, trouble concentrating) during the past week on a 4-point Likert scale from 0 (“None or less than 1 day”) to 3 (“5-7 days”). Scores range from 0 to 30, with higher scores indicating greater degrees of depressive symptomatology and risk of unipolar depression. Students with a score greater than or equal to 10 were classified as having clinically relevant depressive symptoms. The CESD-10 has shown factorial validity and internal consistency when used within adolescent populations(24).

Anxiety was measured using the Generalized Anxiety Disorder 7-item Scale (GAD-7)(25). The scale assesses the frequency of anxiety symptoms (e.g., worrying, nervousness, irritability) over a two-week period on a 4-point Likert scale from 0 (“Not at all”) to 3 (“Nearly every day”). Scores range from 0 to 21 with higher scores indicating greater levels of anxiety symptoms and risk of generalized anxiety disorder. Students with a score greater than or equal to 10 were classified as having clinically relevant anxiety symptoms. The GAD-7 has shown validity for use in assessing anxiety symptoms in adolescents and in distinguishing between mild and moderate generalized anxiety disorder(26).

Flourishing was measured using a modified version of Diener's Flourishing Scale (FS)(27). The scale assesses overall psychosocial wellbeing by asking respondents to indicate level of agreement with self-perceived success in areas of relationships, self-esteem, life purpose and optimism on a 5-point Likert scale from 1 (“Strongly Disagree”) to 5 (“Strongly Agree”). Scores range from 8 to 40 with higher scores indicating greater levels of flourishing. The scale has been shown to have strong internal consistency and criterion validity across a range of age groups(28,29).

4.2.1.2 Demographics

This thesis examined student-level demographics related to sex, grade, ethnicity, and weekly spending money which is a proxy for student-level socioeconomic status. To measure sex, students were asked “Are you female or male?” with response options of “Female” and “Male”. To measure grade, students were asked “What grade are you in?”, with response options ranging from “Grade 9” to “Grade 12”. Students in Quebec were given response options ranging from “Secondary 1” to “Secondary 5” and “Other”. Secondary 3 is equivalent to Grade 9, Secondary 4 is equivalent to Grade 10 and Secondary 5 is equivalent to Grade 11. To measure ethnicity, students were asked “How would you describe yourself? (Mark all that apply)” with response options of “White”, “Black”, “Asian”, “Aboriginal (First Nations, Metis, Inuit)”, “Latin American/Hispanic” and “Other”. Students who indicated more than one ethnicity or who indicated Aboriginal ethnicity were classified as Mixed or Multi-ethnic. To measure weekly spending money, students were asked “About how much money do you usually get each week to spend on yourself or to save? (Remember to include all money from allowances and jobs like baby-sitting, delivering papers, etc.)”. Response options range from ‘Zero” to ‘More than $100” and ‘I do not know how much money I get each week”.

4.2.1.3 Body Weight and Weight Perception

This thesis examined two measures of objective body weight and subjective weight perception. To measure objective body weight, students were asked to provide their height and weight, from which a body mass index was measured. Body mass index values were categorized according to World Health Organization age- and sex-specific cut-offs into categories of “Underweight”, “Normal Weight”, “Overweight”, and “Obese”. Students who did not provide valid height and weight data were classified as “Not Stated”. To measure weight perception, students were asked “How do you describe your weight?”, with response options for “Very underweight”, “Underweight”, “About the right weight”, “Overweight”, “Very overweight”.

4.2.1.4 Eating Behaviours

This thesis examined two eating behaviours related to daily breakfast consumption and consumption of fruits and vegetables. To measure daily breakfast consumption, students were asked “If you do not eat breakfast every day, why do you skip breakfast? (Mark all that apply)”. Students who responded “I eat breakfast every day” were classified as daily breakfast consumers, while students who responded one or more reasons for skipping breakfast were classified as non-daily consumers. To measure fruit and vegetable consumption, students were asked "Yesterday, from the time you woke up to the time you went to bed, how many servings of vegetables and fruits did you have?", with response options ranging from "None" to "9 or more servings".

4.2.1.5 Movement Behaviours

This thesis examined measures of daily physical activity, screen time, and sleep. To measure physical activity, students were asked to indicate the amount of time spent on hard and moderate physical activity each day of the last seven days, and a derived measure of average daily minutes of physical activity was calculated. To measure screen time, students were asked to indicate the amount of time per day they usually spend "watching/streaming TV shoes or movies", "Playing video/computer games", "Talking on the phone", "Surfing the internet", and "Texting, messaging, emailing". A derived measure for average daily screen time was calculated by summing the time spent on each activity. To measure sleep, students were asked to indicate the amount of time per day they usually spend "Sleeping".

4.2.1.6 Substance Use

This thesis examined measures of current use of cigarettes, e-cigarettes, cannabis, and binge drinking. To measure current use of cigarettes, students were asked "On how many of the last 30 days did you smoke one or more cigarettes?", with response options ranging from "0 days" to "30 days (every day)". Students were classified as current cigarette users if they indicated at least one day of use in the last 30 days. To measure current use of e-cigarettes, students were asked "On how many of the last 30 days did you use an e-cigarette?", with response options ranging from "0 days" to "30 days (every day)". Students were classified as current e-cigarette users if they indicated at least one day of use in the last 30 days. To measure current cannabis use, students were asked "In the last 12 months, how often did you use marijuana or cannabis? (a joint, pot, weed, hash)", with response options ranging from "I have never used marijuana" to "Every day". Students were classified as current cannabis users if they indicated "Once a month" or more frequent use. To measure current binge drinking, students were asked "In the last 12 months, how often did you have 5 drinks of alcohol or more on one occasion?", with response options ranging from "I have never done this" to "Daily or almost daily". Students were classified as current binge drinkers if they indicated "Once a month" or more frequent use.

4.2.1.7 Bullying and Educational Measures

This thesis examined measures of bullying victimization, truancy, and educational expectations. To measure bullying victimization, students were asked “In the last 30 days, how often have you been bullied by other students?”, with response options ranging from “I have not been bullied by other students in the last 30 days” to “Daily or almost daily”. Students who indicated any frequency were classified as bully victims. To measure truancy, students were “In the last 4 weeks, how many classes did you skip when you were not supposed to?”, with response options ranging from “0 classes” to “More than 20 classes”. Students skipping six or more classes were grouped so that final response categories included “0 classes”, “1 or 2 classes”, “3 to 5 classes” and “6 or more classes”. To measure educational expectations, students were asked “What is the highest level of education you think you will get? (Choose only one)”, with response options for some high school or less, high school diploma, college or trade, university bachelor’s degree, university advanced degree, or “I don’t know”. Students who indicated a college, trade, or university degree were classified as expecting to pursue post-secondary education.

4.2.1.8 School Connectedness

This thesis examined school connectedness using an adapted version of the National Longitudinal Study of Adolescent Health SCS 5-item scale(127), which asks students to indicate their agreement to the statements “I feel close to people at my school”, “I feel I am part of my school”, I am happy to be at school”, “I feel the teachers at my school treat me fairly”, and “I feel safe in my school” on a four-point Likert scale ranging from “Strongly Agree” to “Strongly Disagree”. A sixth item, “Getting good grades is important to me”, was added and a numeric score ranging from 6 to 24 was generated, with higher scores indicating stronger sense of connection to school.

4.2.1.9 Home Life and Social Support

This thesis examined three measures related to happy home life, family support, and friend support. Students were asked to indicate their agreement to three statements on a five-point Likert scale ranging from “Strongly agree” to “Strongly disagree”. To measure happy home life, students indicated level of agreement with “I have a happy home life”. To measure family support, students indicated level of agreement with “I can talk about my problems with my family”. To measure friend support, students indicated level of agreement with “I can talk about my problems with my friends”.

Three binary indicators were generated for students indicating “Strongly agree” or “Agree” versus all other response options.

4.2.2 School Policies and Practices Questionnaire

The School Policies and Practices questionnaire (SPP) is an online questionnaire completed by a school administrator who is familiar with their school's policy and program environment. The SPP takes approximately 30 minutes to complete and is typically completed within three weeks before or shortly after the data collection date. The SPP is available in French for administrators in Quebec, and in English for administrators in all other provinces. The SPP includes measures on school policies, practices and programs related to healthy eating, physical activity, sedentary behaviour, substance use, mental health, and bullying(118). This thesis used measures from the mental health section of the SPP, which was developed as part of the expanded COMPASS mental health module(128). A complete copy of the mental health section of the SPP used in 2017-18 and 2018-19 is provided in Appendix B. This thesis used measures of on-site school mental health services and programs, availability of mental health staff and training, and coordination with external organizations, described in further detail below

4.2.2.1 On-Site School Mental Health Services and Programs

To examine availability of on-site mental health services, administrators were asked “Are any of the following mental health services available on-site at your school? (Check all that apply)” with options of a) “Assessment for emotional or behavioural problems (including behavioural observation, psychosocial assessment and observation checklists)”, b) Diagnostic assessment (comprehensive psychological evaluation)” c) “Behavioural management consultation with teachers, students, or families”, d) “Case management, including monitoring and coordination of services”, e) “Referral to specialized programs or services for emotional or behavioural problems or disorders”, f) “Crisis intervention (e.g., response to traumatic events, including disasters, serious injury/death of a member of the school community)”, g) “Individual counselling/therapy”, h) “Group counselling/therapy”, i) “Substance abuse counselling”, and j) “Family support services in school setting (e.g., child/family advocacy, counselling) “. Separate binary indicators were generated for availability of each service.

To examine additional school-specific mental health programming, administrators were asked “Other than classes/curriculum, does your school offer any programs to promote mental health?”

Administrators who indicated “Yes” were further prompted to indicate whether programs are new or continuing and given an open-ended text response to describe the programs. Program details were examined for applicability and a binary yes/no indicator of school-specific programming was generated.

4.2.2.2 Mental Health Staffing and Training

To examine availability of mental health professionals, administrators were asked “Please indicate the availability of the following mental health professionals at your school (Select all availability options that apply)” with categories a) “Child and Youth Worker”, b) “Counsellor”, c) “Social Worker”, d) “Psychologist”, e) “Mental Health Nurse” and f) “Other (please list)”. Response options included “On call”, “On-site full-time”, and “Regularly scheduled” with the option to put in hours per month for regularly scheduled professionals. Response options were arranged into ordinal categories for each professional of “None”, “On-call”, “Part-time”, and “Full time”.

To examine availability of mental health training for school staff, administrators were asked `During the past 12 months, how many staff have received the following training related to mental health?” with categories a) “Mental health awareness/literacy (e.g., basic information, key warning signs)”, b) “Providing mental health support (e.g., mental health first aid, Supporting Minds, etc.)” and c) “Suicide prevention”. Response options included “All or most”, “Some (e.g., 1-5)” or “None”, and were arranged into ordinal categories for each type of training.

4.2.2.3 Coordination with External Organizations

To examine school coordination with community organizations related to mental health, administrators were asked “What are your general practices for routine referral to and coordination with community-based mental health organizations or providers? (Check all that apply)” with options of a) “Staff make passive referrals (e.g., give brochures, lists and contact information of providers or organizations)”, b) “Staff make active referrals (e.g., staff complete form with family, make calls or appointments, assist with transportation)”, c) “Staff follow-up with student/family (e.g., calls to ensure appointment kept, assess satisfaction with referral, need for follow-up)”, d) “Staff follow-up with provider (via phone, e-mail, mail)”, e) “Staff host or attend team meetings with community providers” and f) “Staff do not make referrals”. Response options were arranged into ordinal categories of “None”, “Passive referrals”, “Active Referrals”, and “Follow-up”.

To examine school coordination with local public health units, administrators were asked "During the past 12 months, what role did your local Public Health Unit (PHU) play when working with your school on improving mental health for students? (Check all that apply)" with options of a) "No contact with local Public Health Unit", b) "Provided information/ resources/programs (e.g., posters, toolkits)", c) "Solved problems jointly" and d) "Developed/implemented program activities jointly". A binary yes/no indicator was generated for responses b-d to represent having each type of coordination.

4.2.3 School-level Administrative and Census Data

This thesis used administrative data on school province and total enrolment size, which was gathered as part of the recruitment process. School-level sociodemographic data was also gathered by linking school location information to supplemental Statistics Canada data from the 2016 Census. This thesis examined a measure of school urbanicity using population density data collected using the Geosearch lookup tool(129) based on the population centre in which the school resides. Schools located in geographic areas with populations from 100,000 and greater and a population density of at least 400 per square kilometer were classified as "Large Urban", schools with populations between 30,000 to 99,999 and a population density of at least 400 per square kilometer were classified as "Medium Urban", and schools with populations less than 30,000 or a population density under 400 per square kilometer were classified as "Small Urban/Rural". This thesis examined a measure of school socioeconomic status using median household income data. The data were collected from publicly available datafiles(130) based on the school forward sortation area.

4.3 Statistical Analyses

The research questions in this thesis were answered using decision tree techniques. A decision tree is a machine learning technique that examines an outcome of interest by segmenting the sample into distinct subgroups based on similar characteristics of predictor variables. Decision trees segment the predictor space based on a series of hierarchical binary splits, forming a tree structure. This thesis used three different types of decision trees: classification and regression trees (CART), multilevel random effects regression trees (RE-EM), and conditional inference trees (CI). An overview of each tree technique is provided below, along with information on the specific analyses conducted for each research question.

4.3.1 Classification and Regression Trees

Classification and regression trees (CART) methods, also called recursive partitioning, are methods for decision tree creation based on finding the statistically "optimal" split of the sample into subgroups(131) such that subjects within a subgroup are similar and subjects across subgroups are as different as possible. "Optimal" splits are determined by recursively choosing the variables and cut-off levels that produce maximum separation among subgroups and minimal within-group variability with respect to the outcome(131). Splitting occurs until a stopping rule is reached, typically based on minimum subgroup size(113,131,132). Through this recursive process, the predictor space is divided into a final set of distinct and non-overlapping regions(132). For every observation within each region, the same prediction is made for the outcome. In the case of regression trees, this is the mean response value for the subgroup, while for classification trees this is the most commonly occurring outcome(132).

Recursive partitioning methods use a top-down, greedy approach, in which the "optimal" split chosen in each step is the split that provides maximum group separation at the given step. This approach technically results in a statistically sub-optimal split, which is optimal among all possible splits at the given step but may not correspond to a global optimum tree. Despite this, the sub-optimal split is typically referred to as statistically "optimal" within the context of the greedy approach. This statistically optimal split at each step is calculated based on a measure of node impurity. In the case of regression trees for continuous data, node impurity is measured by the residual sum of squares (RSS). RSS measures the sum of the difference between the outcome value for each observation and the mean outcome value for the group. The calculation is given by:

$$\sum_{j=1}^{J}\sum_{i\epsilon R_j}\left(y_{ij}-\hat{y}_{R_j}\right)^2$$

where there are $j = 1, \ldots, J$ distinct subgroups R_j, y_i is the value of the outcome for each observation i, and $\hat{y}_{R_j}$ is the mean outcome value for subgroup $R_j(132)$. In the case of classification trees for categorical outcomes, node impurity is measured by the Gini index, which calculates the total variance across K classes:

$$G = \sum_{k=1}^{K}\hat{p}_{jk}\left(1-\hat{p}_{jk}\right)$$

where $\hat{p}_{jk}$ is the proportion of observations from the j^{th}subgroup that belong to the k^{th} class.

Decision trees, particularly CART, tend to over-fit the sample data, resulting in poor generalizability. To mitigate this, tree pruning is employed, in which a larger tree is created and then pruned to obtain an optimal subtree(132). To do this, cost complexity pruning is performed using K-fold cross-validation, in which a complexity parameter α is determined and then used to find a set of best subtrees for each possible number of total subgroups from 1 to the size of the original tree(132,133). The optimal tree is then chosen to minimize the average error.

4.3.2 Multilevel Regression Trees

When evaluating the influence of the school environment, it is important to consider the hierarchical nature of students clustered within schools. Random effects trees (RE-EM) are an extension to traditional regression trees that account for the non-independence of subjects using random effects terms(114,134,135), analogous to a mixed effects regression model(136). RE-EM trees are estimated by implementing a standard regression tree algorithm within an expectation-maximization algorithm, with random effects estimated using a linear mixed effects model(114,134,135). Tree pruning and stopping rules are implemented in the same manner as in standard regression trees. RE-EM approaches have been found to generally outperform standard regression trees in terms of predictive accuracy in the case of clustered data(134,135). RE-EM approaches also outperform linear mixed effects models when data have an underlying tree structure and have comparable performance even when this is not the case(135).

4.3.3 Conditional Inference Trees

Conditional inference trees (CI) are an alternative decision tree technique with a different recursive splitting algorithm than CART(137). While the CART algorithm simultaneously chooses the optimal splitting variable and value at each split, the CI algorithm splits the choice into two steps. First, the optimal splitting variable is chosen based on having the strongest association to the outcome variable as measured by the smallest *p*-value. The *p*-value is calculated using a regression model appropriate to the outcome type (e.g., linear regression for continuous outcomes). Second, the optimal splitting point is determined for the chosen variable. This splitting approach continues recursively until a node is reached in which no covariates have a significant association to the outcome based on a prespecified significance level. For larger samples, additional stopping rules based on minimum subgroup sizes can also be used. No pruning is performed using the CI algorithm. CI approaches are sometimes preferred to CART since the null hypothesis stopping rule tends to limit overfitting and the two-stage splitting approach tends to limit bias toward variables with many cut points(113,137).

4.3.4 Study Analyses

The research questions for this thesis were answered using different decision tree techniques described above as well as traditional regression techniques. Full descriptions of the analyses used to answer each research question are provided in Chapter 5, Chapter 6, and Chapter 7. The following is a brief overview of the analyses conducted to answer each research question.

The objective of Study 1 was to compare the performance of classification and regression trees (CART) and conditional inference trees (CI) to traditional linear and logistic regression methods in the context of health survey data. Cross-sectional student-level data and school-level census data from Year 7 (2018-19) were used, with the sample split into training and test sets. Five outcome variables were examined: continuous scale scores for GAD-7, CESD-10, and FS, and binary indicators of anxiety and depression. CART and CI models were run for each outcome and performance was compared against linear and logistic regression with backward elimination variable selection. Model performance was assessed using adjusted R^2 (R^2_{adj}) and root mean square error (RMSE) for continuous outcomes, and percent classification accuracy (pCA) and area under the receiver operating characteristic curve (AUC) for binary outcomes. Models were also compared on parsimony and relative variable importance.

The objective of Study 2 was to use decision tree analysis to determine which contextual and behaviour factors are most influential on youth mental health outcomes. Cross-sectional student-level data and school-level census data from Year 7 (2018-19) were used, Decision trees were run to examine continuous score outcomes for GAD-7, CESD-10 and FS. RE-EM trees were used to account for school-level clustering. Linear mixed effects regression models (LME) were also fit for each outcome and compared against RE-EM tree results.

The objective of Study 3 was to determine which, if any, combinations of school mental health practices are associated with better student mental health. Longitudinal student-level data and school-level SPP from Year 6 (2017-18) and Year 7 (2018-19) were used, as well as school-level census data. Continuous score outcomes for GAD-7, CESD-10 and FS were examined, and student-level predictors were chosen based on the results of Study 2. Intraclass correlation coefficients (ICCs) were calculated to determine the amount of variability in mental health scale outcomes attributed to between-school differences. RE-EM trees were run in two stages: first including only school-level variables to examine overall impacts, and second adding student-level demographics to examine differential subgroup impacts.

4.3.5 Software

R version 4.0.3 (R Foundation for Statistical Computing, Vienna, AT) was used for all decision tree analyses. The “rpart” package was used for CART models, the “partykit” package was used for CI models, and the “REEMtree” package was used for RE-EM models. The “rpart.plot” package was used for tree plotting. Additionally, the “lm” and “glm” functions in the “MASS” package were used for linear and logistic regression models, and the “nlme” package was using for linear mixed effects regression models in Study 2. SAS version 9.4 (SAS Institute, Cary, NC) was used for additional data manipulation and descriptive statistics, and the GLIMMIX procedure was used to calculate ICCs for Study 3.

Chapter 5
Manuscript 1

Examining the use of decision trees in population health surveillance research: an application to youth mental health survey data in the COMPASS study

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5.1 Overview

Introduction: In population health surveillance research, survey data are commonly analyzed using regression methods; however, these methods have limited ability to examine complex relationships. In contrast, decision tree models are ideally suited for segmenting populations and examining complex interactions among factors, and their use within health research is growing. This article provides a methodological overview of decision trees and their application to youth mental health survey data.

Methods: The performance of two popular decision tree techniques, classification and regression tree (CART) and conditional inference tree (CI) techniques, is compared to traditional linear and logistic regression models through an application to youth mental health outcomes in the COMPASS study. Data were collected from 74 501 students across 136 schools in Canada. Anxiety, depression and psychosocial well-being outcomes were measured along with 23 sociodemographic and health behaviour predictors. Model performance was assessed using measures of prediction accuracy, parsimony and relative variable importance.

Results: Decision tree and regression models consistently identified the same sets of most important predictors for each outcome, indicating a general level of agreement between methods. Tree models had lower prediction accuracy but were more parsimonious and placed greater relative importance on key differentiating factors.

Conclusion: Decision trees provide a means of identifying high-risk subgroups to whom prevention and intervention efforts can be targeted, making them a useful tool to address research questions that cannot be answered by traditional regression methods.

Keywords: decision trees, population health, survey methods, mental health, youth

5.2 Highlights

- Decision trees can be used within population health research to address important research questions that cannot be answered by traditional regression methods.
- A key advantage of decision trees over regression models is the ability to examine complex interactions among risk factors.

- Decision trees can be used to identify high-risk groups to whom prevention and intervention efforts can be targeted.
- While regression models may have higher prediction accuracy in some settings, decision trees place greater emphasis on key differentiating factors.

5.3 Introduction

Population health surveillance research is often carried out using large-scale survey studies that attempt to assess the impacts of wide-ranging social, economic and environmental factors on various health outcomes. The relationship between these factors and health outcomes is often characterized by complex interactions that make it impractical to identify any single factor as causal. In the context of youth mental health, outcomes have previously been associated with socioeconomic status(138), weight status(139), dietary behaviours(140), physical activity and sedentary behaviours(141), sleep habits(142), cannabis use(143), bullying(144), school connectedness(60,62) and peer and family relationships(145,146), among other factors. However, most research studies focus on examining the impact of any given factor or domain of factors in isolation; in reality, the underlying interrelationships are likely more complex.

Associations are often examined using regression models, which estimate the association between a predictor and an outcome while controlling for other factors. However, these models are rarely used to estimate complex interactions between factors, due to computational limitations and difficulty in interpretation. Additionally, the resulting model estimates do not allow for the development of risk profiles, that is, separating subjects into subgroups based on certain combinations of risk factors. The identification of high-risk subgroups is important to efficiently target resources and interventions. Decision trees comprise a different class of models that are ideally suited for segmenting populations and examining complex interactions among factors(113).

Decision trees are commonly used in clinical research that focusses on screening and diagnostics(116), with emphasis on prediction. Decision trees are less common in population health research, where the focus is on understanding associations and identifying subgroups for targeting behavioural interventions, though their use is increasing. Within the domain of mental health, recent studies using decision trees have primarily examined associations with depression(147–152) and suicide risk(148,153–161).

Two studies examined depression outcomes in youth populations specifically. Hill et al.(149) found that, among students with subclinical depressive symptoms at baseline, friend support was protective against developing major depressive disorder by age 30, with anxiety disorder and substance use disorder increasing risk among those without friend support. Seeley, Stice and Rohde(151) found poor school functioning to be a primary risk factor for major depressive disorder onset among girls with elevated depressive symptoms at baseline, with parental support acting as a protective factor only among girls with low levels of baseline depressive symptoms. Three studies examined suicide ideation in youth populations and found that mediating factors such as family relationships(155,158) and social support(155,156) were only protective among students that did not have high levels of depression.

Among the studies mentioned above, few included direct performance comparisons between tree and regression methods. Smaller studies by Burke et al.,(154) Mitsui et al.(148) and Handley et al.(161) found regression models had higher predictive accuracy than corresponding tree models; however, these studies had small sample sizes (ranging from 359 to 2194 participants). Conversely, two larger studies—one by Dykxhoorn et al.(160) examining a longitudinal sample of 11 088 children, and another by Batterham et al.(150) examining a longitudinal study of 6605 adults—found decision trees to outperform corresponding logistic regression in terms of sensitivity and overall predictive accuracy. Thus, while there is some evidence to suggest that decision trees may have advantages over traditional regression methods in the case of larger sample sizes, there is an overall lack of available evidence within the domain of mental health.

Despite growing use of decision trees, regression models remain commonplace in the population health literature. This results in a missed opportunity to understand the complex interactions among risk factors and the identification of high-risk subgroups to which prevention and intervention efforts can be targeted. The aim of this study was therefore to examine the use of decision trees in the analysis of large-scale population health surveillance data. In this paper, we first provide an overview of two popular types of decision tree, the classification and regression tree (CART) and the conditional inference tree (CI) techniques. Next, the performance of decision tree models is compared to traditional linear and logistic regression models through an application to youth mental health outcomes in the COMPASS study.(118) Tree and regression methods are evaluated based on prediction accuracy and parsimony, with additional considerations given to relative variable importance and model interpretability.

5.4 Methods

5.4.1 Background on Decision Trees

Decision trees are statistical models that examine an outcome of interest by partitioning the sample into distinct subgroups based on predictor variables. The subgroups are determined using a series of binary splits that resemble a tree structure. Various types of decision tree algorithms have been developed(112); this analysis focusses on two popular types of decision tree: CART and CI. Methodological overviews of CART and CI in the context of epidemiological research have been previously published(113,116); a summary of important features follows.

5.4.1.1 Classification and Regression Trees

CART is a widely used class of decision tree for categorical (classification) and continuous (regression) outcomes. Originally developed by Breiman et al.(162), CART methods find optimal splits of the sample into subgroups(131) such that subjects within a subgroup are similar and subjects across subgroups are as different as possible. Optimal splits are determined by recursively choosing the variables and cut-off levels that produce maximum separation among subgroups and minimal within-group variability with respect to the outcome(131). Continuous and categorical variables may be split multiple times throughout the tree on different cut-points. Splitting occurs until a stopping rule is reached, typically based on minimum subgroup size(113,131,132). Through this recursive process, the predictor space is divided into a final set of subgroups, for which the mean outcome value (regression trees) or the percent of the subgroup having the outcome (classification trees) is calculated(132).

A large tree grown by recursively splitting the predictor space tends to overfit the sample data, resulting in poor generalizability. Overfitting is mitigated using tree pruning and a cross-validation procedure, in which the large tree is pruned leading to a sequence of nested subtrees from among which an optimal tree is selected. The most commonly used pruning method is cost complexity pruning, in which an increasing sequence of complexity parameters corresponds to a sequence of nested subtrees with decreasing sizes(132,133). The optimal subtree that minimizes the average error based on cross-validation(132) is then chosen. When working with larger samples, the “1-SE” rule is often used to choose the smallest subtree that has an average error within one standard deviation of the overall minimum error(113,116).

5.4.1.2 Conditional Inference Trees

CI is an alternative to CART developed by Hothorn et al.(137) While CART chooses the optimal split at each step among all potential variable and splitting points simultaneously, CI separates the splitting determination into two steps. First, the optimal variable to split on is chosen based on the strongest association to the outcome. Association to the outcome variable is measured using regression models appropriate for the outcome, for example, linear regression for continuous outcomes and logistic regression for binary outcomes(113,137). The covariate with the smallest p value is chosen for splitting. Second, the optimal splitting point for that variable is determined(113,137). This approach mitigates the selection bias toward variables with many splitting points often found in CART(113,137). This splitting process continues recursively among each subgroup until a stopping rule is reached. As with CART, continuous and categorical variables can be split more than once throughout the tree at different cut-points.

The stopping rule for CI is based on a global null hypothesis: the algorithm stops splitting when no covariates have a significant association to the outcome based on a prespecified significance level (alpha; α)(113,137). For large samples, additional stopping criteria based on minimum subgroup sizes can also be used. No pruning is required in CI; the global test for significance acts as a means to prevent overfitting(113,137).

5.4.2 Application

The relative performance of decision trees and regression methods was compared in the context of population surveillance research using youth mental health data from the COMPASS study(118).

5.4.2.1 Ethics Approval, Study Design and Sample

COMPASS is a prospective cohort study designed to collect hierarchical health data from Canadian secondary school students(118). COMPASS has received ethics clearance from the University of Waterloo Research Ethics Board (ORE 30118). Additional details about the COMPASS host study are available in print(118) and online (https://uwaterloo.ca/compass-system).

We used student-level data from Year 7 (2018/19) of the COMPASS study. The sample consists of 74 501 students from 136 schools in Ontario (61 schools), Alberta (8 schools), British Columbia (15 schools) and Quebec (52 schools). COMPASS uses purposeful sampling to recruit whole-school samples based on their use of active-information, passive-consent parental permission protocols. The participation rate for 2018/19 was 81.9%, with the primary reason for nonparticipation being absenteeism or scheduled spare on the data collection date.

5.4.2.2 Measures

The COMPASS student questionnaire is a paper-based questionnaire completed by students during class time. The questionnaire is anonymous and self-administered, and students may decline to participate at any time. This study examined 5 mental health outcome measures related to depression, anxiety and psychosocial well-being (flourishing), as well as 23 core predictor measures related to demographics, body weight, healthy eating, movement behaviours, substance use, bullying, academics and school support, and perceived family and friend support.

5.4.2.3 Mental Health Outcomes

5.4.2.3.1 Depression

Depression is measured using the Center for Epidemiologic Studies Depression Scale 10 -item scale (CESD-10)(23,126), which has been validated in adolescent populations(24). The CESD-10 is measured as a continuous score ranging from 0 to 30, with higher scores indicating greater degrees of depressive symptomatology and risk of unipolar depression. An additional binary measure of depression is used, with students scoring greater than or equal to 10 classified as having clinically relevant depressive symptoms.

5.4.2.3.2 Anxiety

Anxiety is measured using the Generalized Anxiety Disorder 7-item Scale (GAD-7)(25), which has been validated in adolescent populations(26). The GAD-7 is measured as a continuous score ranging from 0 to 21, with higher scores indicating greater levels of anxiety. An additional binary measure of anxiety is used, with students scoring greater than or equal to 10 classified as having clinically relevant anxiety symptoms.

5.4.2.3.3 Flourishing

Flourishing is a component of psychological well-being and is measured using a modified version of Diener's Flourishing Scale (FS)(28), which has been validated in young adults(29). The FS is a continuous score ranging from 8 to 40, with higher scores indicating greater levels of flourishing.

5.4.2.4 Predictor Variables

Demographic predictor variables include age, sex, ethnicity and weekly spending money (a proxy for socioeconomic status). Body weight is measured using weight perception and body mass index (BMI) classification. Healthy eating is measured using a binary indicator of whether students eat breakfast daily, as well as the number of servings of fruits and vegetables consumed daily. Movement behaviours are assessed using minutes of average daily moderate-to-vigorous physical activity (MVPA), minutes of total daily screen time and daily minutes of sleep. Substance use is measured using binary indicators of past-month use of tobacco, e-cigarettes and cannabis, as well as past-month binge drinking. Bullying is measured using two indicators of whether a student was bullied or had bullied others in the past 30 days. Academics and school support are measured using a binary indicator of whether students expect to attend a postsecondary institution, the number of classes skipped in the past four weeks, and a continuous school connectedness score (with higher scores indicating higher levels of connection to school). Perceived family and friend support are measured using binary indicators of having a happy home life, feeling able to talk about problems with family and feeling able to talk about problems with friends.

In addition to the student-level measures, additional school-level predictors include total school enrolment, province, school area median income and school urbanicity. Measures of income and urbanicity are taken from Statistics Canada's 2016 census and values linked by school forward sortation area(129,130).

5.4.2.5 Analysis

Individual mental health scale items were person-mean imputed for students missing one or two items. While mean imputation may artificially reduce variance, more complex imputation methods were not used given the primary focus of the analysis on performance rather than inference. Students with missing or outlier values on any variables were removed, resulting in a final complete case sample of 52 350 students. Sample characteristics are provided in Table 1. The sample was randomly split into training (41 795; 80%) and test (10 555; 20%) samples.

Table 1. COMPASS Year 7 (2018/19) student sample characteristics

Category	Variable	Levels	n	%
Total			52 350	100.0%
Mental health outcomes	CESD-10 scale	(Mean, SD)	8.50	5.85

	GAD-7 scale	(Mean, SD)	6.02	5.31
	Flourishing scale	(Mean, SD)	32.42	5.39
	Depression	No	33 778	64.5%
		Yes	18 572	35.5%
	Anxiety	No	40 568	77.5%
		Yes	11 782	22.5%
Demographic factors	Sex	Female	27 483	52.5%
		Male	24 867	47.5%
	Age (years)	12	2 310	4.4%
		13	4 564	8.7%
		14	10 282	19.6%
		15	12 221	23.3%
		16	12 198	23.3%
		17	8 628	16.5%
		18	2 147	4.1%
	Ethnicity	White	37 370	71.4%
		Black	1 565	3.0%
		Asian	5 559	10.6%
		Latin American	1 235	2.4%
		Other/multi	6 621	12.6%
	Spending money	$0	8 099	15.5%
		$1–$20	12 701	24.3%
		$21–$40	5 796	11.1%
		$41–$100	6 469	12.4%
		More than $100	10 067	19.2%
		Don't know	9 218	17.6%
	Province	Alberta	2 222	4.2%
		British Columbia	7 298	13.9%
		Ontario	20 450	39.1%
		Quebec	22 380	42.8%
	Urbanicity	Large urban	28 684	54.8%
		Medium urban	5 044	9.6%
		Small urban/rural	18 622	35.6%
	School median income ('000s $CDN)	(Mean, SD)	67.33	17.47
	School size ('00s)	(Mean, SD)	8.49	3.52
Body weight and eating behaviours	Weight perception	Underweight	8 300	15.9%
		About the right weight	31 877	60.9%
		Overweight/obese	12 173	23.3%

	BMI classification	Underweight	985	1.9%
		Normal weight	29 932	57.2%
		Overweight	6 465	12.3%
		Obese	2 843	5.4%
		Not stated	12 125	23.2%
	Eat breakfast daily	No	25 373	48.5%
		Yes	26 977	51.5%
	Servings of fruits and vegetables	(Mean, SD)	2.98	1.93
Movement behaviours	Average daily physical activity (min)	(Mean, SD)	96.40	62.14
	Screen time (min)	(Mean, SD)	350.97	178.28
	Sleep time (min)	(Mean, SD)	451.94	74.78
Current substance use	Tobacco use	No	49 349	94.3%
		Yes	3 001	5.7%
	E-cigarette use	No	38 570	73.7%
		Yes	13 780	26.3%
	Binge drinking	No	44 020	84.1%
		Yes	8 330	15.9%
	Cannabis use	No	46 683	89.2%
		Yes	5 667	10.8%
Bullying in the last 30 days	Was bullied	No	46 412	88.7%
		Yes	5 938	11.3%
	Bullied others	No	49 702	94.9%
		Yes	2 648	5.1%
Academics and school support	Expect to attend postsecondary institution	No	12 380	23.6%
		Yes	39 970	76.4%
	Classes skipped in past 4 weeks	0 classes	34 894	66.7%
		1 or 2 classes	10 634	20.3%
		3 to 5 classes	4 246	8.1%
		6 or more classes	2 576	4.9%
	School connectedness score	(Mean, SD)	18.67	3.14
Family and peer support	Happy home life	No	10 219	19.5%
		Yes	42 131	80.5%
	Talk about problems with family	No	20 770	39.7%
		Yes	31 580	60.3%
	Talk about problems with friends	No	12 748	24.4%
		Yes	39 602	75.6%

Abbreviations: BMI, body mass index; CESD-10, Center for Epidemiologic Studies Depression 10-item scale; GAD-7, Generalized Anxiety Disorder 7-item scale; min, minutes; SD, standard deviation.

CART and CI were run for continuous (CESD-10, GAD-7, FS) and binary outcomes (depression, anxiety). CART pruning was performed using 10-fold cross-validation and the 1-SE rule. CI significance was set at $\alpha = 0.05$ with a Bonferroni adjustment for multiple testing. Given the large sample size, an additional stopping rule was included for both CART and CI to limit the minimum number of observations per bucket to 1% of the sample. Linear and logistic regression models were also run for continuous and binary outcomes including all main effects. Backward elimination variable selection using the Akaike information criterion (AIC) was performed to mimic tree pruning.

Fitted models from the training sample were applied to the test sample. Predictive performance was compared using adjusted R2 (R^2_{adj}) and root mean square error (RMSE) for continuous outcomes, and percent classification accuracy (pCA) and area under the receiving operator characteristic curve (AUC) for binary outcomes. R^2_{adj} is the amount of variation explained by the model, adjusted for the number of covariates, such that R^2_{adj} will decrease if inclusion of a given covariate does not substantially increase the explained variation. RMSE is the average of the squared difference between the actual and predicted outcome values(132). The closer the predicted values are to the true values, the lower the RMSE. pCA simply measures the percentage of observations for which the model correctly assigns the outcome value. AUC (also known as the concordance statistic) is a more sophisticated measure of accuracy that accounts for both the sensitivity and specificity of the model(131). Both measures range from 0 to 1, with higher values indicating higher model accuracy.

Parsimony was evaluated using the number of parameters and unique variables in the model. Relative variable importance measures were calculated based on the decrease in model fit resulting from removing a given variable from each model. For decision trees, this is measured by the sum of the goodness of split for all occurrences where the variable is used as a primary or surrogate split. For linear and logistic regression models, this is measured by the decrease to R^2_{adj} and AUC, respectively.

R version 4.0.3 (R Foundation for Statistical Computing, Vienna, AT) was used for all analyses. The functions “rpart” (package “rpart”) and “CI” (package “partykit”) were used for CART and CI models, respectively. The functions “lm” and “glm” (package “MASS”) were used for linear and logistic regression models, respectively.

5.5 Results

The average CESD-10 score in the sample was 8.50 (SD = 5.85) with 33.5% of the sample classified as having clinically relevant depressive symptoms. The average GAD-7 score was 6.02 (SD = 5.31) with 22.5% classified as having clinically relevant anxiety symptoms. The average FS score was 32.42 (SD = 5.39).

5.5.1 Decision Tree and Regression Model Comparison

As an illustrative example, the CART and logistic regression model results for the binary anxiety outcome are presented. The final fitted CART tree for the binary anxiety outcome is presented in Figure 1. The model identified 9 final subgroups using 5 unique variables. The primary splitting variable was whether students indicated having a happy home life. Both subgroups were then split based on school connectedness, though different cut-off points were used. Splits were also made for some subgroups on sex, sleep duration and whether the student was bullied. The largest final subgroup was of students who indicated having a happy home life and had school connectedness scores of 17.5 or greater, making up 61% of the sample. Within this group, the probability of having clinically relevant anxiety symptoms was 12.7%, which was the lowest of all groups. The highest risk subgroup comprised females who indicated not having a happy home life and low school connectedness (< 16.25), with a 64.6% probability of having clinically relevant anxiety symptoms.

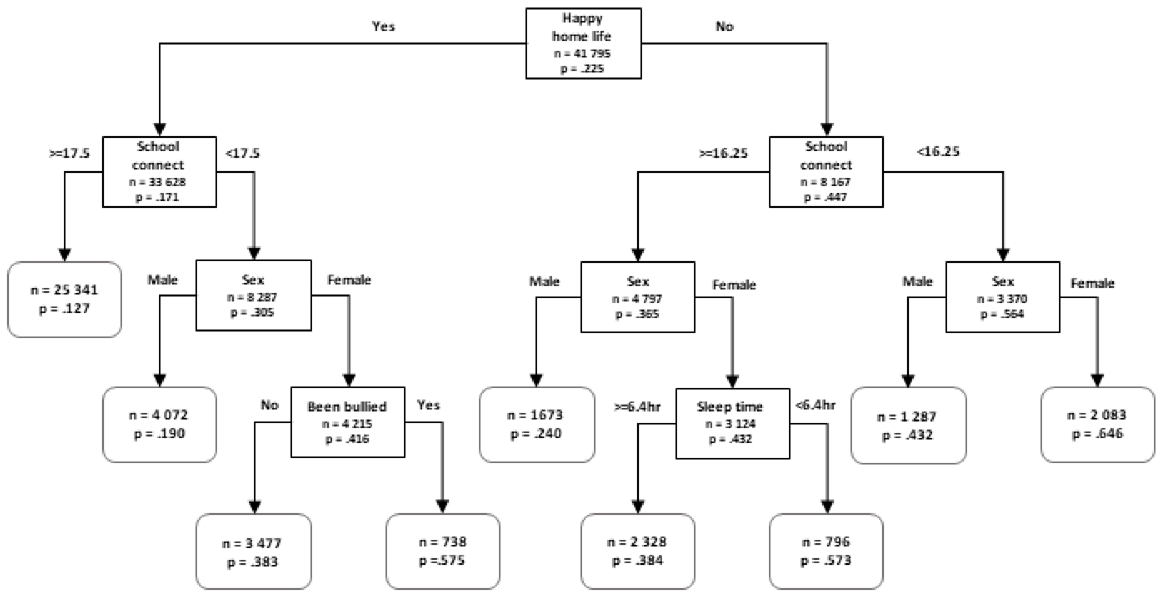

Figure 1. CART tree for having clinically relevant anxiety symptoms (GAD-7 ≥ 10)

Abbreviations: CART, classification and regression tree; GAD-7, Generalized Anxiety Disorder 7-item Scale; school connect, school connectedness.
Note: n is the number of students in subgroup; p is the percentage of the subgroup with clinically relevant anxiety symptoms.

The logistic regression model result for anxiety is presented in Table 2. The final model after applying backward elimination variable selection included 20 variables (33 parameters). Like the CART model, having a happy home life (odds ratio [OR]: 0.33; 95% CI: 0.31–0.34), male sex (OR: 0.33; 95% CI: 0.31–0.34) and school connectedness (OR: 0.88; 95% CI: 0.87–0.89) were found to be important predictors. Other factors including minority ethnicity, higher spending money, living in Quebec, small urban or rural urbanicity, “about right” weight perception, eating breakfast daily, higher sleep time and feeling able to talk about problems with family and friends were associated with lower odds of having clinically relevant anxiety symptoms compared to the respective reference groups for each variable. Older age, eating more fruits and vegetables, higher screen time, current tobacco use and e-cigarette use, being bullied, expecting to attend a postsecondary institution and skipping classes were associated with higher odds of having clinically relevant anxiety symptoms.

Table 2. Logistic regression model for odds of having clinically relevant anxiety symptoms (GAD-7 ≥ 10)

Variable	Level	AOR (95% CI)
Sex (ref = female)	Male	0.33 (0.31–0.34)***
Age (years)	per year	1.05 (1.02–1.07)***
Ethnicity (ref = White)	Black	0.50 (0.43–0.59)***
	Asian	0.73 (0.66–0.81)***
	Latin American	0.83 (0.7–0.98)*
	Other/multi	1.01 (0.94–1.09)
Spending money (ref = $0)	$1–$20	0.93 (0.85–1.01)
	$21–$40	0.86 (0.77–0.95)**
	$41–$100	0.87 (0.79–0.96)**
	More than $100	0.94 (0.86–1.03)
	Don't know	0.87 (0.79–0.96)**
Province (ref = Alberta)	British Columbia	0.89 (0.77–1.03)
	Ontario	0.92 (0.81–1.05)
	Quebec	0.66 (0.58–0.76)***
Urbanicity (ref = large urban)	Medium urban	1.02 (0.93–1.12)
	Small urban/rural	0.86 (0.80–0.91)***
Weight perception (ref = underweight)	About the right weight	0.78 (0.72–0.84)***
	Overweight	1.03 (0.95–1.12)
Eat breakfast daily	Yes	0.76 (0.72–0.80)***
Servings of fruits and vegetables	per serving	1.03 (1.01–1.04)***
Screen time (hours)	per hour	1.05 (1.05–1.05)***
Sleep time (hours)	per hour	0.83 (0.83–0.83)***
Current tobacco use	Yes	1.12 (1.00–1.25)*
Current e-cigarette use	Yes	1.08 (1.01–1.15)*
Was bullied in last 30 days	Yes	2.03 (1.88–2.18)***
Expect to attend postsecondary institution	Yes	1.16 (1.09–1.24)***
Classes skipped in past 4 weeks (ref = 0 classes)	1–2 classes	1.06 (0.99–1.13)
	3–5 classes	1.16 (1.06–1.28)**
	6 or more classes	1.23 (1.10–1.39)***
School connectedness score	per unit	0.88 (0.87–0.89)***
Happy home life	Yes	0.50 (0.47–0.54)***
Talk about problems with family	Yes	0.73 (0.69–0.77)***
Talk about problems with friends	Yes	0.75 (0.71–0.8)***

Abbreviations: AOR, adjusted odds ratio; CI, confidence interval; ref, reference group.

*$p < 0.05$
**$p < 0.01$
***$p < 0.001$

5.5.2 Prediction Accuracy and Parsimony

Prediction accuracy results for continuous outcomes (CESD-10, GAD-7, FS) are presented in Table 3. The linear regression models had the highest test set R^2_{adj} and lowest RMSE for all three outcomes. The R^2_{adj} and RMSE values were similar for CART and CI models, with R^2_{adj} consistently 4% to 5% lower than the linear regression results and RMSE 0.13 to 0.19 higher. The CART trees included the fewest unique variables, followed by CI, with linear regression models including over twice as many variables. However, the number of final parameters (corresponding to number of splits for tree models) was similar for CART and linear regression, and higher for CI models. The absolute value of the R^2_{adj} was relatively low for all models, indicating the predictors explain less than half of the variation in the outcome. Additionally, the R^2_{adj} and RMSE calculated on the test set were similar to the training set for all models, suggesting minimal overfitting.

Prediction accuracy results for binary depression and anxiety outcomes are presented in Table 3. CART produced more parsimonious models than CI and logistic regression, using only 9 splits on 6 variables for depression, and 8 splits on 5 variables for anxiety. CI produced more complex models, using over 50 splits. The larger difference between number of subgroups and variables used in the CI models compared to the CART models is partially due to the model splitting on the same variable multiple times using different cut-points. Logistic regression models included 22 unique variables for depression and 20 for anxiety. Despite the difference in model complexity, the test setpCA and AUC were very similar across models, with logistic regression performing only slightly better. The absolute value of the AUC was 0.71 for depression and ranged from 0.59 to 0.63 for anxiety, which suggests mediocre discriminatory ability. As in the continuous case, training and test set performances were similar, suggesting minimal overfitting.

Table 3. Prediction accuracy comparison for continuous and binary outcomes for CART, CI and regression models

Continuous outcome	Method	# Parameters	# Unique variables	Training R^2_{adj}	Training RMSE	Test R^2_{adj}	Test RMSE
CESD-10	CART	38	9	0.35	4.73	0.33	4.76
	CI	57	10	0.36	4.70	0.34	4.73
	Linear reg.	34	20	**0.39**	**4.59**	**0.38**	**4.57**

GAD-7	CART	39	11	0.28	4.50	0.27	4.55
	CI	63	15	0.29	4.49	0.27	4.55
	Linear reg.	40	23	**0.32**	**4.39**	**0.31**	**4.42**
FS	CART	43	9	0.47	3.94	0.46	3.97
	CI	70	12	0.47	3.93	0.46	3.96
	Linear reg.	40	24	**0.51**	**3.79**	**0.51**	**3.78**
Binary outcome	**Method**	**# Parameters**	**# Unique variables**	**Training pCA**	**Training AUC**	**Test pCA**	**Test AUC**
Depression	CART	9	6	0.75	0.71	0.74	0.70
	CI	53	14	0.75	0.71	0.74	0.70
	Logistic reg.	39	22	**0.76**	**0.71**	**0.76**	**0.70**
Anxiety	CART	8	5	0.80	0.60	0.79	0.59
	CI	52	11	0.80	0.61	0.79	0.61
	Logistic reg.	34	20	**0.80**	**0.63**	**0.80**	**0.63**

Abbreviations: AUC, area under the receiving operator characteristic curve; CART, classification and regression tree; CESD-10, Center for Epidemiologic Studies Depression 10-tiem scale; CI, conditional inference tree; GAD-7, Generalized Anxiety Disorder 7-item scale; FS, flourishing scale; pCA, percent classification accuracy; reg., regression; R^2_{adj}, adjusted R^2; RMSE, root mean square error.

5.5.3 Relative Variable Importance

Relative variable importance percentages for continuous outcomes (CESD-10, GAD-7, FS) are presented in Figure 2. For CESD-10 and GAD-7 outcomes, CART, CI and logistic regression all consistently identified school connectedness, having a happy home life and sex as the three most important variables. Sleep time also ranked fourth highest in relative importance in all except the anxiety linear regression model, which ranked bullying as fourth highest. However, the CART and CI models gave more weight to the highest ranked variables than the linear regression models. CART and CI attributed 78% to 87% of the total importance to the top four variables, while linear regression attributed only 47%, with the remainder split more evenly across other variables in the model.

Similar results are seen for FS, though sex is not identified as important in any of the models, while talking about problems with friends is ranked within the top four for all models, family was identified as important for CART and CI models, and spending money was identified as important for linear regression. Again, CART and CI attributed 86% to 93% of total importance to the top four ranked variables, while linear regression attributed only 43%.

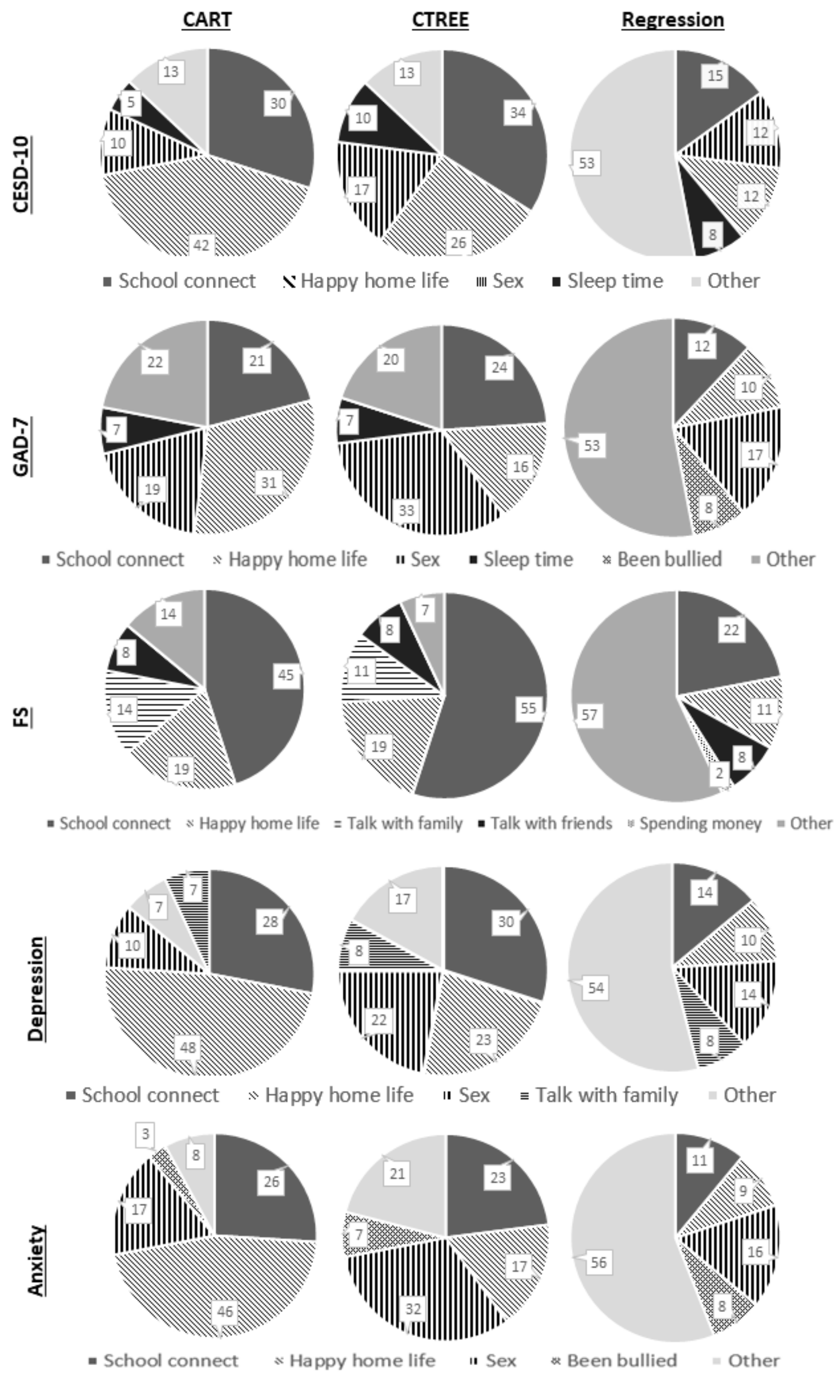

Figure 2. Relative variable importance percentages of top contributing predictor variables for CART, CI and regression models for continuous and binary outcomes

Relative variable importance percentages for binary outcomes are presented in Figure 2. As was seen for continuous outcomes, school connectedness, happy home life and sex were consistently identified as the three most important variables across depression and anxiety models. Talking about problems with family was ranked as fourth highest for depression across all models, while having been bullied was ranked as fourth highest for all anxiety models. CART attributed 92% to 93% of total importance to the top four variables, while CI attributed 79% to 83% and logistic regression attributed 44% to 46%.

5.6 Discussion

This study provided a methodological overview and comparison of two types of decision tree, CART and CI, to traditional linear and logistic regression methods using a novel application to large-scale youth mental health survey data. This study adds to the limited existing evidence on decision tree performance in this domain(148,150,154,160,161) by examining a large sample of youth and wide breadth of predictors. This study also examines methodological considerations of decision trees in the context of population surveillance research, in which prediction accuracy must be weighed against model interpretability. Beyond the subject matter knowledge gleaned from the results of this application to youth mental health, the implications discussed below can be used as a guide for researchers examining other large-scale survey datasets.

In the case of prediction accuracy, for linear scale outcomes linear regression outperformed CART and CI, with 4% to 5% higher R^2_{adj} values and 3% to 5% lower RMSE values. The number of model parameters was similar for CART and linear regression, while CI resulted in more complex models. However, while CART and linear regression had a similar number of parameters, CART identified far fewer unique variables as significant, with the high number of parameters due to multiple splits on the same continuous predictor variables. In contrast, regression models assumed a linear effect of continuous variables and provided only a single estimate representing the effect of a one-unit increase in the variable, regardless of the starting value.

In the case of binary outcomes, logistic regression models again had higher predictive performance than CART and CI; however, overall performance was closer than for continuous outcomes, with 1% to 2% higher prediction accuracy and 0% to 3% higher AUC. In these cases, CART produced far more parsimonious models than both CI and logistic regression, both in terms of total parameters and number of unique variables. Previous small studies by Burke et al.(154), Mitsui et al.(148) and

Handley et al.(161) found AUCs ranging 4% to 8% lower for CART than logistic regression, while in contrast, a study by Batterham et. al(159) found AUC 2% higher for CART than logistic regression. While direct comparison of AUC findings from these studies is difficult given the differences in study samples, outcomes and model specifications, it is still noteworthy that across all studies performance between the two techniques did not drastically differ. Thus, while linear and logistic regression may provide slight advantages in predictive ability, the simpler models generated by CART may be more desirable, particularly for knowledge translation in the context of population health research where the focus is on understanding associations and communicating results to a nontechnical audience.

Decision tree and regression models consistently identified the same sets of most important predictors for each outcome, indicating a general level of agreement between methods. However, CART and CI weighted the relative importance of these top predictors much higher than the regression models, attributing more than three-quarters of total importance to the top four predictors, compared to regression models, which attributed less than half of total importance to the top predictors. This is in line with the greater parsimony seen in the CART and CI models and highlights the ability of decision trees to single out the most important factors.

Additionally, a common limitation of regression models is that factors with high multicollinearity tend to “wash out” when entered simultaneously, leading to inflated variance estimates or variable omission bias, which could cause factors to be overlooked(163). This has been seen in past research comparing trees and regression(160), suggesting that decision tree methods can offer a clearer representation of key factors to aid in decision making. This advantage of parsimony can be particularly beneficial in the domain of population-level disease prevention research, in which a myriad of competing risk factors and confounders may be present.

Higher levels of school connectedness and having a happy home life were consistently identified as key predictors and were associated with lower levels of depression and anxiety and higher flourishing. This is consistent with previous research linking family relationships to adolescent anxiety(146) and school connectedness to emotional distress and depression in youth(60,62). Additionally, previous classification tree analysis on adolescent girls found poor school functioning to be a major risk factor for depression onset but found that parental support was only protective among subgroups with low depression at baseline(151). The protective association to school connectedness highlights the role of the school environment for helping to shape youth mental health and highlights why schools are an appropriate context for intervening, given the ability to reach a large section of the youth population. The decision tree method highlighted in the current study is well suited to future research evaluating complex environmental characteristics and co-occurring interventions.

As previously mentioned, an advantage of decision trees is the ability to examine complex interactions between predictors and identify high-risk subgroups to whom prevention and intervention efforts can be targeted. In the illustrated example with anxiety, bullying was significantly associated with the odds of having clinically relevant anxiety symptoms in the regression model; however, in the CART model, bullying only appears as a risk factor for higher anxiety among the subset of female students with a happy home life and lower school connectedness.

Similarly, sleep time was associated with greater odds of anxiety in the regression model, though the magnitude was small; in contrast, the CART model found sleep to be a protective factor among females without a happy home life and with high school connectedness. Estimates in the regression model correspond to the overall average association across the entire sample and do not provide any insight into the differential impacts on various subgroups. In this case, the low effect size for sleep time in the regression model masks its importance among a specific subgroup.

Studies by Handley et al.(161) and Batterham et al.,(159) which examined suicide ideation in adults, each found important factors present in decision tree analyses that were not significant in corresponding regression models. As noted by Handley, this suggests a multiplicative rather than independent impact of these factors, which would not be detected using a standard regression model of main effects. Thus, decision trees can be much more useful than regression models for researchers and practitioners seeking to identify unique characteristics of the highest risk groups to whom to tailor interventions.

Despite these findings, the stronger predictive performance of regression models compared to decision tree models seen in this study could suggest that the underlying nature of predictors is somewhat linear. In the illustrative anxiety example, school connectedness was found to be an important factor both for those with and without a happy home life, while sex was found to be the next most important factor across three of four subsequent subgroups. This suggests that the effect of these factors is similar across the entire sample, meaning a regression analysis would adequately capture this effect through the single model estimate. Decision trees have a greater advantage over regression models when the true underlying relationships in the data are nonlinear(113). Researchers should therefore carefully consider underlying data structures based on theory and descriptive exploration when contemplating the most appropriate analysis technique.

This study examined two types of decisions tree: CART and CI. Both models segment the population into distinct subgroups by recursively choosing the variables and cut-off levels that produce maximum separation among subgroups and minimal within-group variability. While CART and CI performed similarly in terms of prediction accuracy, CART consistently produced more parsimonious models, including fewer total model parameters and unique variables. Both CART and CI models tended to include multiple splits on different values of the same variable, particularly for the continuous outcomes examined. Tendency to favour continuous predictors over categorical due to the greater number of potential splits is a commonly noted drawback of decision trees(113,162). For binary outcomes, this limitation seems to be more of a concern for CI than CART.

Another commonly mentioned drawback of decision trees is the tendency for the models to overfit to the sample data(137), which is partially mitigated by pruning in the case of CART and stopping rules based on tests of statistical significance in the case of CI(137). In this study, similar model performance for training and test sets showed that overfitting is not a concern using either method, which may potentially be credited to the large sample size in this dataset. Interestingly, CI produced much more complex models than CART. CI models in this study used a standard statistical significance threshold of $\alpha = 0.05$ with Bonferroni correction, suggesting that perhaps more stringent criteria should be used with CI in the case of large sample size. Thus, while previous literature tends to favour CI(113), this study suggests that researchers working with larger-scale health data should instead consider using CART when parsimony and interpretability are primary concerns.

5.6.1 Strengths and limitations

This study provides a novel application of decision trees using large-scale Canadian health survey data. In contrast to previous limited research, this study benefits from a large sample size that allows for more complex tree structures involving a greater number of levels and final nodes.

However, the resulting increased tree complexity makes interpretation difficult, which diminishes one of the primary benefits of tree analysis. While this study used standard stopping and pruning criteria, additional restrictions such as limiting the number of levels and using more stringent significance thresholds could produce smaller, more easily interpretable trees. The impact of varying restrictions on overall model fit should be tested in future work. Additionally, only main effects were included in the regression models for this study; inclusion of interaction terms could have increased the relative performance, though as previously noted this can lead to issues in computation and interpretation.

Another limitation of this study is the low overall model fit. Test set R^2_{adj} values for continuous outcomes ranged from 0.27 to 0.51, indicating that the included predictors explain less than half of the overall variation in the outcomes. AUCs for binary outcomes ranged from 0.59 to 0.70, indicating low to moderate discriminative ability. While it is not uncommon for behavioural studies to have lower model fits, this suggests that other intrinsic factors that are not captured in this study may play an important role in predicting mental health outcomes. Previous studies of suicide ideation outcomes have generally seen higher AUCs around 0.80(148,154,161); however, these studies included baseline depression, which is already a well-established predictor.

Additionally, this study uses a cross-sectional, nonrandomized study design, meaning that neither decision trees nor regression models can show causal relationships between the predictors and mental health outcomes in this case. More broadly, decision trees are generally considered to be exploratory methods(113) used for hypothesis generation. Further, decision trees are not deterministic methods and are highly sensitive to the sample and parameter choices. Methods such as random forest, which grow multiple trees and aggregate the results into overall measures of variable importance, have been developed to overcome this instability(115), though interpretability is sacrificed. Finally, the CART and CI methods used in this study do not account for the hierarchical nature of data (i.e., students clustered within schools). Newer tree methods such as RE-EM(114,135) and M-CART(164) have been developed to account for this nonindependence of observations and should be examined in future research.

5.7 Conclusion

Despite growing use in other domains, decision trees remain an underutilized analysis technique in population health research. While the predictive performance of decision trees was found to be slightly lower than that of traditional regression methods, trees provide a means of examining complex interactions between predictors, and present results in a form that is easily interpretable by nontechnical audiences, aiding in knowledge translation. The ability of decision trees to identify high-risk subgroups to whom prevention and intervention efforts can be targeted is particularly valuable to public health practitioners facing limited resources. Decision trees can be a powerful addition to population health researchers' methodology repertoire to address research questions that cannot be answered by traditional regression methods.

Chapter 6
Manuscript 2

Using Decision Trees to Examine Environmental and Behavioural Factors Associated with Youth Anxiety, Depression, and Flourishing

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6.1 Overview

Modifiable environmental and behavioural factors influence youth mental health; however, past studies have primarily used regression models that quantify population average effects. Decision trees are an analytic technique that examine complex relationships between factors and identify high-risk subgroups to whom intervention measures can be targeted. This study used decision trees to examine associations of various risk factors with youth anxiety, depression, and flourishing. Data were collected from 74,501 students across Canadian high schools participating in the 2018–2019 COMPASS Study. Students completed a questionnaire including validated mental health scales and 23 covariates. Decision trees were grown to identify key factors and subgroups for anxiety, depression, and flourishing outcomes. Females lacking both happy home life and sense of connection to school were at greatest risk for higher anxiety and depression levels. In contrast with previous literature, behavioural factors such as diet, movement and substance use did not emerge as differentiators. This study highlights the influence of home and school environments on youth mental health using a novel decision tree analysis. While having a happy home life is most important in protecting against youth anxiety and depression, a sense of connection to school may mitigate the negative influence of a poor home environment.

Keywords: decision trees; mental health; youth; school climate; home environment

6.2 Introduction

Mental illness has garnered increased global concern in recent years as a leading contributor to global disease burden(30,165). Youth have been identified as a priority group for addressing mental health concerns(4,166), given that the onset of mental illness primarily occurs during adolescence(167) and untreated mental illness during adolescence can lead to negative consequences in adulthood(168). Depression and anxiety are among the mental illnesses associated with highest suicide risk(13), and have also been associated with increased substance use during adolescence(169,170). While previous efforts around youth mental health have primarily focused on combating mental illnesses such as anxiety and depression, recent approaches have also emphasized the importance of enhancing mental well-being(9,19,20). Flourishing, defined as a state of psychosocial wellbeing, has been associated with increased life expectancy(10). Among youth, flourishing has also been associated with lower likelihood of substance use(169–171) and improved academic performance(172–174).

Following Bronfenbrenner's social-ecological model(33), the causal mechanisms driving mental illness onset in youth involve complex interactions between a hierarchical network of individual (e.g., genetic, biological) and environmental (e.g., inter-personal, organizational, community, public policy) factors. Past studies have found widely varying estimates of the proportion of mental illness onset attributable to genetic vs. environmental influences: anywhere from 15% to 80% of youth-onset depression (175) and 18% to 35% of youth-onset anxiety(176) are heritable, with the remaining attributable to environmental factors. Genetic and environmental influences on flourishing are less understood, though one past study examining related well-being constructs found heritability estimates of 34% for subjective happiness and 44% for life satisfaction(177). Thus, while there is evidence of a genetic component to youth mental illness and well-being, the contextual environment plays an influential role.

From a public health perspective, the contextual environment is important as many environmental risk and protective factors can be considered modifiable and hence potential intervention leverage points. The importance of context on youth mental health outcomes is recognized within national public policy guidance. The Mental Health Strategy for Canada(5) published by the Mental Health Commission of Canada (MHCC) prioritizes support for youth mental health with calls to "increase the capacity of families, caregivers, schools, post-secondary institutions and community organizations". Publicly funded community- and school-based supports can act as universal access points for prevention and early intervention efforts and are consistently highlighted as pillars in federal(5,19) and provincial mental health strategies. Related interpersonal factors such as family relationships(62,178,179), peer relationships(60,145), bullying(180), and school connectedness(60,62,63) have previously been linked to youth mental health outcomes. Previous research has also found associations to modifiable behavioural factors such as diet(181), movement behaviours(182,183), sleep(142), and substance use(143). However, two major limitations of past studies are that associations to domains of risk and protective factors are generally examined in isolation, and that the primarily regression-based analytic methods focus on quantifying average effects across the study population without consideration for potential high-risk subgroups.

Decision trees are a machine learning-based analytic technique comprising several classes of modeling algorithms(112), which group similar subjects with respect to an outcome using a tree structure. While more commonly used in medical screening and diagnostics for disease prediction, decision trees have seen recent increasing use in public health research(116) to examine complex relationships between outcomes and risk factors and identify high-risk subgroups to whom prevention and intervention measures can be targeted. Decision trees have previously been used to examine depression outcomes in various adult populations; past studies involving various environmental factors have found social connection(147) and aspects of financial stability(147,150) to be important, while substance use was only found to be a risk factor among certain subgroups(150). However, youth face distinct contextual risk factors, and previous research using decision trees to examine youth mental health is limited. Seely et al.(151) examined major depressive disorder (MDD) onset among adolescent females and found that the subgroup of previously depressed females with poor school functioning was at greatest risk for MDD onset, while family support was only a protective factor among the subgroup of females without previous depressive symptoms. Hill et al.(149) found friend support to be a protective factor against the development of MDD among those with subclinical symptoms, while subgroups with history of anxiety and substance use disorder were at higher risk. These studies highlight the importance of interpersonal factors (school and family support) and behavioural factors (substance use); however, sample sizes in both studies were small. To our knowledge, no previous studies have used decision trees to examine anxiety or flourishing outcomes among youth.

Given the importance of environmental factors on youth mental health, the purpose of this study is therefore to use decision tree analysis to examine associations of modifiable behavioural and interpersonal risk factors with youth anxiety, depression, and flourishing, with a focus on characterizing groups at highest risk of mental ill-health. Results of this exploratory analysis are contrasted against those of traditional regression-based analysis and compared to findings from previous literature to highlight the unique insights gleaned from decision tree analysis.

6.3 Materials and Methods

6.3.1 Study Design and Sample

COMPASS is a prospective cohort study (2012–2021) designed to examine the impact of policies and environmental characteristics on Canadian secondary school students(118). COMPASS collects data on multiple health behaviours and risk factors including mental health, substance use, healthy eating, movement behaviours, bullying and academics. Additional details about the COMPASS study design and methods are available in print(118) and online (https://uwaterloo.ca/compass-system accessed on 13 July 2022). The COMPASS study received ethics clearance from the University of Waterloo Research Ethics Board (ORE 30118) and participating school boards.

The current study uses student-level data from 2018–2019 (Year 7) of the COMPASS Study. The sample consists of 74,501 students from 136 schools in Ontario (61 schools), Alberta (8 schools), British Columbia (15 schools) and Quebec (52 schools). Schools were purposefully recruited into the COMPASS study according to their use of active-information, passive-consent protocols, which have been shown to be important for collecting unbiased data among youth(119). Further details on general school recruitment procedures(120) and 2018–2019 sample recruitment(122) are available. All students within a recruited school who received passive parental permission(118) were invited to participate, and students could withdraw at any time. The participation rate for 2018–2019 was 81.9%, with the primary reason for non-participation being absenteeism at the time of data collection.

6.3.2 Measures

6.3.2.1 Compass Student Questionnaire

The COMPASS student questionnaire is an anonymized, self-administered, paper-based questionnaire. The questionnaire is completed during class time and takes approximately 40 minutes to complete. Data collection procedures for student questionnaire administration are documented(123). This study examined three mental health scale outcomes measuring anxiety, depression, and flourishing, as well as 23 predictor measures related to questionnaire items on demographics, body weight, healthy eating, movement behaviours, substance use, bullying, academics, and perceived school, family, and friend support.

6.3.2.2 Mental Health Outcome Measures

Depression is measured using the Centre of Epidemiologic Studies Depression Scale 10—Revised (CESD-10)(23,126). The CESD-10 is measured as a continuous score ranging from 0 to 30, with higher scores indicating greater degrees of depressive symptomatology, and scores at or above 10 indicating clinically relevant depressive symptoms(23). Anxiety is measured using the Generalized Anxiety Disorder 7-item Scale (GAD-7)(25). The GAD-7 is measured as a numeric score ranging from 0 to 21, with higher scores indicating greater levels of anxiety, and scores at or above 10 indicating clinically relevant anxiety symptoms(25). Flourishing is measured using a modified version of Diener's Flourishing Scale (FS)(28). The FS is a numeric score ranging from 8 to 40 with higher scores indicating greater levels of flourishing. Consistent with recommendations for Likert-style scales(184,185) all individual mental health scale items were person-mean imputed for students missing 1 or 2 items. Students missing three or more scale items on the GAD-7, CESD-10, or FS outcomes were not found to be significantly different on any predictor measures from students missing two or fewer values and were therefore excluded from the respective analyses.

6.3.2.3 Predictor Measures

Demographics: Students are asked to indicate their sex (male, female) and age (12 to 18 years). Students self-identify their ethnicity with options for White, Black, Asian, Hispanic, and Other, with the option to select multiple ethnicities. Weekly spending money is measured as a proxy for socioeconomic status, with options ranging from "$0" to "More than $100".

Weight Status and Perception: Students are asked how they describe their weight with options for Slightly/Very Underweight, About the Right Weight, or Slightly/Very Overweight. An objective measure of Body Mass Index (BMI) is calculated based on self-reported height and weight, and classified into Underweight, Normal Weight, Overweight, or Obese based on World Health Organization age- and sex-adjusted cut-offs. Students with missing height or weight data are included in a separate Not Stated category due to the tendency for BMI data to have non-random missingness mechanisms(186).

Diet and Eating Behaviours: Students are asked whether they eat breakfast daily and their number of daily servings of fruits and vegetables.

Movement Behaviours: Daily moderate-to-vigorous physical activity is measured by asking students the amount and the intensity of activity performed on each of the last seven days. Total daily screen time is measured by asking students the amount of time they usually spend texting/messaging/emailing, playing video/computer games, talking on the phone, watching TV/movies and surfing the internet. Daily sleep time is also measured by asking how much time they usually spend sleeping. These measures have been shown to have moderate validity when compared to objective measures and high test–retest reliability(187).

Substance Use: Current use of cigarettes and e-cigarettes is measured based on students indicating any use in the last 30 days. Current use of cannabis is measured based on use at least once a month in the past 12 months. Current binge drinking is measured based on having five or more drinks at least once a month in the past 12 months.

Bullying and Academics: Bullying is measured using two indicators of whether students have been bullied or have bullied others in the past 30 days. Academic expectations are measured based on students indicating expectations to attend some form of post-secondary education. Truancy is measured based on the number of classes skipped in the past four weeks.

School Connectedness: School connectedness (SC) is measured using an adapted version of the National Longitudinal Study of Adolescent Health SCS-5 item scale(127). The SC scale is as a numeric score ranging 6 to 24, with higher scores indicating greater SC. Scale items include the SCS-5 measures “I feel close to people at my school”, “I feel I am part of my school”, “I am happy to be at my school”, “I feel the teachers at my school treat me fairly”, and “I feel safe in my school”, and an additional measure “Getting good grades is important to me”, with response options ranging from Strongly Agree to Strongly Disagree.

Social Support: Family and friend support are measured based on three individual items from the Multidimensional Scale of Perceived Social Support(188). Students are asked to indicate level of agreement with the statements “I have a happy home life”, “I can talk about my problems with my family”, and “I can talk about my problems with my friends”.

6.3.2.4 School-Level Census Data

Province and school enrolment size are recorded for each participating school. School area median income and school urbanicity are measured by linking to Statistics Canada 2016 Census data based on each school's forward sortation area(129,130).

6.3.3 Analysis

Mixed effects regression trees were separately grown for GAD-7, CESD-10 and FS outcomes including all predictor variables. Random Effects EM (RE-EM) trees were used following the algorithm proposed by Sela and Simonoff(135) and Hajjem(134) to account for school-level clustering based on the assumption that students from the same school may have greater similarity in responses than students from different schools. Students with missing values on a given outcome were therefore excluded from the analysis, while missing predictor values were included and accounted for using surrogate splitting. Given the large sample size, a splitting rule was set requiring a minimum increase to adjusted R-squared (R^2_{adj}) of 0.005 to limit splits that would be unlikely to improve overall prediction accuracy. Tree pruning using 10-fold cross-validation was performed to limit overfitting to the sample data. The smallest tree within one standard deviation of the minimum cross-validation error was chosen. The R software was used for all analyses(189); package "REEMtree"(190) was used to grow the trees, and the package "rpart.plot"(191) was used for plotting.

To provide a comparison of the RE-EM tree results, linear mixed effects regression (LME) models were also fit for each outcome including all predictor variables, using the R package "nlme"(192). Students with missing values on a given outcome or any predictors were excluded from the analysis; maximum likelihood estimation is used within LME to account for missing at random data. A random intercept term was included to account for school-level clustering. Backward elimination variable selection was implemented based on Akaike's Information Criterion (AIC). Intraclass correlation coefficients (ICCs) were calculated on null LME models to quantify the amount of variability in mental health outcomes that can be attributed to differences between schools.

6.4 Results

6.4.1 Sample Characteristics

Sample characteristics are shown in Table 4. The mean GAD-7 score in the sample was 6.2 (SD 5.6) with 24.0% of the sample having scores of 10 or higher, which indicates clinically relevant anxiety symptoms. The mean CESD-10 score was 8.8 (SD 6.1) with 37.0% of the sample having scores of 10 or higher, indicating clinically relevant depressive symptoms. The average FS score was 32.2 (SD 5.7). The sample was 49.1% female with mean age 15.2 (SD 1.5) and predominantly identified as white (68.5%). ICCs showed modest between-school variability of 3.35% in student GAD-7 scores, 2.12% in CESD-10 scores, and 4.29% in FS scores.

Table 4. Sample characteristics for students participating in Year 7 (2018–2019) of the COMPASS Study (N = 74,501)

Continuous Variables	Mean (s.d.)
CESD-10 [N = 70,610]	8.82 (6.05)
GAD-7 [N = 71,736]	6.2 (5.56)
FS [N = 72,415]	32.16 (5.73)
Age [N = 73,960]	15.15 (1.49)
School Area Median Income (‘000s) [N = 74,501]	67.59 (17.45)
School Size (‘00s) [N = 74,501]	8.41 (3.52)
Servings of Fruits and Vegetables [N = 71,679]	2.98 (2.01)
Average Daily Physical Activity (h) [N = 66,007]	1.6 (1.05)
Screen Time (h) [N = 67,181]	5.87 (3.04)
Sleep Time (h) [N = 69,630]	7.52 (1.28)
School Connectedness Score [N = 71,413]	18.5 (3.36)
Binary Variables	**% (n)**
Eat Breakfast Daily [N = 74,501]	0.49 (36,197)
Tobacco Use [N = 73,852]	0.07 (5532)
E-cigarette Use [N = 73,466]	0.28 (20,852)
Binge Drinking [N = 74,254]	0.17 (12,884)
Cannabis Use [N = 73,299]	0.13 (9662)
Was Bullied [N = 70,753]	0.88 (61,940)
Bullied Others [N = 71,063]	0.06 (4339)
Expect to Attend Post Secondary Education [N = 70,753]	0.06 (4339)
Happy Home Life [N = 72,830]	0.79 (57,444)
Talk About Problems with Family [N = 72,234]	0.59 (42,833)
Talk About Problems with Friends [N = 72,622]	0.75 (54,246)
Categorical Variables	**% (n)**
Sex [N = 73,672]	
Female	0.5 (36,546)
Male	0.5 (37,126)
Ethnicity [N = 73,839]	
White	0.69 (51,017)
Black	0.04 (2951)
Asian	0.1 (7465)
Hispanic	0.03 (1886)
Other/Mixed	0.14 (10,520)

Spending Money [N = 73,422]	
$0	0.16 (11,684)
$1–$20	0.24 (17,744)
$21–$40	0.11 (8071)
$41–$100	0.12 (8722)
More than $100	0.19 (14,216)
Don't Know	0.18 (12,985)
Province [N = 74,501]	
AB	0.04 (3301)
BC	0.14 (10,402)
ON	0.41 (30,675)
QC	0.4 (30,123)
Urbanicity [N = 74,501]	
Large Urban	0.54 (40,421)
Medium Urban	0.1 (7573)
Small Urban/Rural	0.36 (26,507)
Weight Perception [N = 73,071]	
Underweight	0.17 (12,140)
About the right weight	0.6 (43,893)
Overweight/Obese	0.23 (17,038)
BMI Classification [N = 74,501]	
Underweight	0.02 (1397)
Normal Weight	0.53 (39,388)
Overweight	0.12 (8682)
Obese	0.05 (4027)
Not Stated	0.28 (21,007)
Classes Skipped in Past 4 Weeks [N = 71,571]	
0 classes	0.65 (46,785)
1 or 2 classes	0.2 (14,555)
3 to 5 classes	0.08 (5988)
6 or more classes	0.06 (4243)

N = number of non-missing responses to questionnaire measure; s.d. = standard deviation.

6.4.2 GAD-7

The RE-EM tree fitted to the GAD-7 outcome is provided in Figure 3. The R^2_{adj} for the model was 0.23. Having a happy home life was identified as the primary splitting factor; that is, the factor that best distinguishes between high and low GAD-7 scores. Among students without a happy home life, school connectedness (SC) was identified as a protective factor. The highest risk subgroup comprised students without a happy home life and with low SC (score < 15.3); the average GAD-7 score in this group was 11.9, which is above the threshold of 10 for having clinically relevant anxiety symptoms. This subgroup constituted 7% of the total sample. Among students with higher SC (score ≥ 15.3) females had average GAD-7 scores nearly 3 points higher than their male counterparts (9.89 compared to 6.97), closely approaching the clinical threshold.

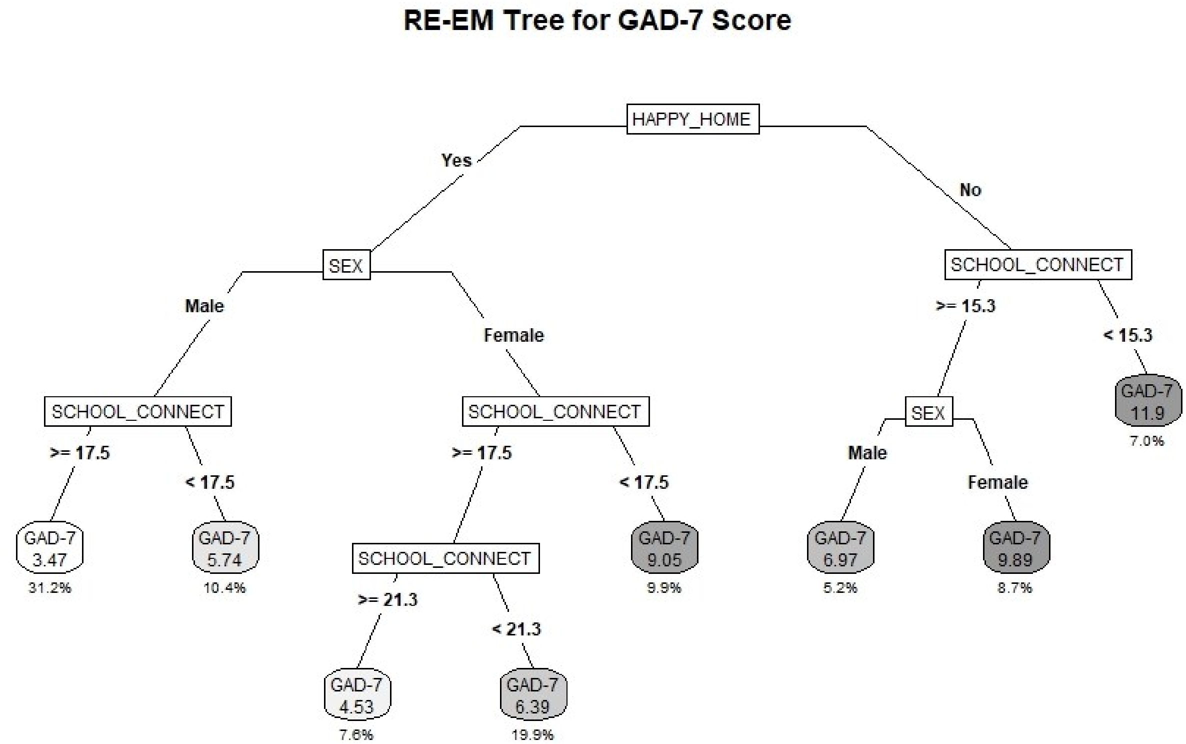

Figure 3. RE-EM Tree predicting average GAD-7 score for students participating in Year 7 (2018–2019) of the COMPASS Study (N = 71.736). The GAD-7 score represents the average scale score within the subgroup. The percentage below represents the total percentage of the sample comprised by the subgroup.

Among those with a happy home life, sex was identified as a key differentiating factor; however, SC was a protective factor for both males and females. Both sub-groups of males with high and low SC had lower average GAD-7 scores than females, except for the small subgroup of females with very high SC scores. Notably, females with low SC (score <17.5) had much higher average GAD-7 scores than their male counterparts (9.07 compared to 5.74). The largest final subgroup comprised males with high SC who indicated having a happy home life (31.2% of sample), and this group had the lowest average GAD-7 score of 3.47.

The LME model for GAD-7 score is provided in Table 5. The R^2_{adj} for the model was 0.32. Consistent with the RE-EM tree, having a happy home life (Est. −1.96 [−2.07,−1.85]), male sex (Est. −2.57 [−2.65,−2.49]), and higher SC (Est. −0.32 [−0.33,−0.30] per unit) were significantly associated with lower GAD-7 scores. Additionally, 18 other covariates were found to have some magnitude of significant association, likely due to the large sample size. Notably, being bullied in the past 30 days was associated with higher GAD-7 scores (Est. 1.92 [1.79,2.05]).

Table 5. Linear Mixed Effects Models for GAD-7, CESD-10, and FS Outcomes among students in Year 7 (2018–2019) of the COMPASS Study

[Estimate (95% Confidence Interval)]		GAD-7 (N = 52,875)	CESD-10 (N = 52,591)	FS (N = 52,997)
Male Sex		−2.57 (−2.65,−2.49) ***	−2.11 (−2.19,−2.03) ***	0.1 (0.04,0.17) **
Age		0.09 (0.06,0.12) ***	0.06 (0.02,0.09) ***	−0.06 (−0.09,−0.03) ***
Ethnicity (ref = White)	Black	−1.54 (−1.77,−1.31) ***	−1 (−1.24,−0.76) ***	1.1 (0.91,1.3) ***
	Asian	−0.69 (−0.84,−0.53) ***	0.15 (−0.01,0.3)	−0.43 (−0.56,−0.3) ***
	Hispanic	−0.4 (−0.65,−0.15) **	−0.08 (−0.34,0.19)	0.6 (0.38,0.81) ***
	Other/Mixed	−0.02 (−0.14,0.09)	0.17 (0.04,0.29) **	0.19 (0.09,0.29) ***
Spending Money (ref = USD 0)	USD 1–USD 20	−0.05 (−0.17,0.07)	0 (−0.13,0.13)	0.35 (0.24,0.45) ***
	USD 21–USD 40	−0.29 (−0.44,−0.14) ***	−0.2 (−0.36,−0.05) *	0.58 (0.45,0.71) ***
	USD 41–USD 100	−0.16 (−0.31,−0.01) *	−0.19 (−0.34,−0.03) *	0.66 (0.53,0.79) ***
	More than USD 100	−0.08 (−0.22,0.06)	−0.35 (−0.49,−0.2) ***	0.87 (0.75,0.99) ***
	Don’t Know	−0.22 (−0.36,−0.09) ***	−0.25 (−0.39,−0.11) ***	0.37 (0.26,0.49) ***
Province (ref = AB)	BC	−0.11 (−0.48,0.26)	NI	−0.56 (−0.91,−0.21) **
	ON	−0.07 (−0.38,0.24)	NI	−0.29 (−0.59,0.01)
	QC	−0.61 (−0.93,−0.29) ***	NI	0.21 (−0.1,0.52)
Urbanicity (ref = Large Urban)	Medium Urban	−0.02 (−0.26,0.22)	−0.23 (−0.47,0.02)	NI
	Small Urban/Rural	−0.29 (−0.44,−0.14) ***	−0.26 (−0.41,−0.1) **	NI
School Size (‘00s)		NI	NI	0.03 (0.01,0.05) **
Weight Perception (ref = Underweight)	About the right weight	−0.57 (−0.68,−0.46) ***	−0.6 (−0.72,−0.49) ***	0.37 (0.27,0.46) ***
	Overweight/Obese	0.23 (0.09,0.36) **	0.34 (0.2,0.48) ***	−0.6 (−0.71,−0.48) ***
BMI Classification (ref = Underweight)	Normal Weight	−0.02 (−0.31,0.26)	0.13 (−0.17,0.42)	−0.22 (−0.46,0.02)
	Overweight	−0.29 (−0.6,0.01)	−0.05 (−0.37,0.27)	0.08 (−0.18,0.35)
	Obese	−0.17 (−0.5,0.17)	0.09 (−0.26,0.43)	0.09 (−0.19,0.38)
	Not Stated	−0.13 (−0.42,0.16)	0.03 (−0.28,0.33)	−0.39 (−0.64,−0.15) **
Eat Breakfast Daily		−0.57 (−0.65,−0.48) ***	−0.77 (−0.86,−0.69) ***	0.31 (0.24,0.38) ***
Servings of Fruits and Vegetables		0.06 (0.04,0.08) ***	0.04 (0.01,0.06) ***	0.14 (0.12,0.15) ***
Average Daily Physical Activity (h)		0.05 (0.01,0.08) *	NI	0.43 (0.4,0.47) ***
Screen Time (h)		0.1 (0.09,0.12) ***	0.11 (0.1,0.13) ***	−0.07 (−0.08,−0.06) ***
Sleep Time (h)		−0.43 (−0.47,−0.4) ***	−0.6 (−0.64,−0.56) ***	0.31 (0.28,0.34) ***
Tobacco Use		0.2 (0.02,0.39) *	0.46 (0.27,0.65) ***	−0.12 (−0.27,0.03)
E-cigarette Use		0.2 (0.1,0.3) ***	0.39 (0.29,0.5) ***	NI
Binge Drinking		NI	NI	0.25 (0.15,0.35) ***
Cannabis Use		0.15 (0,0.29) *	0.16 (0.01,0.31) *	NI
Was Bullied		1.92 (1.79,2.05) ***	2.05 (1.93,2.18) ***	−0.47 (−0.58,−0.36) ***
Bullied Others		0.19 (0.01,0.37) *	NI	−0.56 (−0.71,−0.4) ***
Expect to Attend Post-Secondary Education		0.41 (0.32,0.51) ***	−0.18 (−0.28,−0.08) ***	0.63 (0.55,0.71) ***
Classes Skipped in Past 4 Weeks (ref = 0 classes)	1 or 2 classes	0.26 (0.16,0.36) ***	0.36 (0.25,0.46) ***	−0.09 (−0.18,−0.01) *
	3 to 5 classes	0.48 (0.34,0.63) ***	0.6 (0.44,0.75) ***	−0.18 (−0.3,−0.05) **
	6 or more classes	0.72 (0.54,0.91) ***	0.95 (0.76,1.14) ***	−0.24 (−0.4,−0.09) **
School Connectedness Score		−0.32 (−0.33,−0.3) ***	−0.45 (−0.46,−0.43) ***	0.68 (0.67,0.69) ***
Happy Home Life		−1.96 (−2.07,−1.85) ***	−2.75 (−2.86,−2.64) ***	2.59 (2.5,2.68) ***
Talk about Problems with Family		−0.84 (−0.92,−0.75) ***	−1.31 (−1.4,−1.22) ***	1.49 (1.41,1.56) ***
Talk about Problems with Friends		−0.6 (−0.69,−0.51) ***	−0.85 (−0.95,−0.76) ***	1.63 (1.55,1.71) ***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, NI = variable not included in final model after backward elimination variable selection.

6.4.3 CESD-10

The RE-EM tree fitted to the CESD-10 outcome is provided in Figure 4. The R^2_{adj} for the model was 0.30. Like the GAD-7 tree, having a happy home life was identified as the primary splitting factor. Among those without a happy home life, SC was the most important factor, followed by sex, with the highest risk subgroup comprising females without a happy home life and with low SC (average CESD-10 score 16). Among both subgroups with low and high SC, males had lower average CESD-10 scores than fe-males. Notably, the average CESD-10 score met or exceeded the threshold for clinically relevant depressive symptoms of 10 or higher among all subgroups without a happy home life.

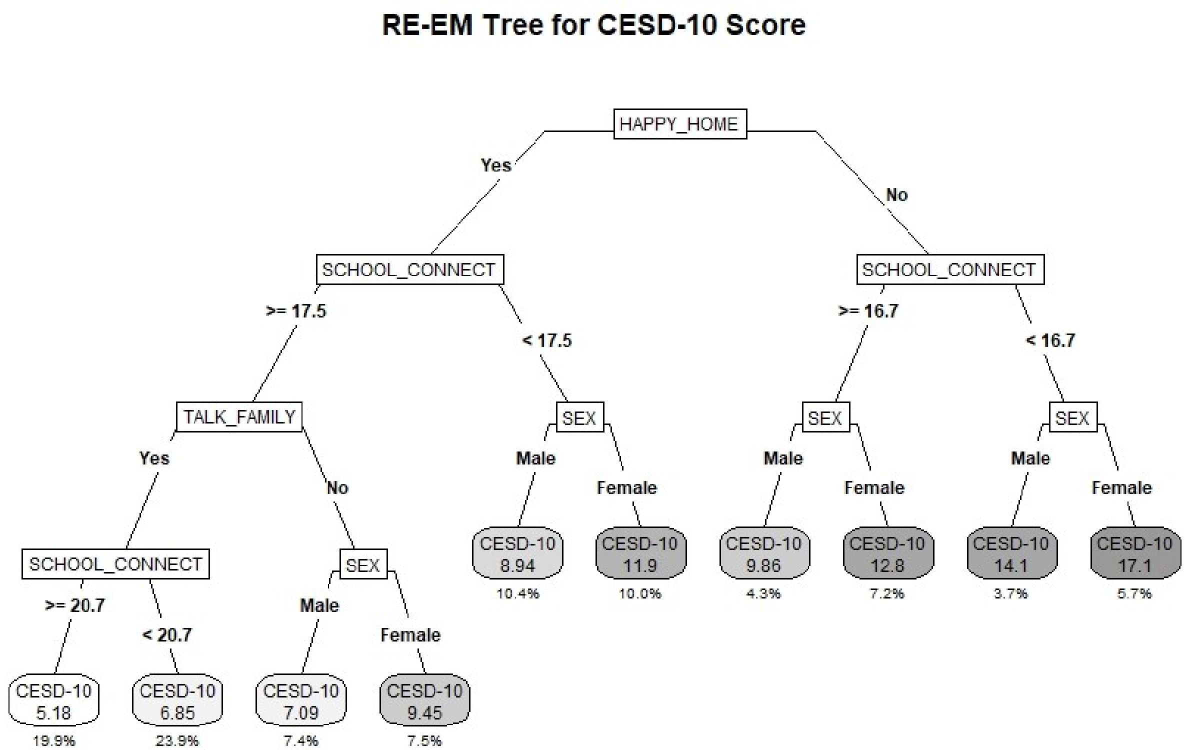

Figure 4. RE-EM Tree predicting average CESD-10 score for students participating in Year 7 (2018–2019) of the COMPASS Study (N = 70,610). The CESD-10 score represents the average scale score within the subgroup. The percentage below represents the total percentage of the sample comprised by the subgroup.

Among those with a happy home life, SC was again the most important factor. Females with a happy home life but low SC (score <17.5) had an average CESD-10 score of 11.9, exceeding the threshold for clinically relevant depressive symptoms. Students of both sexes with a happy home life and high SC were further differentiated by whether they felt comfortable talking about problems with their family. Among those who did not feel comfortable, females had higher average CESD-10 scores than males. Those who did feel comfortable were further split based on having very high SC, with those students having the lowest average CESD-10 score of 5.18, followed by those with moderately high SC scores who had an average CESD-10 score of 6.85. Notably, being able to talk about problems with family was identified as a protective factor only among the subgroup of students with a happy home life and high SC.

The LME model for CESD-10 score is provided in Table 5. The R^2_{adj} for the model was 0.39. Consistent with the RE-EM tree, having a happy home life (Est. −2.75 [−2.86,−2.64]), higher SC (Est. −0.45 [−0.46,−0.43] per unit), male sex (Est. −2.11 [−2.19,−2.03]), and feeling able to talk about problems with family (Est. −1.31 [−1.40,−1.22]) were significantly associated with lower CESD-10 scores. Additionally, 17 other covariates were found to have some magnitude of significant association. Like the GAD-7 outcome, being bullied in the past 30 days was associated with higher CESD-10 scores (Est. 2.05 [1.93,2.18]).

6.4.4 Flourishing Scale

The RE-EM tree fitted to the FS outcome is provided in Figure 5. The R^2_{adj} for the model was 0.42. The primary splitting variable is SC score. Among those with both moderately high and very high SC, having a happy home life was identified as the next most important factor. Students with very high SC and a happy home life had the highest average flourishing score of 36.9. Among students with moderately high SC and a happy home life, those who felt able to talk about problems with family had higher FS scores than those without (34.55 vs. 32.6), though this factor was not identified as important among students who did not already have a happy home life.

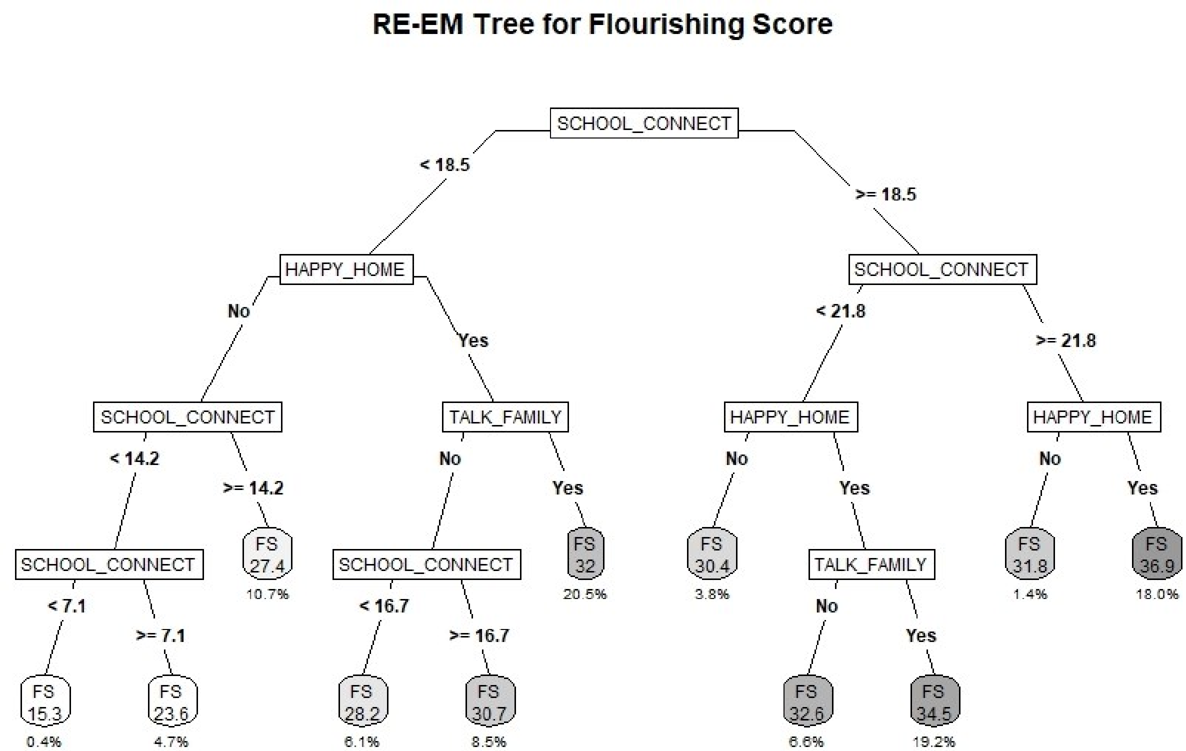

Figure 5. RE-EM Tree predicting average FS score for students participating in Year 7 (2018–2019) of the COMPASS Study (N = 72,415). The FS score represents the average scale score within the subgroup. The percentage below represents the total percentage of the sample comprised by the subgroup.

Among those with low SC, having a happy home life was again identified as the most important factor, and being able to talk about problems with family was identified as important among those with a happy home life. The tree further differentiated subgroups by SC among those either without a happy home life or who felt unable to talk about problems with family. The highest risk subgroups comprised students without a happy home life and with low or very low SC, having average FS scores of 23.8 and 15.3, respectively.

The LME model for FS score is provided in Table 5. The R^2_{adj} for the model was 0.51. Consistent with the RE-EM tree, higher SC (Est. 0.68 [0.67,0.69] per unit), having a happy home life (Est. 2.59 [2.50,2.68]), and feeling able to talk about problems with family (Est. 1.49 [1.41,1.56]) were significantly associated with higher FS scores. Additionally, 19 other covariates were found to have some magnitude of significant association. Feeling able to talk about problems with friends had a considerable magnitude of association with higher FS score (Est. 1.63 [1.55,1.71]). While no sex differences were identified in the RE-EM tree, male sex was significantly associated with higher FS score in the LME model (Est. 0.10 [0.04,0.17]), though the magnitude of association was small.

6.5 Discussion

This study used decision trees to examine associations between a range of behavioural and interpersonal risk factors and anxiety, depression, and flourishing outcomes among a large sample of Canadian youth. For all outcomes, the two factors that consistently emerged from the decision trees models as most important were having a happy home life and strong sense of connection to school. The consistency in association seen across three related but distinct measures of mental health provides strong support for the importance of positive home and school environments. Notably, while this study also included a wide array of modifiable behavioural measures that have previously been shown to be related to youth mental health outcomes(142,143,181–183) none of these emerged as important in the final tree models. This suggests that interpersonal relationships, particularly those related to home and school environments, are more strongly associated with youth anxiety, depression and flourishing than the individual health behaviours more commonly examined in isolation in the literature. This is important as some characteristics of social support related to school connectedness (SC) and happy home life are potentially modifiable through prevention and intervention efforts by schools and public health professionals. These findings support calls by the MHCC and provincial mental health strategies for prioritization of resources to families and schools for mental health promotion and primary prevention efforts.

The decision tree analysis used in this study is a hypothesis-generating approach in which all available potential risk factors are entered into the models without a priori assumptions. This contrasts with most past research in this field, which has generally taken a hypothesis-testing approach based on theorized associations to a particular risk factor or domain of factors. Despite the difference in approach, the results of the current study align with previous research into the influence of home(178,179,193–197) and school environments(53,54,60,63,147) on youth mental health. However, behavioural factors such as diet, movement behaviors, and substance use which have previously been associated with mental health outcomes (142,143,181–183) were not identified as important differentiating factors within the decision tree models in the present study. In fact, the most important factors identified here around social support are typically not included in traditional analyses examining behavioural factors. Given that decision trees also tend to be more parsimonious than regression models in isolating key differentiating factors, the current findings do not necessarily contradict the associations seen in past studies, but rather suggest that the interpersonal relationships from home and school environments are influential factors that require additional consideration in the literature moving forward.

Having a happy home life was identified as the primary distinguishing factor between groups with low and high anxiety and depression scores. Students who indicated not having a happy home life had the highest average GAD-7 scores, with values for females approaching or exceeding the threshold for clinically relevant anxiety symptoms even among those with high SC. Average CESD-10 scores also approached or exceeded the clinical threshold for students of both sexes who indicated not having a happy home life. The influence of the home environment on youth anxiety and depression is well-documented. Past reviews have found consistent associations between parenting style(178,193), interparental conflict(194), and early life stressors(195) on anxiety and depression during adolescence. A review of various sources of social support also found parents and family to be among the most important sources of support to protect against depression in children and adolescents, especially for females(179). These findings also align with previous decision tree results from Seeley et al.(151) which found family support to be protective among females without previous MDD. In the current study, the home environment was also influential on flourishing: students who indicated having a happy home life had higher average FS scores across all sub-groups. While this area of research is newer, these findings are consistent with past studies which have found family resilience and connection to be associated with greater flourishing(196) and adverse family experiences to be associated with lesser flourishing(197) in children and youth. The measure of home environment used in the current study does not provide a definition of the term "happy home life" and is therefore subjective to an individual respondent's interpretation. Nevertheless, the strong differentiation seen on this measure justifies the need for future validation work to understand how it is interpreted by students. Given that this study also included a measure on feeling able to talk about problems with family, this suggests that the concept of happy home life in relation to mental health is broader than merely the perception of open communication. The perception of happy home life could also be affected by early childhood experiences. While some elements of home life such as parenting style may be considered modifiable through educational interventions, other factors surrounding family dynamic may not be considered modifiable from the perspective of external policymakers and public health professionals. Future work should examine more specifically which aspects of perceived happy home life are contributing to the protective effect seen in this study.

SC was also identified as a key differentiating factor across all outcomes, highlighting the importance of a positive school environment to youth mental health. Past research has similarly found SC and belonging to be protective against depression(60,63). In the current study, SC was protective among students without a happy home life; average GAD-7 scores were at or below the clinical threshold for those who had high SC, compared to exceeding the threshold for those with low SC. Average CESD-10 scores were also over 4 points lower for those with high SC among both sexes without a happy home life. This is consistent with past research which found that SC moderated the relationship between family obligations and emotional distress among middle and high school students(62). SC was also identified as the primary distinguishing factor between groups with low and high FS scores. Smaller studies have found consistent associations between sense of school community or belonging with measures of wellbeing(53,54). This finding has important implications for school-based interventions since it suggests that schools can play a meaningful role in increasing mental wellbeing among students— even among those who may not have a happy home life—by cultivating a climate of connection and belonging. Further research into evidence-based policy and program interventions for increasing school connection is warranted.

Consistent with literature regarding adolescent mental illness prevalence(30), differences by sex were identified for anxiety and depression outcomes in the decision trees, with female subgroups having consistently higher average GAD-7 and CESD-10 scores than corresponding male subgroups. These differences are commonly posited to be related to sociocultural gender norms(30), with females being more likely than males to exhibit internalizing symptoms(31,32). Notably, no differences by sex emerged in the decision tree for flourishing. This is an important finding in the context of school-based intervention as it suggests that males and females could benefit equally from initiatives to increase school connection. Other demographic factors such as ethnicity and age were found to be statistically significantly associated with mental health outcomes in the LME models but did not emerge in the decision tree models.

While the decision tree results provide insight into distinguishing factors and high-risk subgroups, the LME results describe the average effect of each factor on the total sample after controlling for all other factors. The LME models in this study had higher fit indices, as measured by R^2_{adj}, than the corresponding tree models but were also much more complex. Notably, R^2_{adj} was at or below 50% for all models, which is unsurprising given a likely genetic component to youth mental health outcomes that cannot be explained by environmental factors. For most variables identified as statistically significant in the LME models but not included in the corresponding decision trees, the LME magnitude of association was small. One exception to this was having been bullied in the past 30 days, which had a large magnitude of association with anxiety and depression outcomes. Post hoc t-tests found a moderately strong negative association between bullying and SC ($p < 0.0001$, Cohen's d 0.588), suggesting that the impact of bullying on groups with higher GAD-7 and CESD-10 scores may already be accounted for through differentiation on SC in the tree models. This hypothesis is sup-ported by previous studies which have found SC to be a mediating factor in the relationship between bullying and mental health indicators(198,199). Aside from this factor, the decision trees captured the key distinguishing factors in more parsimonious and easily interpretable and flexible models than LME, allowing for effective knowledge translation. Decision trees also identified underlying non-linear associations for SC, as can been seen by this factor being split recursively across different cut points. This highlights the ability of decision trees to capture complex relationships that are often missed when using standard regression analysis.

6.5.1 Strengths and Limitations

This is one of the first studies to use decision tree methods to examine youth de-pression, anxiety, and flourishing outcomes and associated behavioural and interpersonal risk factors. Unlike past research which commonly used regression approaches, the use of decision trees allows for the identification of key differentiating factors and high-risk subgroups. This study also used hierarchical RE-EM trees which properly account for the clustered nature of the data and are novel to public health research. However, decision tree techniques have limitations, including lower prediction accuracy than other methods, and a tendency to overfit the sample data which is only partially mitigated by pruning. Additionally, while this study benefits from a large sample size, the sampling method used is not representative and therefore results may not be reflective of all Canadian youth. Additionally, this study uses self-report data and thus mental health indicators are not based on clinical assessment. Further, this study is cross-sectional and thus temporality between risk factors and mental health outcomes cannot be inferred. Notably, perceptions of happy home life and school connection may be consequences of or bi-directionally associated with mental health status. Further longitudinal research into the directionality of associations is warranted. Lastly, some measures used in this study contained meaningful amounts of missing data, which could introduce bias if missingness does not occur completely at random. LME models use maximum likelihood estimation and are unbiased when outcome missing-ness can be explained by the observed covariates; however, this assumption is untestable. RE-EM trees handle missing covariate data using surrogate splits but cannot correct for missing outcome data. Mental health scales were person-mean imputed for students missing 1 or 2 items to partially recover missing responses. Multiple imputation has been suggested as the preferred approach to handle missing data in Likert-type scales such as the CESD(200); however, there is limited research into how to apply multiply imputed datasets to the generation of a single interpretable decision tree.

6.6 Conclusions

This study found that, across a range of interpersonal and behavioural factors, having a happy home life and SC were key differentiators of youth anxiety, depression, and flourishing levels. This highlights the importance of the influence of home and school environments on youth mental health and supports calls for national policy focus and investment in family and school resources. While having a happy home life is most important in protecting against youth anxiety and depression, a sense of connection to school may mitigate the negative influence of a poor home environment. Schools can also play a meaningful role in contributing to positive mental health among students by cultivating a sense of belonging.

Chapter 7
Manuscript 3

Examining changes in school mental health practices over time and associations to youth depression, anxiety, and psychosocial wellbeing

Status: Submitted for Publication

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7.1 Overview

Schools have been identified as ideal contexts in which to address youth mental health; however, a lack of evidence exists on the effectiveness of various school practices at improving youth mental health outcomes. Further, traditional analysis techniques have limited ability to discern the impacts of multiple concurrent practice changes. This study examined variation in a broad range of ongoing school mental health practices and services over time and used decision trees to comprehensively determine which, if any, combinations of practice and service changes are associated with student depression, anxiety, and psychosocial wellbeing outcomes. The sample comprised 28,567 students across 116 Canadian secondary schools followed over two school years in 2017-18 and 2018-19. An administrator questionnaire measured changes in school mental health staff, training, on-site services, and coordination with external organizations. A student questionnaire measured depression, anxiety, and flourishing levels. Multilevel regression trees were used to find potential combinations of practice changes associated with student depression, anxiety, and flourishing levels. Substantial variability was seen in the mental health practices and services offered between schools and across years. Decision tree analysis found no combinations of practice changes that meaningfully contributed to better student mental health outcomes, suggesting incremental changes were not effective over a one-year period. Despite these findings, schools continue to play an important role as universal access points for prevention and early intervention. More comprehensive approaches to school mental health are needed along with dedicated training, expertise, and resources.

Keywords: youth, school policies, mental health, decision trees

7.2 Introduction

Youth have been identified as a priority group for mental illness prevention and intervention efforts in Canada(1,5), given that nearly 1 in 4 young people are living with a mental illness, and nearly 70% of all mental illness occurs before age 18(7). The school environment can play an influential role on youth mental health and wellbeing. Past research has found a sense of connection and belonging to school to be protective against depression(63,201) and negative affect(202), and positively associated with measures of mental wellbeing(53,54).

Schools have been identified as ideal contexts in which to address youth mental health(7,19), given the amount of time youth spend in school and the ability to reach populations who may otherwise face barriers to accessing community supports. Several federal and provincial governmental organizations have developed strategies to address youth mental health within the school setting. Recommended strategies from the Mental Health Commission of Canada (MHCC) and the Pan-Canadian Joint Consortium for School Health (JCSH) include universal promotion of positive mental health combined with targeted prevention for at-risk students(5,19). Provincial governments responsible for overseeing healthcare and education also highlight school-based mental health initiatives as key pillars in strategic mental health plans(67–70). However, the availability of best practices guidance and detailed implementation plans varies across provinces, and it is primarily the responsibility of individual school boards and schools to establish and implement policies, practices, and programming.

While a multitude of school-based initiatives related to youth mental health have been implemented federally, provincially, and locally across Canada, most do not appear to be based on past evidence of effectiveness. The MHCC has reported that less than half of mental health programs in schools have been evaluated(5,203), while in Ontario less than half of public health initiatives focused on youth mental health are considered evidence-based(83). While the body of evidence is growing, most information on the effectiveness of programs and practices comes from studies based in the United States and Europe, and reviews consistently note a need for broader and higher quality evidence(99,109). The external validity of specific findings within a Canadian context is also difficult to discern, given small sample sizes, artificial study environments, and lack of reporting on school-specific contextual components. Further, while much international research exists on the evaluation of one-time intervention programs, there is little if any evidence on the effectiveness of ongoing school practices and services at improving youth mental health outcomes.

Studies of policy and program evaluation often aim to assess the impact of a singular intervention; however, policy and practice changes within school settings rarely occur in isolation. Schools often implement concurrent changes to staffing, policies, practices, and program availability in any given year. To properly evaluate the impact of a given change, it is important to account for these co-occurring changes, as well as quantify potential compounding contextual effects. In observational and quasi-experimental studies, these co-occurring contextual changes are typically treated as nuisance confounders in quantitative analysis. The traditional regression-based modelling approaches used have limited ability to account for the complexity of these concurrently changing components(113), which can have non-additive interacting effects as well as potential differential impacts on various student subgroups. Decision trees are an alternative machine-learning based method with emerging use in public health research(113,116) that allow for a comprehensive evaluation of school policy and practice changes by simultaneously examining the effectiveness of all possible combinations of intervening factors. This exploratory approach can be used to help determine the most effective combinations of policy and practice changes out of a range of concurrent changes and is well-suited to evaluation of large-scale natural experiments. Despite this, to the authors' knowledge no previous studies have applied decision tree methods to school-based policy and program evaluation.

Thus, while there is clear directive for school-based mental health initiatives within Canada, there is limited understanding of what is being implemented at the school level and very limited evidence on the effectiveness of those interventions with respect to youth mental health outcomes. The current study aimed to address this evidence gap through three objectives: 1) to examine the variability in student mental health outcomes among a large sample of Canadian schools, 2) to examine variation in a broad range of ongoing practices and services over time and, 3) to use decision trees to comprehensively determine which combinations of practices and service changes are associated with better or worse student mental health outcomes.

7.3 Methods

7.3.1 Study and Sample

The COMPASS (Cannabis, Obesity, Mental health, Physical activity, Alcohol, Smoking, Sedentary behaviour) Study is an ongoing prospective rolling cohort study from a convenience sample of Canadian secondary schools in Ontario, Alberta, British Columbia, and Quebec. COMPASS annually collects student- and school-level data related to a variety of health behaviours to evaluate how changes in school environment, policies, and programs influence youth health. Additional details about the COMPASS study design and methods are available in print(118) and online (https://uwaterloo.ca/compass-system). The COMPASS study received ethics clearance from the University of Waterloo Research Ethics Board (ORE 30118) and participating school boards.

COMPASS uses active-information passive-consent parental permission to survey all students within each participating school. Students may refuse to participate and withdraw at any time. The current study uses data from 116 schools who participated in 2017-18 (Year 6) and 2018-19 (Year 7) of the study. Within these schools, 60,760 students participated in 2017-18 with a participation rate of 82%, and 60,997 students participated in 2018-19 with a participation rate of 83%. COMPASS uses an anonymous linking process to follow students over time by use of a self-generated code(124), resulting in a two-year cohort of 28,567 students who were successfully followed across 2017-18 and 2018-19, corresponding to 59% of participating students in eligible grades. Primary reasons for non-linkage are absenteeism during a given data collection and missing values in the linkage measures.

7.3.2 Tools and Measures

7.3.2.1 Student Questionnaire

The COMPASS student questionnaire in 2017-18 and 2018-19 was anonymous, self-administered paper questionnaire completed by students during class time. The current study uses three validated mental health scales measured in both 2017-18 and 2018-19. Depression is measured using the Centre of Epidemiologic Studies Depression Scale 10 - Revised (CESD-10)(23,126). The CESD-10 is measured as a continuous score ranging from 0 to 30, with higher scores indicating greater degrees of depressive symptomatology. Anxiety is measured using the Generalized Anxiety Disorder 7-item Scale (GAD-7)(25). The GAD-7 is measured as a numeric score ranging from 0 to 21, with higher scores indicating greater levels of anxiety. Flourishing, which is a component of psychosocial wellbeing, is measured using a modified version of Diener's Flourishing Scale (FS)(28). The FS is a numeric score ranging from 8 to 40 with higher scores indicating greater levels of flourishing. Consistent with recommendations for Likert-style scales(184,185) all individual mental health scale items were person-mean imputed for students missing 1 or 2 items, while scales were set to missing if missing three or more items.

Additionally, this study uses 2018-19 predictor measures of sex (female, male), school connectedness (continuous score ranging from 6 to 24, higher scores represent greater perceived connection) and perceptions of happy home life and ability to talk about problems with family (strongly agree/agree, neutral/disagree/strongly disagree). These predictors were chosen based on previous research(204) that established these as providing the highest levels of differentiation with respect to the outcomes out of 23 core questionnaire measures.

7.3.2.2 School Policies and Practices Questionnaire

The School Policies and Practices questionnaire (SPP) is an online questionnaire completed annually by school administrator(s) familiar with their school's policy and program environment. The current study uses 2017-18 and 2018-19 SPP measures related to school mental health staffing and training, on-site services and programs, and coordination with external organizations.

<u>Staffing and Training:</u> School staff training over the past 12 months is assessed using three measures of training topics: "Mental health awareness/literacy (e.g., basic information, key warning signs)", "Providing mental health support (e.g., mental health first aid, Supporting Minds, etc.)", and "Suicide prevention". Ordinal response options for number of staff receiving training include "None", "Some (e.g., 1-5)", and "All". The availability of on-site mental health professionals is measured for five professions "Child and Youth Worker", "Counsellor", "Social Worker", "Psychologist", and "Mental Health Nurse", along with an "Other" write-in option, for which the most common response was "Psychoeducator". Ordinal response options for availability included "On-site full-time", "Regularly scheduled", and "On-call". A derived ordinal measure was then created for availability of any profession type.

<u>On-Site Services and Programs:</u> Availability of on-site mental health services is assessed using binary measures of ten services: "Assessment for emotional or behavioural problems (including behavioural observation, psychosocial assessment and observation checklists)", "Diagnostic assessment (comprehensive psychological evaluation)", "Behavioural management consultation with teachers,

students, or families", “Case management, including monitoring and coordination of services", “Referral to specialized programs or services for emotional or behavioural problems or disorders", “Crisis intervention (e.g., response to traumatic events, including disasters, serious injury/death of a member of the school community)", “Individual counselling/therapy", “Group counselling/therapy", “Substance abuse counselling", and “Family support services in school setting (e.g., child/family advocacy, counselling)”. A binary measure of additional mental health programming is also captured by asking “Other than classes/curriculum, does your school offer any programs to promote mental health?".

Coordination with External Organizations: Level of referral and coordination practices with community organizations is measured with ordinal response options “Staff do not make referrals", “Staff make passive referrals (e.g., give brochures, lists and contact information of providers or organizations)", “Staff make active referrals (e.g., staff complete form with family, make calls or appointments, assist with transportation)", and “Staff follow-up with student/family (e.g., calls to ensure appointment kept, assess satisfaction with referral, need for follow-up) and/or Staff follow-up with provider (via phone, e-mail, mail)”. Coordination with local public health units is assessed on three binary types of collaboration “Provided information/resources/programs (e.g., posters, toolkits)", “Solved problems jointly", and “Developed/implemented program activities jointly".

Changes in school policies and practices over time were classified as either “Decreased”, “No Change”, or “Increased” for ordinal measures, and as “Removed”, “None”, “Added”, or “Kept” for binary measures.

7.3.2.3 School Administrative and Census Data

School total enrolment is collected from school administrators during the recruitment process as a measure of school size. School area median income and school urbanicity are measured by linking to Statistics Canada 2016 Census data based on each school’s forward sortation area(129,130).

7.3.3 Analysis

To assess variability in overall student mental health between schools, summary statistics and correlations were calculated for school-average CESD-10, GAD-7, and FS scores in each year as well as the change in score from 2017-18 to 2018-19. To determine the amount of variability in student score that can be attributed to differences between schools, intraclass correlation coefficients (ICCs) were calculated using linear mixed models with school ID random intercept. The GLIMMIX procedure in SAS 9.4 was used for all models (SAS Institute, Cary, NC).

To examine variability in school practices and services over time, frequency statistics were calculated for school SPP responses in 2017-18 and 2018-19, as well as change in response between years. School-average change in CESD-10, GAD-7, and FS scores was calculated by response change category for each measure, and ANOVA was used to assess significant differences.

Student sample characteristics were calculated for CESD-10, GAD-7, and FS outcomes in 2017-18 and 2018-19, as well as all student-level predictors in 2018-19. To comprehensively determine whether any potential combination of school policies and practices was associated with better or worse mental health outcomes at follow-up, decision trees were run using student 2018-19 CESD-10, GAD-7, and FS scores as outcomes. Tree models were run in two stages: 1) including all school-level demographics and changes to policies and practices, as well as and student baseline score as predictors to assess overall impact, and 2) adding all student-level predictors to assess potential differential impacts by student subgroups. Sensitivity testing was conducted by excluding baseline scores from stage 1 models; however, results are not presented as trees failed to produce any nodes due to lack of association.

Random Effects EM (RE-EM) trees were used(134,135) to account for school-level clustering. Students with missing values on a given outcome were excluded from the respective analysis, while missing predictor values were included and accounted for using surrogate splitting. Given the large sample size, a splitting rule was set requiring a minimum increase to adjusted R-squared (R^2_{adj}) of 0.005 to limit splits that would be unlikely to improve overall prediction accuracy. Tree pruning using 10-fold cross-validation was performed to limit overfitting to the sample data(134,135). The smallest tree within one standard deviation of the minimum cross-validation error was chosen. The R package "REEMtree"(190) was used to grow the trees, and the package "rpart.plot"(191) was used for plotting.

7.4 Results

7.4.1 Variation in Student Mental Health Outcomes

Figure 6 shows the range of average CESD-10, GAD-7, and FS scores across schools in 2017-18 and 2018-19. Table 6 shows corresponding summary statistics and correlations between measures. School average CESD-10 scores ranged from 6.77 to 12.29 in 2018-19, with scores increasing between 2017-18 and 2018-19 in all but five schools (mean 0.80, sd 0.50). School average GAD-7 scores ranged from 4.24 to 9.12 in 2018-19, with nearly all schools showing an increase from 2017-18 (mean 0.64, sd 0.47). School average FS scores ranged from 28.12 to 36.13 in 2018-19, with most schools showing a decrease from 2017-18 (mean -0.43, sd 0.48). Approximately 2% of the variability in students' CESD-10 scores, 3% of the variability in GAD-7 scores, and 3-4% of the variability in FS scores can be attributed to school-level factors. For all scales, the amount of variation attributed to school factors was lower in 2018-19 than in 2017-18, with FS showing the largest decrease.

Table 6. Summary statistics and correlations for average CESD-10, GAD-7, and FS scores across participating COMPASS schools in 2017-18 and 2018-19 (N=116)

	CESD-10			GAD-7			FS		
	2017-18	**2018-19**	**Change**	**2017-18**	**2018-19**	**Change**	**2017-18**	**2018-19**	**Change**
Summary Statistics:									
Mean	8.32	9.12	0.80	6.00	6.63	0.64	32.19	31.77	-0.43
SD	1.04	1.00	0.50	1.08	1.06	0.47	1.27	1.16	0.48
Min	5.43	6.77	-0.21	3.00	4.24	-0.67	28.57	28.12	-1.95
Max	10.37	12.29	2.41	7.98	9.12	1.79	37.75	36.13	0.73
ICC	2.43%	1.83%		3.03%	2.91%		4.15%	3.09%	
School Average Correlations:									
CESD-10	1.00	1.00	1.00	0.87	0.86	0.53	-0.83	-0.76	-0.46
GAD-7	0.87	0.86	0.53	1.00	1.00	1.00	-0.68	-0.61	-0.40
FS	-0.83	-0.77	-0.46	-0.68	-0.61	-0.40	1.00	1.00	1.00

SD = standard deviation; ICC = intraclass correlation coefficient

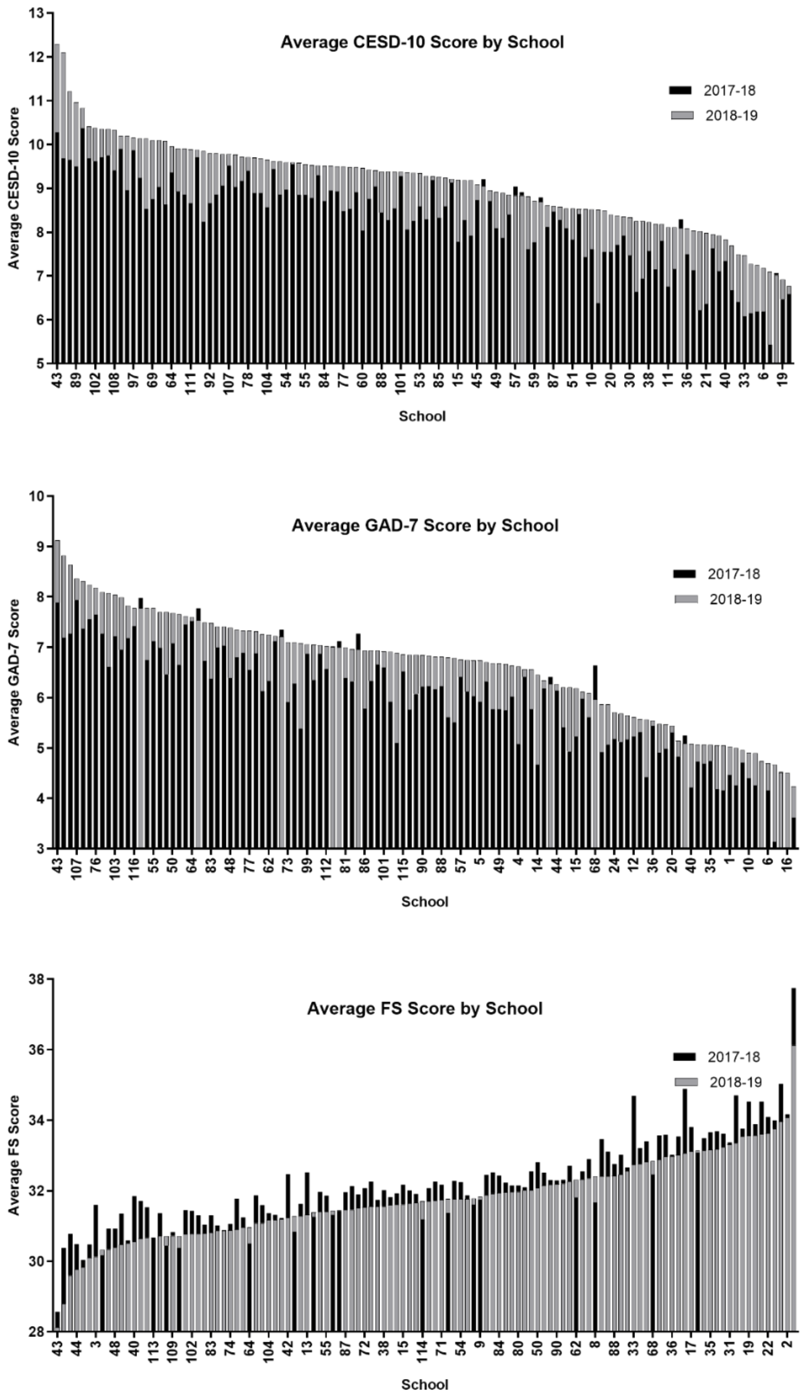


Figure 6. Average CESD-10, GAD-7 and FS scores by participating COMPASS schools (N=116) in 2017-18 and 2018-19 among students linked across two years

A strong positive correlation exists between school average CESD-10 and GAD-7 scores in each year, as well as a strong negative correlation between CESD-10 and FS, and moderately strong negative correlation between GAD-7 and FS. A moderate positive correlation exists between the change in average CESD-10 and GAD-7 scores (r=0.53), and moderate negative correlation between change in CESD-10 and FS scores (r=-0.46) and change in GAD-7 and FS scores (r=-0.40).

7.4.2 Variation in School Mental Health Practices and Services

Table 7 shows staffing, services, and coordination practices in place in 2017-18 and 2018-19 and Table 8 shows changes between years. Approximately half of schools provided some form of mental health training to all staff in 2017-18 while only 9% provided no training. Between 2017-18 and 2018-19, 24% of schools increased the level of training provided while 14% decreased overall training. While the specific roles of on-site mental health staff varied across schools, 74% of schools had at least one full-time staff in 2017-18. Between 2017-18 and 2018-19, 70% of schools maintained the overall availability of on-site mental health staff; however, there was more variation in availability of specific staff roles year to year.

Table 7. School staffing, services, programming, and coordination practices in place in participating COMPASS schools (N=116) in 2017-18 and 2018-19

		2017-18		2018-19				2017-18		2018-19	
		n	**%**	**n**	**%**			**n**	**%**	**n**	**%**
Staff Mental Health Training						**Mental Health Services**					
Awareness	None	15	13%	8	7%	Emotional Assessment	No	49	42%	58	50%
	Some	53	46%	52	45%		Yes	67	58%	58	50%
	All	48	41%	56	48%	Diagnostic Assessment	No	69	59%	71	61%
Support	None	17	15%	10	9%		Yes	47	41%	45	39%
	Some	73	63%	73	63%	Behaviour Consultation	No	70	60%	65	56%
	All	26	22%	33	28%		Yes	46	40%	51	44%
Suicide	None	20	17%	16	14%	Case Management	No	50	43%	54	47%
	Some	81	70%	75	65%		Yes	66	57%	62	53%
	All	15	13%	25	22%	Specialist Referral	No	35	30%	39	34%
On-Site Mental Health Professionals							Yes	81	70%	77	66%
Youth Worker	None	22	19%	24	21%	Crisis Intervention	No	27	23%	42	36%
	On-Call	20	17%	19	16%		Yes	89	77%	74	64%
	Part-time	19	16%	19	16%	Individual Counselling	No	41	35%	37	32%
	Full-time	55	47%	54	47%		Yes	75	65%	79	68%

Counsellor	None	20	17%	25	22%	Group Counselling	No	90	78%	89	77%
	On-Call	24	21%	29	25%		Yes	26	22%	27	23%
	Part-time	22	19%	19	16%	Substance Use Counselling	No	51	44%	51	44%
	Full-time	50	43%	43	37%		Yes	65	56%	65	56%
Social Worker	None	27	23%	35	30%	Family Support	No	94	81%	90	78%
	On-Call	46	40%	39	34%		Yes	22	19%	26	22%
	Part-time	33	28%	27	23%	**School Additional Programming**					
	Full-time	10	9%	15	13%	Prevention Programs	No	41	35%	43	37%
Psychologist	None	32	28%	38	33%		Yes	75	65%	73	63%
	On-Call	51	44%	43	37%	**Referral Practices**					
	Part-time	22	19%	27	23%	Referral to external services/programs	None	10	9%	8	7%
	Full-time	11	9%	8	7%		Passive Referrals	5	4%	5	4%
Mental Health Nurse	None	43	37%	36	31%		Active Referrals	24	21%	17	15%
	On-Call	44	38%	48	41%		Follow-up	77	66%	86	74%
	Part-time	26	22%	30	26%	**Coordination with Public Health**					
	Full-time	3	3%	2	2%	Provide information	No	58	50%	57	49%
Psychoeducator	None	106	91%	106	91%		Yes	58	50%	59	51%
	On-Call	0	0%	0	0%	Solve problems jointly	No	90	78%	88	76%
	Part-time	5	4%	1	1%		Yes	26	22%	28	24%
	Full-time	5	4%	9	8%	Develop/ implement programs jointly	No	96	83%	98	84%
							Yes	20	17%	18	16%

Table 8. Changes to school staffing, services, programming, and coordination practices in participating COMPASS schools (N=116) between 2017-18 and 2018-19 and corresponding changes in school-average CESD-10, GAD-7 and FS scores

		n	%	CESD_delta	GAD7_delta	FLOURISH_delta
Staff Mental Health Training						
Awareness	Decrease	14	12%	0.89	0.66	-0.45
	Same	76	66%	0.80	0.64	-0.42
	Increase	26	22%	0.78	0.61	-0.45
Support	Decrease	18	16%	0.67	0.52	-0.31
	Same	67	58%	0.79	0.64	-0.47
	Increase	31	27%	0.91	0.71	-0.40
Suicide	Decrease	20	17%	0.76	0.46	-0.38
	Same	64	55%	0.80	0.67	-0.36

	Increase	32	28%	0.84	0.68	-0.60
On-Site Mental Health Professionals						
Youth Worker	Decrease	18	16%	0.74	0.71	-0.33
	Same	82	71%	0.82	0.62	-0.43
	Increase	16	14%	0.76	0.61	-0.52
Counsellor	Decrease	32	28%	0.92	0.75	-0.34
	Same	61	53%	0.80	0.60	-0.45
	Increase	23	20%	0.65	0.58	-0.48
Social Worker	Decrease	27	23%	0.84	0.70	-0.52
	Same	70	60%	0.84	0.66	-0.44
	Increase	19	16%	0.62	0.46	-0.27
Psychologist	Decrease	24	21%	0.78	0.66	-0.41
	Same	72	62%	0.80	0.65	-0.44
	Increase	20	17%	0.84	0.55	-0.39
Mental Health Nurse	Decrease	20	17%	0.78	0.77	-0.58
	Same	70	60%	0.82	0.61	-0.43
	Increase	26	22%	0.77	0.60	-0.30
Psychoeducator	Decrease	4	3%	0.69	0.52	-0.18
	Same	106	91%	0.80	0.64	-0.43
	Increase	6	5%	0.97	0.71	-0.57
Any staff	Decrease	20	17%	0.88	0.78	-0.27
	Same	81	70%	0.82	0.62	-0.45
	Increase	15	13%	0.63	0.53	-0.54
Coordination with Public Health						
Provide Information	Removed	18	16%	0.74*	0.60*	-0.39
	None	39	34%	0.94*	0.65*	-0.56
	Added	19	16%	0.51*	0.31*	-0.20
	Kept	40	34%	0.83*	0.79*	-0.42
Solve Jointly	Removed	14	12%	0.77	0.55	-0.53
	None	74	64%	0.81	0.66	-0.43
	Added	16	14%	0.68	0.54	-0.31
	Kept	12	10%	1.00	0.71	-0.44
Develop/ implement programs	Removed	13	11%	0.52	0.73	-0.41
	None	85	73%	0.82	0.61	-0.39
	Added	11	9%	0.87	0.71	-0.70
	Kept	7	6%	0.99	0.64	-0.52
Mental Health Services						
	Removed	21	18%	0.65	0.61	-0.25

Emotional Assessment	None	37	32%	0.79	0.67	-0.44
	Added	12	10%	0.80	0.43	-0.30
	Kept	46	40%	0.89	0.67	-0.54
Diagnostic Assessment	Removed	19	16%	0.66	0.64	-0.09*
	None	52	45%	0.89	0.66	-0.53*
	Added	17	15%	0.68	0.53	-0.49*
	Kept	28	24%	0.81	0.66	-0.43*
Behaviour Consultation	Removed	15	13%	0.69	0.63	-0.23
	None	50	43%	0.89	0.65	-0.55
	Added	20	17%	0.74	0.71	-0.43
	Kept	31	27%	0.77	0.57	-0.33
Case Management	Removed	26	22%	0.66	0.53	-0.43
	None	28	24%	0.80	0.70	-0.47
	Added	22	19%	0.93	0.69	-0.41
	Kept	40	34%	0.82	0.63	-0.41
Specialist Referral	Removed	21	18%	0.78	0.65	-0.37
	None	18	16%	0.58	0.53	-0.50
	Added	17	15%	0.91	0.74	-0.39
	Kept	60	52%	0.85	0.63	-0.43
Crisis Intervention	Removed	28	24%	0.71	0.62	-0.40
	None	14	12%	0.92	0.71	-0.64
	Added	13	11%	0.88	0.54	-0.34
	Kept	61	53%	0.80	0.65	-0.41
Individual Counselling	Removed	15	13%	0.83	0.48	-0.47
	None	22	19%	0.82	0.83	-0.47
	Added	19	16%	0.92	0.59	-0.57
	Kept	60	52%	0.75	0.62	-0.36
Group Counselling	Removed	12	10%	0.44	0.47	-0.26
	None	77	66%	0.84	0.66	-0.46
	Added	13	11%	0.87	0.64	-0.49
	Kept	14	12%	0.83	0.66	-0.32
Substance Use Counselling	Removed	13	11%	0.90	0.63	-0.29
	None	38	33%	0.72	0.62	-0.43
	Added	13	11%	0.64	0.50	-0.46
	Kept	52	45%	0.88	0.68	-0.46
Family Support	Removed	10	9%	0.81	0.95*	-0.52
	None	80	69%	0.84	0.63*	-0.45
	Added	14	12%	0.73	0.74*	-0.47

	Kept	12	10%	0.66	0.29*	-0.14
School Additional Programming						
Prevention Programs	Removed	22	19%	0.82	0.64	-0.40
	None	21	18%	0.83	0.60	-0.31
	Added	20	17%	0.55	0.62	-0.41
	Kept	53	46%	0.88	0.66	-0.49
Referral Practices						
Community Referral	Decrease	18	16%	0.82	0.56	-0.56
	Same	71	61%	0.79	0.61	-0.41
	Increase	27	23%	0.84	0.76	-0.40

**Statistically significant difference between categories at alpha=0.05*

The most offered on-site mental health services were crisis intervention, specialist referral, and individual counselling, while 8% of schools in 2017-18 did not report offering any on-site services. On-site crisis intervention was offered in 77% of schools in 2017-18, however nearly one-third of these schools stopped offering this service in 2018-19. Additional school-specific prevention programming was offered in over 60% of schools each year. Nearly 90% of schools offered active referrals to community providers in each year, and intensity of referral practices with community providers increased for 23% of schools and decreased for 16% of schools, primarily driven by changes to follow-up practices. While nearly 60% schools reported some form of coordination with local health units in each year, coordination status changed for approximately 30% of schools, with equal numbers starting and stopping collaborations.

7.4.3 Associations between Changes in Practices and Services and Mental Health Outcomes

7.4.3.1 School-level Associations

Table 8 shows differences in the change in school average CESD-10, GAD-7 and FS scores by changes to school staffing, services, programming, and coordination practices. Very minimal variation in changes to school average mental health scores was observed across any individual factor. Statistically significant differences in score changes were seen for three service changes. First, schools that maintained family support services had lower average increase in GAD-7 scores. Second, schools that removed diagnostic assessment services had lower average decrease to FS scores. Third, schools that initiated coordination with public health in the form of providing information or resources had lower average increase to CESD-10 and GAD-7 scores. However, the magnitudes of differentiation were small in all above cases and the statistical differences should be interpreted with caution given the possibility for spurious association seen when performing multiple tests.

7.4.3.2 Student-level Associations

Table 9 shows student sample characteristics. The sample is 53.4% female, with 77.5% of students indicating they have a happy home life, and 56.2% indicating they can talk about problems with their family. The average school connectedness score in the sample is 18.4 (SD 3.2). Average CESD-10 scores increased by 0.8 points from 2017-18 to 2018-19, while average GAD-7 scores increased by 0.7 points and flourishing scores decreased by 0.4 points.

Table 9. Sample characteristics of students (n=28,567) participating in years 2017-18 and 2018-19 of the COMPASS study

Categorical Variables:		**n**	**%**	
Sex	**Female**	15257	53.4%	
	Male	13299	46.6%	
	Missing	11	0.0%	
Grade	**8**	2616	9.2%	
	9	2232	7.8%	
	10	9201	32.2%	
	11	8772	30.7%	
	12	5480	19.2%	
	Missing	266	0.9%	
Happy Home Life	**No**	6036	21.1%	
	Yes	22152	77.5%	
	Missing	379	1.3%	
Talk About Problems with Family	**No**	11952	41.8%	
	Yes	16062	56.2%	
	Missing	553	1.9%	
Continuous Variables:		**n**	**mean**	**sd**
School Connectedness Score	**[0:24]**	27801	18.4	3.2
	Missing	766		
CESD-10 Score at Baseline	**[0:30]**	27466	8.2	5.8
	Missing	1101		
CESD-10 Score at Follow-up	**[0:30]**	27631	9.0	6.0
	Missing	936		
GAD-7 Score at Baseline	**[0:21]**	27836	5.9	5.4
	Missing	731		

GAD-7 Score at Follow-up	**[0:21]**	27927	6.6	5.6
	Missing	640		
FS Score at Baseline	**[8:40]**	28107	32.4	5.4
	Missing	460		
FS Score at Follow-up	**[8:40]**	28111	32.0	5.5
	Missing	456		

**sd = standard deviation*

Figures 7 to 9 show decision trees for 2018-19 student CESD-10, GAD-7 and FS scores, respectively. Figure 7-9a include student baseline score and all school-level demographics and changes to mental health policies and practices included as potential predictors, while Figures 7-9b show the corresponding trees with student-level predictors additionally included.

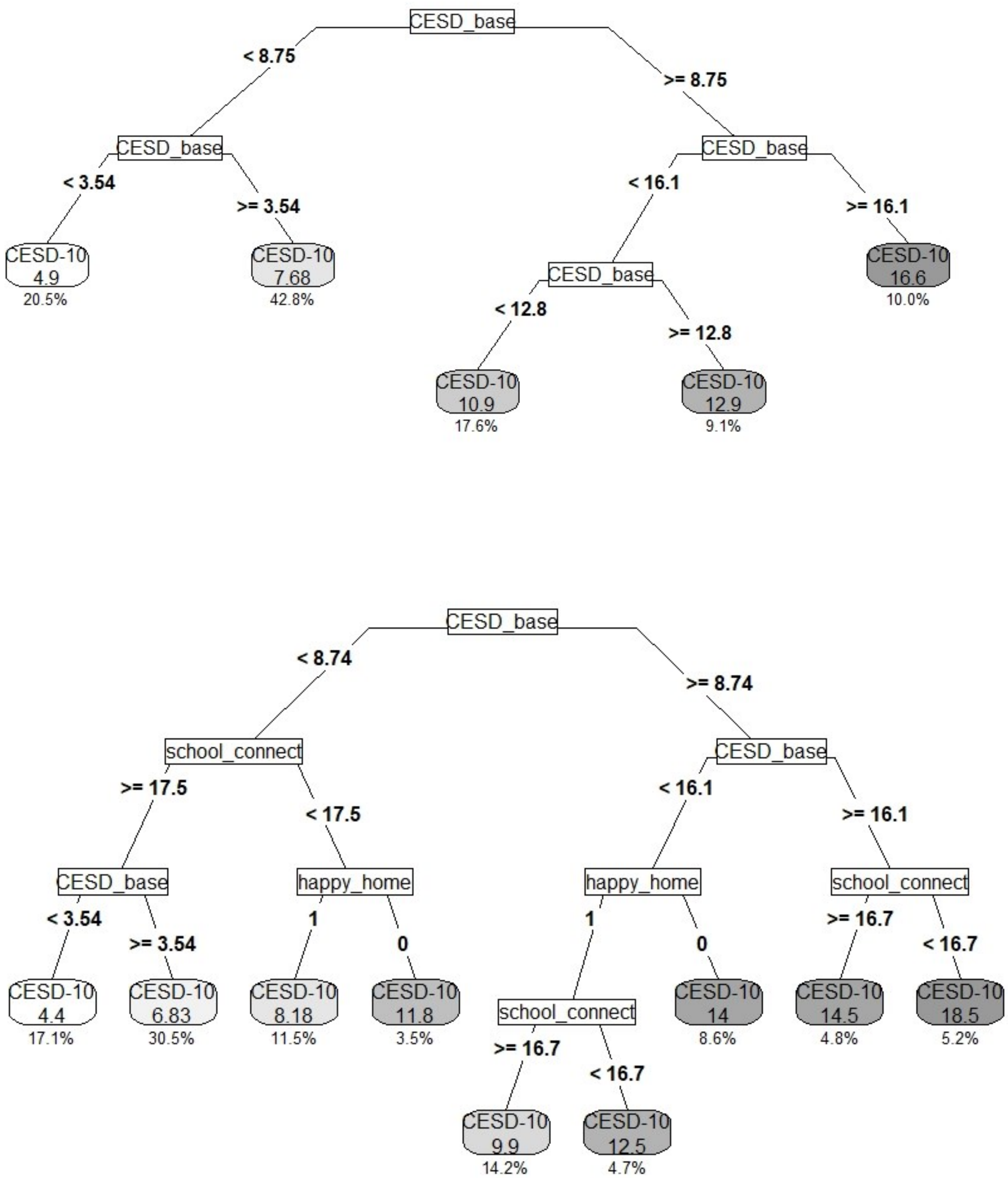
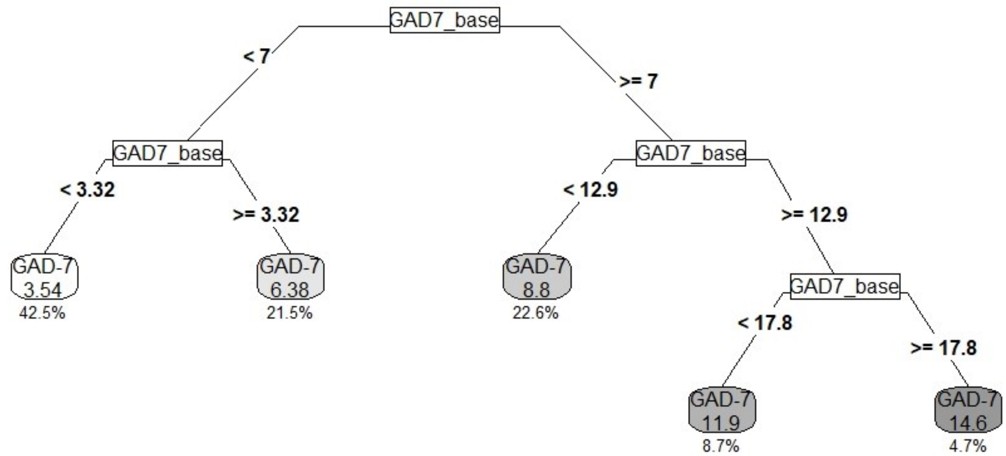


Figure 7. Decision tree for student CESD-10 score in 2018-19 including (a) school-level demographics and changes to policies and practices, and (b) both school and student level factors



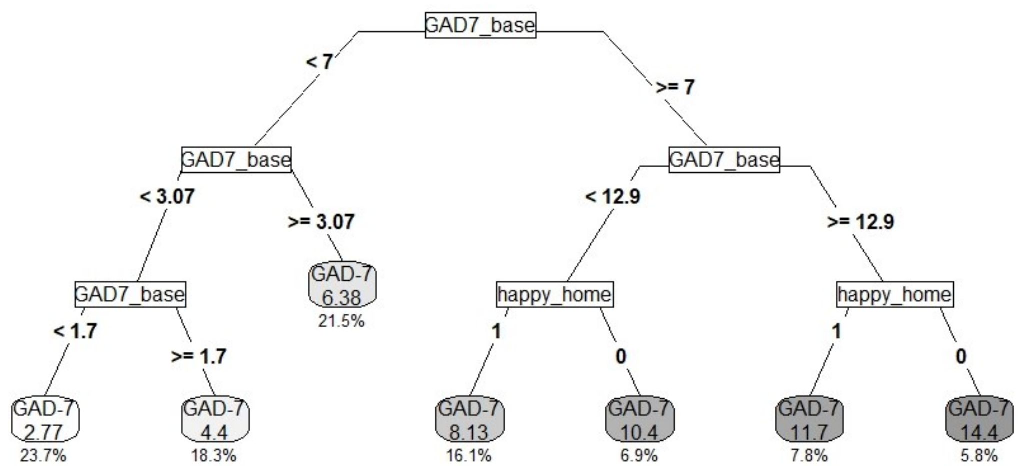
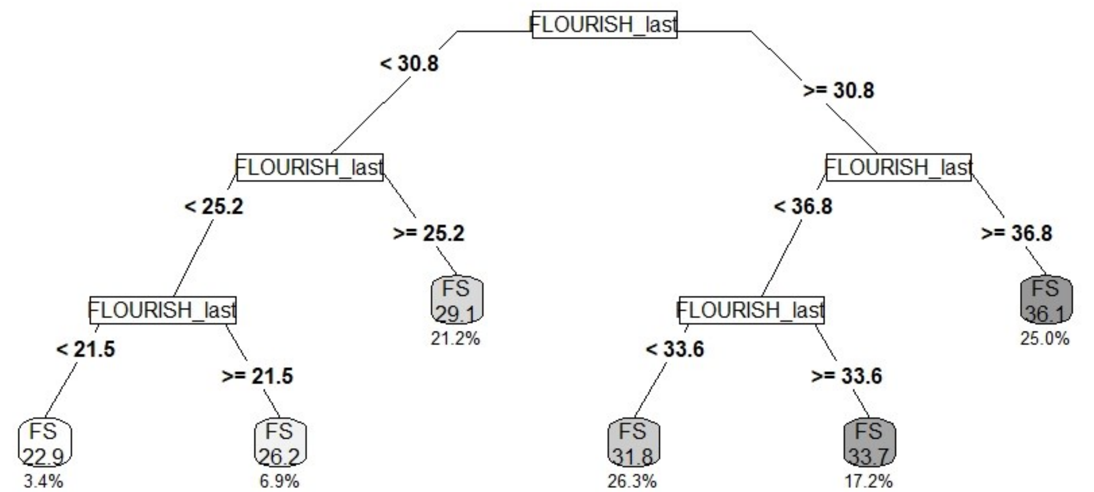


Figure 8. Decision tree for student GAD-7 score in 2018-19 including (a) school-level demographics and changes to policies and practices, and (b) both school and student level factors



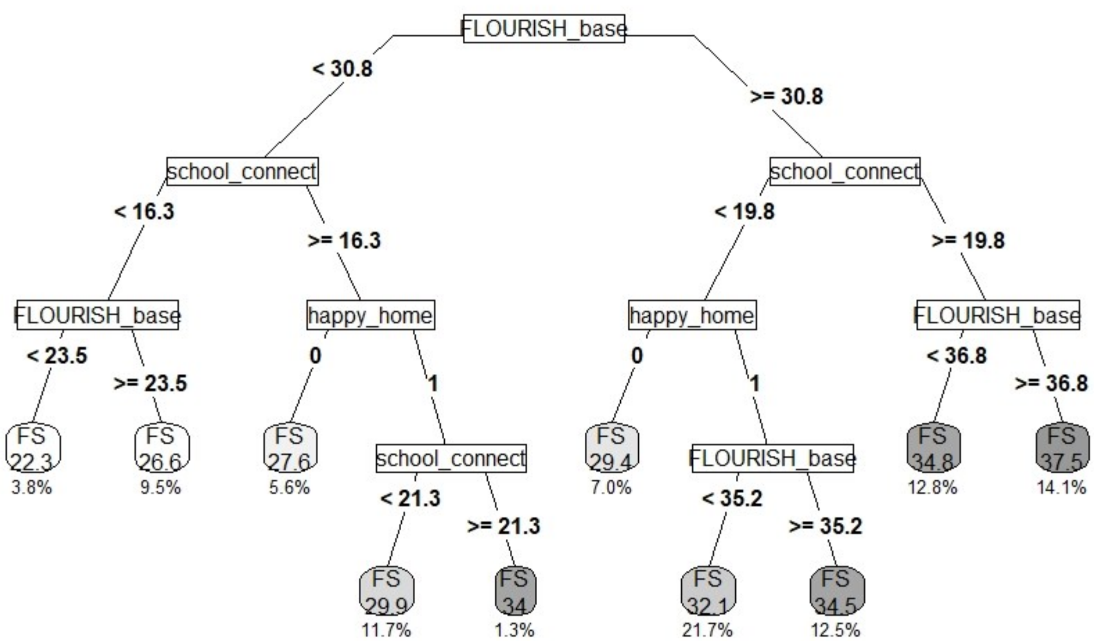


Figure 9. Decision tree for student FS score in 2018-19 including (a) school-level demographics and changes to policies and practices, and (b) both school and student level factors

As seen in Figure 7a, and consistent with school-level bivariate tests, no school-level predictors were associated with student CESD-10 score, with baseline score emerging as the only meaningful predictor of score at follow-up. As seen in Figure 7b, school connection and happy home life were identified as protective factors, while no school-level characteristics emerged as meaningful predictors for any subgroups. Among students with very high baseline CESD-10 scores above 16, those with high school connectedness scores had a lower average follow-up CESD-10 score of 14.5 while those with low school connectedness had a higher average follow-up score of 18.5. Similar protective effects are seen for students with moderate or low baseline CESD-10 levels, with happy home life showing protective effects for students with baseline CESD-10 scores between 8.7 and 16.1, as well as those with baseline scores less than 8.7 but with low school connection.

Similar to results seen for CESD-10 score, Figure 8a shows no association between school-level predictors and student GAD-7 score. As shown in Figure 8b, happy home life was a protective factor among students with baseline GAD-7 scores of 7 or greater only. No student-level factors were found to be meaningfully related to follow-up GAD-7 score for those with baseline scores under 7.

Consistent with results for CESD-10 and GAD-7, Figure 9a shows no association between school-level predictors and student and FS score. As shown in Figure 9b, school connectedness score was a protective factor across students with both lower and higher baseline flourishing scores. Among students with lower baseline flourishing, happy home life was a protective factor only among students with higher school connection. Conversely, among students with higher baseline flourishing, happy home life was protective among students with lower school connection.

7.5 Discussion

This study examined variation in school-level mental health practices over time using a sophisticated decision tree modelling approach to comprehensively explore various permutations of policy and practice changes, with the goal of understanding how changes can influence student mental health outcomes. Despite seeing substantial variability in school practices over time, no association was found between any of these incremental practice changes related to staffing, on-site services, community coordination, or one-off programs and student depression, anxiety, or flourishing levels. While discouraging, these results may provide evidence for the need for more comprehensive and coordinated approaches to school-based mental health. The variation in practices seen in the current study echo an earlier 2013 MHCC review of Canadian programming, which found a “patchwork of tested and untested school mental health initiatives" with a "lack of integration and common vision across initiatives"(203). In contrast, available evidence suggests whole school, long-term approaches to the promotion of mental health are most effective(98,109), thus the current findings demonstrate a clear disconnect between best and actual practice. The results of this study may therefore provide evidence in support of calls from the MHCC(5) and JSCH(205) on the need for increased comprehensive approaches to school mental health. Comprehensive approaches are also supported by previous success in the related domain of comprehensive tobacco control, which led to meaningful decreases in Canadian youth cigarette use(206).

School average CESD-10, GAD-7, and FS scores worsened for nearly all schools between baseline and follow-up. This worsening over time is expected in the longitudinal sample, given that mental health outcomes tend to deteriorate as youth age(207,208). Strong correlations between average depression, anxiety and flourishing scores in each year suggests an overall school environment of relatively better or poorer mental health, while moderately strong correlations between changes in scores further suggest that relative improvements on one measure of mental health correspond to overall improvements across measures. Studies assessing flourishing as a predictor of depression and anxiety among children and young adults show similar associations and recommend the use of interventions focused on mental health promotion as a means to protect against mental illness(209,210).

While a repeat cross-sectional view shows stability in the percentage of schools employing various practices each year, a longitudinal examination of within-school changes shows substantial inconsistency in what schools offer year-to-year. This inconsistency over time could inhibit student utilization of resources and help-seeking behaviour. Previous COMPASS research found that more than half of students were reluctant to seek help for mental health concerns(211), with those most in need being the least likely to seek help. Familiarity with sources of help and having trusting relationships with adults such as schoolteachers and counsellors have been found to be key facilitators of help-seeking(212). Thus, frequent staffing changes could impact student trust, while changes to the availability of on-site services could impact awareness, ultimately limiting utilization rates and potential effectiveness. This is consistent with previous evidence that longer-term, consistently applied programs are more effective(98,109). The lack of improvement from staffing and resource increases seen in the current study may therefore be due to the relatively short one-year follow up period, with consistency in trusted staff and program availability being important for longer term effectiveness.

While no significant associations were found at the overall school level, one benefit of the decision tree approach used in this study is the ability to identify high-risk subgroups of students who may be differentially impacted by practice changes(113). Indeed, a past meta-analytic review of mental health promotion and prevention programs found that while overall effect sizes tended be small to moderate, the real-world impact of mental health initiatives can be particularly meaningful to high-risk students(98). Unsurprisingly, this study found that students with worse baseline mental health were at greater risk at follow-up. Additionally, consistent with previous cross-sectional (204), students with perceptions of unhappy home lives were at greater risk across all outcomes, and students with low school connectedness were at greater risk for worse depression and flourishing outcomes. However, no differential impact of school practice changes was seen among these highest risk groups. Despite this, the decision trees for CESD-10 show that school connection acts as a protective factor among students with very high levels of baseline depression (CESD-10 >= 16.1); students with high school connection showed a decrease in average scores at follow-up (CESD-10=14.5) while those with low school connection had an average increase at follow-up (CESD-10 = 18.5). Similar protective effects were seen for students with lower levels of baseline depression and across all levels of baseline flourishing. These findings are consistent with previous research showing protective effects of school connection (53,54,63,201). This suggests that rather than focus on implementing individual mental health practices and programs, schools can better promote student mental health by fostering an overall climate of connection and support.

Importantly, the null result of the current study does not imply that schools should discontinue practices or services related to mental health. The MHCC notes unique advantages of school-based mental health programming, including the ability to reach students who would otherwise not have access to formal supports(203). School mental health services act as an important gateway to out-of-school supports, particularly for high-risk students(92). In particular, the availability of in-school early identification and screening programs has been associated with increased community service use(93,94). However, many schools do not have the financial resources or capacity needed to provide on-site services or programming(203). Proper training, consistent implementation, and sufficient funding support are consistently noted as vital for program effectiveness(98,109,111). In alignment with evidence on program interventions, our results further demonstrate limited effectiveness of sporadic or incremental practice and service changes. Rather, comprehensive universal approaches to school mental health developed at the provincial level are needed, along with dedicated training, expertise, and resources.

7.5.1 Limitations

Several limitations in the current study are noteworthy. First, while COMPASS benefits from diverse whole-school samples and a large total sample size, the study does not use representative sampling and therefore results may not be indicative of mental health practices across all Canadian schools. Additionally, while the longitudinal design is a key strength, the one-year follow-up period may not be long enough to see the full impacts of practice changes. Additionally, this study did not collect data on student utilization of resources and therefore is unable to link student mental health outcomes to actual service use or to determine whether low utilization rates contributed to lack of significant effect. Lastly, while the study examined various individual practices and services, this does not necessarily provide a comprehensive picture of school approaches to mental health. Other unmeasured aspects of school climate and culture may be contributing to variation in mental health outcomes, and more in-depth examination is warranted.

7.6 Conclusions

Substantial variability exists in the mental health practices and services offered by schools, with high inconsistency in school staff and service availability across years. Incremental practice changes related to staffing, on-site services, community coordination, or one-off programs did not meaningfully contribute to changes in student mental health outcomes over a one-year period. Despite these findings, schools continue to play an important role as universal access points and gateways to community mental health services. Comprehensive, universal approaches to school mental health developed at the provincial level are needed, along with dedicated training, expertise, and resources.

Chapter 8
Discussion

8.1 Overview

Youth mental health is a public health concern in Canada, with nearly 1 in 4 young people living with a mental illness(7). Mental illnesses are complex and can be affected in part by contextual factors(15). For youth, the school context can be particularly influential given the amount of time youth spend in school. School climate has been previously associated with student depression(60,63), anxiety(63), and overall wellbeing(53). Schools are also seen as ideal contexts for prevention and early intervention initiatives. National organizations and provincial ministries emphasize school-based mental health initiatives as key pillars in their youth mental health strategies(5,67–70,205). Despite this, research suggests that fewer than half of all mental health programs used in schools are based on evidence of effectiveness(7,83). Evidence of ongoing school policy and practice effectiveness is extremely limited in the peer reviewed literature, while reviews of school-based intervention programs note inconsistent results and a need for higher-quality evidence(99,109). Controlled evaluation trials generally examine individual program effects in isolation and do not account for differences in contextual factors or effects of practical implementation constraints. Traditional analysis techniques such as regression have limited ability to quantify non-linear interactions among simultaneously changing practices or identify differential impacts among various subgroups(113). Decision trees are an alternative machine-learning based method that allows for a comprehensive examination of complex factor interactions and identification of high-risk subgroups(113,115,116).

This thesis therefore aimed to fill an important knowledge gap by using decision trees to examine the influence of the school environment and school mental health practices on youth depression, anxiety, and psychosocial wellbeing. This was achieved through three studies which showed (1) the applicability of decision trees to addressing youth mental health research gaps, (2) the influence of school connection on youth mental health outcomes, and (3) the inconsistency in current school mental health practices and corresponding need for comprehensive school mental health approaches. The following sections provide a summary of key findings from this thesis, implications for public health practice, and implications for future research.

8.2 Summary of Key Findings

Study 1 provided a methodological overview of two decision tree techniques: Classification and Regression Trees (CART) and Conditional Inference Trees (CI) and compared the performance of these techniques to traditional linear and logistic regression through an application to COMPASS youth mental health survey data. For continuous GAD-7, CESD-10, and FS scale outcomes, prediction accuracy was 4-5% higher for linear regression than CART and CI. For binary depression and anxiety outcomes, prediction accuracy was 1-2% higher for logistic regression than CART and CI. All models consistently identified the same sets of most important predictors; however, decision trees identified fewer unique variables as meaningful. CART and CI models attribute 78-93% of relative variable importance to the top four variables, while regression attributed only 43-47%. Thus, while regression models had marginally better predictive ability, decision tree models were more parsimonious and placed greater emphasis on key differentiating factors. CART and CI models also detected complex non-linear associations between risk factors and identified the highest risk subgroup (females with unhappy home life and low school connection), which was not easily discernible from the regression model results. The simpler models generated by CART provided a clear visual representation of key risk factors to aid in decision making and knowledge translation. This study therefore demonstrated the suitability of decision trees for identifying key risk factors and high-risk subgroups within large-scale population health surveillance systems.

Given the suitability established in Study 1, Study 2 used decision trees to explore cross-sectional associations between a broad range of socioenvironmental and behavioural factors and youth depression, anxiety, and flourishing levels. This study took a hypothesis-generating approach to explore potential complex interactions of demographics, diet, movement behaviours, sleep, substance use, academics, bullying, peer relationships, school connection, and home life. Across all three outcomes examined, perceived happy home life and school connectedness emerged as the most important predictors, while behavioural factors did not emerge as important. Females without happy home life and with low school connection were the highest risk group for depression, with average CESD-10 score of 17.1, far above the cut-off of 10 considered for clinically relevant symptoms and over three times higher than the lowest risk group. Students of both sexes without happy home life and with low school connection were at highest risk for anxiety, with an average score of 11.9, above the cut-off of 10 considered for clinically relevant symptoms. Students with very low school connection and without happy home life were at highest risk for languishing (low flourishing) with an average score of 15.3, compared to the highest flourishing group of students with high school connection and happy home life with an average score of 36.9. This study found that interpersonal relationships related to the home and school environments were more strongly associated with youth depression, anxiety, and psychosocial wellbeing than individual health behaviours. The study demonstrated the meaningful role that schools can potentially have in contributing to student mental wellbeing if they can effectively cultivate and foster a climate of connection and belonging for students.

Given the association between student perceptions of school environment and youth mental health outcomes established in Study 2, Study 3 used longitudinal data to examine changes in school mental health practices and comprehensively explored if potential combinations of practice changes were associated with improvements in depression, anxiety, and flourishing levels. The availability of staff training, on-site mental health professionals, on-site mental health services, referral practices, and coordination with community public health varied widely between schools. Additionally, there was substantial inconsistency in these practices and services offered year-to-year within the same schools. Despite this, decision trees identified no meaningful combinations of practice changes associated with better depression, anxiety, or flourishing levels. Further, while unhappy home life and low school connection again emerged as important risk factors, no differential impacts of school practice changes were seen among these highest risk subgroups. This study suggested the ineffectiveness of haphazard one-off, incremental school-level practice changes at improving youth mental health outcomes and suggested the need for more comprehensive and coordinated approaches to school-based mental health.

The above three studies consistently demonstrated novel insights into the influence of the school environment on youth mental health that can be gleaned from decision tree analysis. Four main themes emerged from the above findings: contextual environment influences on youth mental health, the protective effect of school connection, approaches to school-based mental health initiatives, and the value of decision trees in health systems surveillance research. These themes are explored further in the following sections.

8.2.1 Contextual Environment Influences on Youth Mental Health

The first theme that emerged throughout these findings was the relative influence of environmental factors, specifically contextual and interpersonal factors, on youth mental health outcomes. Across all three studies, having a happy home life and sense of connection to school were identified as the most important predictors of youth mental health outcomes out of all covariates examined. Additionally, feeling able to talk about problems with family was found to be meaningfully important to some subgroups for flourishing scores in Study 1 and Study 2, and depression scores in Study 2. Being bullied also had meaningful relative importance for anxiety outcomes in Study 1. While previous decision tree analysis on youth mental health outcomes is limited, the influence of interpersonal relationships aligns with previous decision tree results which found friend support(149) and parental support(151) to be protective against major depressive disorder onset among at-risk youth. These findings also align with previous research finding various aspects of home(146,178,179,193–197) and school environments(53,54,60,62,63) to be associated with youth mental health outcomes. The consistency in associations seen across all studies and across anxiety, depression, and flourishing outcomes highlights the importance of positive home and school environments at influencing overall student mental wellbeing. This has important implications given that many aspects of home and school environment can be considered modifiable. These findings provide further evidence in support of The Mental Health Strategy for Canada(5) published by the Mental Health Commission of Canada (MHCC), which recommends increased resources and support for families, caregivers, schools, and community organizations to improve youth mental health.

Perhaps just as significant a finding is the lack of importance seen in modifiable behavioural factors such as diet, movement behaviours, and substance use. While Study 1 identified sleep time as having some importance for depression and anxiety outcomes in Study 1, no other behavioural factors emerged as important predictors of youth mental health outcomes across any study findings after the environmental and interpersonal influences of home and school were considered. This contrasts with past literature which has shown associations of diet(181), movement behaviours(182,183), sleep(142), and substance use(143) to youth mental health outcomes. However, as was highlighted in Study 2, most past research examined these behavioural factors in isolation and did not account for the environmental and interpersonal factors included in this thesis work. Thus, the findings from Study 1 and Study 2 suggest that home life and school connection are more important factors than any individual health behaviours. This does not, however, suggest that these behavioural factors have no influence on mental health outcomes. There could be many hypotheses for potential mediating or bi-directional associations between contextual and interpersonal influences and health behaviours, and the ultimate association to mental health outcomes. Thus, this thesis work highlights the need for future studies examining behavioural risk factors to account for these important contextual and interpersonal influences.

While the importance of home and school environments is clearly established across all three studies, further insight into the magnitude of this impact can be seen by examining model fit results across studies. As noted in Study 1 and Study 2, decision tree model fit was low to moderate. Across both studies, adjusted R^2 was at or below 50% across GAD-7, CESD-10, and FS outcomes. Lower model fit is not uncommon in behavioural studies but does suggest that the environmental and behavioural factors examined in this work only account for a portion of the overall variability in mental health outcomes in the sample. Following Bronfenbrenner's social-ecological model(33), youth mental health can be influenced by both contextual and intrinsic factors. Past research suggests there are competing influences of genetic and environmental factors(175–177), though the exact proportions of attribution vary by study, sample, and mental health outcome. Study 3 more directly quantified the variation in mental health outcomes attributable to the school environment specifically by calculating the intraclass correlation coefficient, which attributed 2% of the variability in CESD-10 scores, 3% of the variability in GAD-7 scores, and 3-4% of the variability in FS scores to school-level differences. These percentages are small when compared to the individual-level heterogeneity. However, when these results are considered in tandem with the importance of school connection, they could suggest that the low variability is due to lack of impactful differentiation between current school practices rather than a lack of overall influence of the school environment.

8.2.2 Protective Effect of School Connection

The second theme that emerged across all three studies was the protective effect of school connection on youth mental health. Cross-sectional associations were consistent between Study 1 and Study 2. In Study 1, school connectedness score had the second-highest variable importance for anxiety and depression outcomes in CART models, and the highest variable importance for flourishing score. In Study 2, school connectedness score was protective among all subgroups for GAD-7 and CESD-10 outcomes and was the primary differentiating factor for FS. This is consistent with previous cross-sectional research showing school connection to be protective against emotional distress(62), anxiety(59) and depression(59,60), and positively associated with mental wellbeing(53). In Study 3, which used a longitudinal sample and controlled for baseline mental health score, school connectedness was again protective among all subgroups for CESD-10 and was a primary differentiator after considering baseline score for FS; however, it no longer emerged as an important variable for GAD-7. Previous longitudinal research is mixed. One past study found school connection to be protective against a combined anxiety/depression measure after controlling for baseline measure(63), while another found school connection to be protective against depression in both boys and girls, but only protective against anxiety in girls after controlling for baseline measures(201). While anxiety and depression are closely related and commonly co-occurring outcomes, more longitudinal research is needed to understand nuances in the influence of school connection on these outcomes. Despite these differences for anxiety outcomes, one notable finding consistent across Study 2 and Study 3 was the protective effect of school connection on students at highest risk for depression. In Study 2, among the highest risk students with unhappy home life, average CESD-10 scores were over four points lower among those with high school connectedness scores. In Study 3, among students with highest baseline depression levels (CESD-10 scores over 16), follow-up CESD-10 scores were again four points lower among those with high school connectedness scores, with scores decreasing from baseline on average. While the findings from this thesis show that cultivating positive school connection can be beneficial among all students, the benefit to those at highest risk is important as these students are often most reluctant to seek help from formal supports(211).

8.2.3 Approaches to School-based Mental Health Initiatives

The third theme that emerged throughout this thesis was the need for more evidence-based approaches to school mental health initiatives. Across all three studies, school connection was found to be the most important factor for better flourishing outcomes. While home life ranked above school connection for anxiety and depression outcomes in Study 1 and Study 2, school connection was the primary differentiator for flourishing. In Study 3, school connection was the most important predictor among students with both high and low levels of baseline flourishing. This suggests that schools may be more directly influential on enhancing positive psychosocial wellbeing than on mitigating clinical anxiety and depression. Past multi-level research has shown both individual sense of school connection and school-wide levels of connection to be predictive of student wellbeing(54). Thus, schools may be able to improve mental wellbeing by creating an overall climate of connection and belonging. Focusing on positive mental health and school ethos are two key characteristics of effective school-based interventions(98). While evidence on the link between school ongoing practices and student psychosocial wellbeing is more limited, the results of Study 3 found school connection to be a primary factor for flourishing and correspondingly found no effect of individual policy or practice changes. Thus, there may be greater benefit in schools focusing efforts on improving overall sense of connection rather than implementing one-time mental health interventions or incremental practice changes. Study 3 also found that school-wide flourishing, depression, and anxiety levels were strongly correlated, and so by focusing on improvements to positive wellbeing through school connection initiatives, schools may also be able to indirectly improve anxiety and depression outcomes. Indeed, studies that have established flourishing as a predictor of depression and anxiety have recommended the use of mental health promotion interventions for ultimately protecting against mental illness(209,210).

Study 3 expanded on the findings of the importance of school connection in Study 1 and Study 2 by comprehensively examining the impacts of school mental health practice changes. However, as noted above, no changes to practices or services were associated with better or worse mental health outcomes. These findings align with reviews of mental health interventions, which have found that short-term interventions are ineffective when not accompanied by larger environmental change(110), while long-term, whole-school approaches are more effective(98,109). Study 3 also showed that mental health practices vary widely across schools and over time, and therefore suggests that sporadic approaches and incremental changes are not sufficient to produce meaningful impacts on health outcomes. This lack of association is unsurprising given that most mental health initiatives currently being implemented in schools are not based on evidence of effectiveness(83,203) and highlights the gap between best and actual practice. The findings of this thesis therefore do not allow for recommendations of specific practices or services. Rather, they support calls(5,205) for more comprehensive approaches to school-based mental health implemented at the provincial or federal level. These calls align with past evidence that consistent implementation and sustained funding are critical for programs to be effective(98,109,111) and are supported by previous success in related domains such as comprehensive tobacco control(206).

8.2.4 Decision Trees in Systems Surveillance

The final theme that emerged across all three studies was the broader usefulness of decision trees in health systems surveillance research. Four key strengths of decision trees were demonstrated throughout this thesis. The first strength is the ability of decision trees to identify non-linear associations and complex relationships between factors, which may be overlooked using a traditional theory- or model-based approach. This is seen across all three studies by examining differences in the various tree branches. For example, when examining the GAD-7 outcome in Study 2, the effect of sex differs by level of happy home life and school connection: sex appears as a second level branching factor for those without happy home life, as a third level factor among those with happy home life and high school connection, and not at all among those with unhappy home life and low school connection. This type of complex interaction would be difficult to see in standard regression analysis unless tested through higher-order interactions. Additionally, the tree in the above example splits on different values of school connection depending on the subgroup. This ability to identify distinguishing thresholds for continuous variables is missed in standard regression modeling that typically assumes a single linearly increasing estimate across all values of the variable. Similar patterns can be seen from the trees in Study 1 and Study 3. This is beneficial for systems surveillance research, particularly when many predictor variables are being monitored, because it allows researchers to identify underlying complex relationships without the need to explicitly test for a multitude of potential higher order interactions. Interpreting these complex interactions within regression modeling can also be difficult, whereas decision trees present a simple visual diagram to clearly demonstrate these relationships. The visual output of decision trees is also particularly useful for communicating complex findings to end knowledge users.

A second closely related strength of decision trees is the ability to identify the most important predictors out of a wide range. This was seen across Study 1 and Study 2 where happy home life and sense of connection to school were consistently identified as more important out of a range of 23 potential predictors. Study 1 also directly contrasted this ability against regression models by showing that decision trees placed far greater emphasis on the key differentiating factors. In large surveillance studies with many risk factors being examined at once, regression models can "wash out" potentially strong associations due to collinearity, meaning important factors could be missed(160,163). Conversely, decision trees will identify and choose only those factors that are most strongly associated with the outcome, allowing researchers to isolate the most important risk and protective factors.

Stemming from the first two strengths, a third strength of decision trees is the ability to identify high-risk subgroups. Decision trees will group subjects based on different values of factors that correspond to different levels of the outcome variable, allowing researchers to identify similar characteristics of subjects with the more adverse outcome values. For example, examining the decision tree for the GAD-7 outcome in Study 2, students with unhappy home life and school connectedness scores under 15.3 were at highest risk for anxiety, with average GAD-7 scores of 11.9 which is above the threshold for clinical relevance. This subgroup corresponded to 7% of the total sample. In contrast, the largest final subgroup of males with happy home life and school connection over 17.5 comprised 31.2% of the sample and had average GAD-7 scores of only 3.47. This ability to identify the highest and lowest risk subgroups allows researchers to develop risk profiles of students and tailor interventions. Targeted prevention and intervention initiatives can then be developed and provided to these highest risk groups, which is particularly beneficial in public health and school-based health initiatives which often have limited funding and scarce resources.

The final strength identified was the ability of decision trees to examine the impacts of simultaneously changing factors on core outcomes. This novel application of decision trees demonstrated in Study 3 has important implications for natural experiment evaluation. As seen in Study 3, schools made several concurrent practice changes over a school year. Decision tree analysis allowed for the comprehensive examination of all different combinations of these changes while accounting for different contextual factors. This approach allows researchers to use large-scale surveillance data to perform quasi-experimental evaluation by investigating a multitude of natural policy and program changes. This approach can be used to find early indications of potentially effective combinations of policies and programs, which can then be further studied through formal trial testing(213). Additionally, in contrast to controlled intervention trials which isolate singular interventions and artificially control contextual factors to test efficacy, this decision tree approach allows for the detection of real-world effectiveness while accounting for the complex interacting influences of contextual factors and concurrent changes, as well as identifying differential impacts on various subgroups. This application could be a powerful tool to leverage systems surveillance data for natural experiment evaluation.

8.3 Implications for Public Health Practice

The results of this thesis have implications for public health practice in youth mental health. Recommended actions for future school-based mental health practice are outlined below.

1. *Schools should focus on building an overall sense of connection among all students.*

The findings of this thesis clearly highlighted the important protective role that school connection plays in youth mental health. Students reporting high school connectedness consistently had lower average CESD-10 and FS scores than their counterparts across all risk levels, and this protective effect was particularly evident among highest risk students. Notably in Study 3, while school connection was protective for students, none of the incremental mental health practice changes made by schools had protective effects. Thus, rather than focusing on specific practice and program changes, schools should adopt approaches that focus on building an overall climate of connection and support. Several federal and provincial governmental organizations have developed policy guidance and resource kits for improving school climate and promoting a positive school environment. For example, the Joint Consortium for School Health (JCSH) offers a module within its Positive Mental Health Toolkit(214) with strategies for improving school connectedness. This focus on building sense of connection could have additional benefits to other outcomes, as school connection has been shown to have a protective association to health behaviour outcomes such as substance use, physical activity, and screen time(215–217).

2. *School-based initiatives should focus on positive psychosocial wellbeing for both females and males, as well as targeted intervention programming for females.*

While this thesis identified happy home life as the most important factor for anxiety and depression outcomes, school connectedness consistently ranked as most important for flourishing outcomes. Moreover, no differences between males and females were noticed in relation to flourishing. Thus, schools may be best situated to implement initiatives to improve all students' positive wellbeing. This recommendation already forms the basis of many provincial school mental health strategies, such as the School Mental Health Ontario pyramid model(218). Many school-based resources and interventions have been developed to focus on positive mental health, such as the JCSH Positive Mental Health Toolkit(214) noted above. Additionally, given that females consistently emerged as being at higher risk for worse anxiety and depression outcomes than males, additional targeted interventions involving female-focused programming should be implemented, with a focus on anxiety and depression prevention and early intervention. This recommendation corresponds to the second level of the School Mental Health Ontario pyramid model(218).

3. *Schools should avoid frequent incremental mental health practice changes.*

Study 3 found no evidence that incremental changes to school mental health practices led to any improvement in youth mental health outcomes. Despite this, substantial variability in practice and service offerings were seen across schools and years. Inconsistency in the availability of supports over time could deter students from seeking help due to a lack of knowledge of what is available to them. It may also be particularly important to maintain continuity in support staff to give students the opportunity to build trusting relationships. Familiarity with support sources trusting relationships with support staff are key factors in encouraging help-seeking among students(212). Thus, schools should attempt to maintain consistency in mental health practices and services over time, and clearly communicate available resources to students.

4. *Governments and school boards should adopt comprehensive approaches to school mental health.*

The lack of consistency in school mental health practices seen in this thesis echo earlier findings by the MHCC of a "patchwork of tested and untested school mental health initiatives" across Canada(203). The findings from this thesis clearly supports calls by the MHCC(5,203) and JCSH(205) for more comprehensive approaches to school mental health. While this thesis strengthens the evidence base, the knowledge of the effectiveness of comprehensive approaches has been documented in past systematic reviews(98), and in related domains of comprehensive approaches to tobacco control(206), yet a disconnect between best and actual practice remains. Dedicated resources from federal and provincial governments are needed for successful implementation of comprehensive school mental health strategies.

8.4 Implications for Future Research

This thesis also has implications and directions for future public health research. Recommended actions for future research are outlined below.

1. *Future mental health research should account for home and school environment factors.*

Across all studies, happy home life and school connectedness emerged as the most important factors for anxiety, depression, and flourishing outcomes. Despite this, most studies examining the impact of behavioural factors such as diet, physical activity, screen time, and substance use do not account for measures of the home or school environments in their analyses. Future research examining behavioural factors should account for the potential contextual influence of home and school environments on the association between behavioural risk factors and mental health outcomes. Additionally, this thesis focused on exploratory analysis of a wide breadth of factors, and as such used a broad measure of perceived happy home life, which could be interpreted differently by different students. This measure could be affected by a range of factors including adverse childhood experiences and family dynamics. Interpretation of this measure could also be reciprocally affected by a student's mental health status at the time of response. Future research should expand on these preliminary findings to understand more specifically which aspects of positive home and school environments drive the protective associations seen in this thesis.

2. *Future studies should more comprehensively measure school environment characteristics.*

Study 3 measured a wide range of school mental health practices; however, while school connection was identified as an important protective factor, none of the individual practice changes associated to better mental health outcomes. The measures used in this study are limited to formal practices and services offered by schools and do not fully capture the overall school mental health climate. For example, formal practices do not capture teacher or student attitudes toward mental health. This study also did not capture aspects of the built environment such as dedicated wellbeing spaces. Future research should more comprehensively examine school mental health environment through in-depth qualitative or mixed methods approaches, in order to better understand which aspects of school climate and context are most important for influencing youth mental health outcomes.

3. *Decision tree analysis should be applied to different health topics within large-scale surveillance data.*

As highlighted in Study 1, the decision tree approach used in this thesis has potential broader applications in population health surveillance and natural experiment research. Decision trees are ideally suited for answering research questions regarding identification of high-risk groups for targeted prevention and early intervention initiatives. This advantage of decision trees is particularly beneficial in large population health studies such as COMPASS, which gather data on a broad range of risk factors with potential complex relationships. Within the COMPASS study, the methods used in this thesis could be applied to examine the complex drivers of behavioural factors such as substance use. Decision tree methods would also be well suited to examining differential impacts of national and global ecological events such as COVID-19 on various groups of students. Further, the novel application of decision trees to examining co-occurring changes in school practices highlighted in Study 3 could be expanded to examine the full breadth of school environment data available in COMPASS, in order to capture overall school climate more comprehensively in relation to mental health and other behavioural outcomes. Beyond the COMPASS study, these methods could be applied to other existing health datasets to uncover novel and complex relationships that may have previously been difficult to examine using traditional regression analysis due to the size and complexity of the datasets. Given the numerous potential applications of decision trees, future researchers should expand the collection of broad-focused, large-scale surveillance data including environmental characteristics to be able to evaluate future public health priorities and natural experiments as they arise.

8.5 Strengths and Limitations

8.5.1 Overall Strengths

This thesis has several strengths. First, the novel use of decision trees to examine the influence of the school environment on youth mental health fills an important research gap. Past studies on behavioural risk factors for youth mental health generally examined health behaviour domains in isolation and used traditional regression methods that do not easily allow for the examination of complex interactions among factors(113). This study used a decision tree approach that simultaneously examined a broad range of risk factors and identified the most important factors and highest risk subgroups to whom interventions can be targeted. Further, while there have been many previous studies of individual school-based mental health interventions, the quality of existing evidence is considered weak(99,109), and there is very little evidence of the impact of ongoing school practices. This thesis filled a research gap by comprehensively examining ongoing school mental health practices using a method that accounts for real-world contextual influences on effectiveness.

Second, the COMPASS study includes longitudinal hierarchical data from a large sample of Canadian students. The breadth of health topics covered in the COMPASS study allowed for the examination of a wide range of risk and protective factors to youth mental health outcomes. The school-level data collected in COMPASS is also unique to large scale surveillance studies and allowed for examination of school characteristics within a large sample. The longitudinal study design of COMPASS is a key strength that allowed for the examination of within-student changes in mental health over time, as well as the impact of school-level changes. Longitudinal study designs are ideal for natural experiment evaluation. Additionally, the large longitudinal sample size at both the student and school level was a key strength over previous smaller studies employing decision tree analysis. Further, COMPASS uses active-information, passive-consent permission protocols that limit selection and reporting bias(119,219), as well as an anonymous linking process that allows for the creation of a longitudinal sample while encouraging honest reporting by maintaining student anonymity.

Finally, the decision tree methods used in this thesis were a key strength. As detailed above, decision trees have several key strengths over regression methods traditionally used in public health research. Namely, decision trees can be used to examine non-linear associations and complex relationships among risk factors and can have higher predictive accuracy than regression models when true underlying structures are non-linear(113). Decision trees also allow for subgroup identification and provide a parsimonious view of key differentiating factors in a visual format that aids in decision-making and knowledge translation. Studies 2 and 3 also employed multilevel random effects trees that outperform standard CART trees and have comparable accuracy to linear mixed effects models when working with clustered data(134,135). The novel application of decision tree techniques in this thesis provides a foundation to apply this method to answer future research questions in other health domains.

8.5.2 Overall Limitations

While this thesis work has several strengths, there are also limitations. First, there are limitations to the COMPASS study design. COMPASS uses a non-representative convenience sample of schools and therefore results may not be generalizable to all Canadian youth and school-level data may not be indicative of mental health practices across all Canadian secondary schools. However, the large whole-school sampling, high response rates, and passive consent procedures mean results may still be meaningful for many Canadian youth. Additionally, while COMPASS employs a longitudinal study design, Study 1 and Study 2 used cross-sectional data, and thus temporality in associations and causality cannot be inferred. The key identified predictor measures of happy home life and school connection may be bidirectionally associated with mental health status. While Study 3 used longitudinal data to better address temporality, the one-year follow-up period may be too short to see lasting impacts of school practice changes. Ideally, a four-year follow-up period would best allow for assessment of overall impacts on students throughout their time in high school, while providing adequate time for students to overcome barriers to help-seeking surrounding familiarity and trust. However, this long follow-up period may be impractical to assess if schools continue to enact high rates of practice changes throughout the follow-up period. Additionally, as COMPASS collects data annually, the exact timing between each practice change and data collection date is unknown. Future research should take advantage of the longitudinal study design to examine environmental impacts over a longer follow-up period.

There are also limitations to the questionnaire measures used in this analysis. While the mental health outcome measures are based on previously validated scales(23,25,28,126), the self-report nature of the questionnaire does not correspond to clinical evaluation and thus threshold cutoffs do not infer clinical anxiety or depression diagnoses. As with any self-report study, response bias may be present in any of the measures used, particularly given the sensitive nature of the questionnaire topics. Additionally, the measure of happy home life used is non-specific and individual respondent interpretation could vary. Given the breadth of health topics in COMPASS, it is not feasible to ask about any individual topic in depth. Thus, while this measure was useful for general exploratory analysis, future research examining the aspects of happy home life contributing to better or worse mental health outcomes is needed. The school policies and practices questionnaire is also limited in its ability to capture the overall school climate toward mental health as it does not provide information on beliefs and attitudes. This study also did not have a measure of resource utilization rates at the student or school level and therefore mental health outcomes cannot be directly linked to service use, which limits the ability to examine practice effectiveness.

Finally, there are limitations to the decision tree methods used in this thesis. While decision trees have several strengths over regression methods as noted above, they often have lower prediction accuracy, as was the case in this thesis. In fact, both tree and regression methods had relatively low prediction accuracy in this study, meaning the behavioural and environmental factors included in the analysis did not fully explain the differentiation in mental health outcomes among students. Decision trees also have a tendency to overfit the sample data which is only partially mitigated by tree pruning. However, this limitation is less of a concern given the large sample size used in this study and the similarity in prediction accuracy between training and test sets seen in Study 1. More complex machine learning methods such as random forests, which grow multiple decision trees and aggregate results into an overall variable importance ranking, have shown improved predictive ability(115). This improved accuracy comes at the cost of interpretability through the loss of a single visual tree. Nevertheless, random forest and other tree ensemble approaches may be preferrable if prediction and overall variable rankings are of greater importance than understanding the exact nature of relationships between factors. Future research should examine the use of these more complex methods in addressing public health research questions.

8.6 Conclusions

This dissertation used a novel application of decision trees to fill a research gap in the influence of the school environment on youth anxiety, depression, and psychosocial wellbeing. Decision trees provide a means of examining complex interactions between predictors and identifying high-risk subgroups in an interpretable format beyond what is readily available with traditional regression modeling. These benefits of decision trees aid researchers and public health practitioners in decision making and knowledge translation for prevention and intervention initiatives. Using decision trees, this thesis found that happy home life and school connection were key differentiating factors for youth anxiety, depression, and flourishing levels, highlighting the protective role that schools can play on youth mental wellbeing by fostering a climate of connection and support. A further longitudinal examination found that despite seeing substantial variability in school mental health practices, incremental practice changes were not associated with better mental health actions. Comprehensive approaches to school mental health at the federal and provincial level are needed along with dedicated resources. The decision tree method used in this thesis provide a template for further research into other public health domains and highlight the potential power in combining machine learning methods with large population health surveillance data for natural experiment evaluation.

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Appendices

Appendix A: COMPASS Student Questionnaire (2017-18, 2018-19)

• **This is NOT a test.** All of your answers will be kept **confidential**. No one, not even your parents or teachers, will ever know what you answered. So, please be honest when you answer the questions.

• Mark only **one option per question** unless the instructions tell you to do something else.

• Choose the option that is the **closest** to what you think/feel is true for you.

Please, use a pencil to complete this questionnaire

Please mark all your answers with full, dark marks like this: ○ ● ○ ○

START HERE

Please read each sentence below carefully. Write the correct letter, number, or word on the line and then fill in the corresponding circle.

Note: These five questions are only used to link data from one year to the next. They cannot be used to identify participants. Only University of Waterloo researchers have access to the responses, and they never have access to student names or other information. All responses are strictly confidential.

The first letter of your **middle** name (if you have more than one middle name use your first middle name; if you don't have a middle name use "Z"):____	The name of the month in which you were born: ________	The **last** letter of your full **last** name: ___	The **second** letter of your full **first** name: ___	The **first** initial of your **mother's** first name (think about the mother you see the most):___
Ⓐ Ⓙ Ⓢ	① January	Ⓐ Ⓙ Ⓢ	Ⓐ Ⓙ Ⓢ	Ⓐ Ⓙ Ⓢ
Ⓑ Ⓚ Ⓣ	② February	Ⓑ Ⓚ Ⓣ	Ⓑ Ⓚ Ⓣ	Ⓑ Ⓚ Ⓣ
Ⓒ Ⓛ Ⓤ	③ March	Ⓒ Ⓛ Ⓤ	Ⓒ Ⓛ Ⓤ	Ⓒ Ⓛ Ⓤ
Ⓓ Ⓜ Ⓥ	④ April	Ⓓ Ⓜ Ⓥ	Ⓓ Ⓜ Ⓥ	Ⓓ Ⓜ Ⓥ
Ⓔ Ⓝ Ⓦ	⑤ May	Ⓔ Ⓝ Ⓦ	Ⓔ Ⓝ Ⓦ	Ⓔ Ⓝ Ⓦ
Ⓕ Ⓞ Ⓧ	⑥ June	Ⓕ Ⓞ Ⓧ	Ⓕ Ⓞ Ⓧ	Ⓕ Ⓞ Ⓧ
Ⓖ Ⓟ Ⓨ	⑦ July	Ⓖ Ⓟ Ⓨ	Ⓖ Ⓟ Ⓨ	Ⓖ Ⓟ Ⓨ
Ⓗ Ⓠ Ⓩ	⑧ August	Ⓗ Ⓠ Ⓩ	Ⓗ Ⓠ Ⓩ	Ⓗ Ⓠ Ⓩ
Ⓘ Ⓡ	⑨ September	Ⓘ Ⓡ	Ⓘ Ⓡ	Ⓘ Ⓡ
	⑩ October			
	⑪ November			
	⑫ December			

○○○○○○○○○○○○○○○○○○○○○○○○ [serial]

About You

1. What grade are you in?

- ○ Grade 9
- ○ Grade 10
- ○ Grade 11
- ○ Grade 12

Quebec students only

- ○ Secondary I
- ○ Secondary II
- ○ Secondary III
- ○ Secondary IV
- ○ Secondary V
- ○ Other

2. How old are you today?

- ○ 12 years or younger
- ○ 13 years
- ○ 14 years
- ○ 15 years
- ○ 16 years
- ○ 17 years
- ○ 18 years
- ○ 19 years or older

3. Are you female or male?

- ○ Female
- ○ Male

4. How would you describe yourself? *(Mark all that apply)*

- ○ White
- ○ Black
- ○ Asian
- ○ Aboriginal (First Nations, Métis, Inuit)
- ○ Latin American/Hispanic
- ○ Other

5. About how much money do you usually get <u>each week</u> to spend on yourself or to save?
(Remember to include all money from allowances and jobs like baby-sitting, delivering papers, etc.)

- ○ Zero
- ○ $1 to $5
- ○ $6 to $10
- ○ $11 to $20
- ○ $21 to $40
- ○ $41 to $100
- ○ More than $100
- ○ I do not know how much money I get each week

6. How do you usually travel to and from school? *(If you use two or more modes of travel, choose the one that you spend most time doing)*

To school
- ○ By car (as a passenger)
- ○ By car (as a driver)
- ○ By school bus
- ○ By public bus, subway, or streetcar
- ○ By walking
- ○ By bicycling
- ○ Other

From school
- ○ By car (as a passenger)
- ○ By car (as a driver)
- ○ By school bus
- ○ By public bus, subway, or streetcar
- ○ By walking
- ○ By bicycling
- ○ Other

7. Did you attend this school last year?
- ○ Yes, I attended the same school last year
- ○ No, I was at another school last year

8. How tall are you without your shoes on? (Please write your height in feet and inches **OR** in centimetres, and then fill in the appropriate numbers for your height.)

○ **I do not know how tall I am**

"My height is ____feet, _____inches"

OR

"My height is ______ centimetres"

Height	
Feet	Inches
0 1 2 3 4 5 6 7	0 0 / 1 1 / 2 / 3 / 4 / 5 / 6 / 7 / 8 / 9

OR

Height
Centimetres
0 0 0 / 1 1 1 / 2 2 2 / 3 3 / 4 4 / 5 5 / 6 6 / 7 7 / 8 8 / 9 9

***Example*:**
My height is 5 ft 7 in

Height	
Feet	Inches
0 1 2 3 4 ● 6 7	● 0 / 1 1 / 2 / 3 / 4 / 5 / 6 / ● / 8 / 9

9. How much do you weigh without your shoes on? (Please write your weight in pounds **OR** in kilograms, and then fill in the appropriate numbers for your weight.)

○ **I do not know how much I weigh**

"My weight is _______ pounds"

OR

"My weight is _______ kilograms"

Weight
Pounds
0 0 0 / 1 1 1 / 2 2 2 / 3 3 3 / 4 4 / 5 5 / 6 6 / 7 7 / 8 8 / 9 9

OR

Weight
Kilograms
0 0 0 / 1 1 1 / 2 2 / 3 3 / 4 4 / 5 5 / 6 6 / 7 7 / 8 8 / 9 9

***Example*:**
My weight is 127 lbs

Weight
Pounds
0 0 0 / ● 1 1 / 2 ● 2 / 3 3 3 / 4 4 / 5 5 / 6 6 / 7 ● / 8 8 / 9 9

○○○○○○○○○○○○○○○○○○○○○○○○ [serial]

10. How do you describe your weight?

- ◯ Very underweight
- ◯ Slightly underweight
- ◯ About the right weight
- ◯ Slightly overweight
- ◯ Very overweight

11. Which of the following are you trying to do about your weight?

- ◯ **Lose** weight
- ◯ **Gain** weight
- ◯ **Stay** the same weight
- ◯ I am **not trying to do anything** about my weight

12. How much time per day do you *usually* spend doing the following activities?

For example: If you spend about 3 hours watching TV each day, you will need to fill in the 3 hour circle, and the 0 minute circle as shown below:

	Hours										Minutes			
a) Watching/streaming TV shows or movies	0	1	2	●	4	5	6	7	8	9	●	15	30	45

	Hours										Minutes			
a) Watching/streaming TV shows or movies	0	1	2	3	4	5	6	7	8	9	0	15	30	45
b) Playing video/computer games	0	1	2	3	4	5	6	7	8	9	0	15	30	45
c) Doing homework	0	1	2	3	4	5	6	7	8	9	0	15	30	45
d) Talking on the phone	0	1	2	3	4	5	6	7	8	9	0	15	30	45
e) Surfing the internet	0	1	2	3	4	5	6	7	8	9	0	15	30	45
f) Texting, messaging, emailing **(note: 50 texts = 30 minutes)**	0	1	2	3	4	5	6	7	8	9	0	15	30	45
g) Sleeping	0	1	2	3	4	5	6	7	8	9	0	15	30	45

13. In the last 30 days, did you gamble online for money?

- ◯ Yes
- ◯ No

Physical Activity

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

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

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

	Hours					Minutes			
Monday	0	1	2	3	4	0	15	30	45
Tuesday	0	1	2	3	4	0	15	30	45
Wednesday	0	1	2	3	4	0	15	30	45
Thursday	0	1	2	3	4	0	15	30	45
Friday	0	1	2	3	4	0	15	30	45
Saturday	0	1	2	3	4	0	15	30	45
Sunday	0	1	2	3	4	0	15	30	45

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

	Hours					Minutes			
Monday	●	1	2	3	4	0	15	30	●

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

	Hours					Minutes			
Monday	0	1	2	3	4	0	15	30	45
Tuesday	0	1	2	3	4	0	15	30	45
Wednesday	0	1	2	3	4	0	15	30	45
Thursday	0	1	2	3	4	0	15	30	45
Friday	0	1	2	3	4	0	15	30	45
Saturday	0	1	2	3	4	0	15	30	45
Sunday	0	1	2	3	4	0	15	30	45

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

	Hours					Minutes			
Monday	0	●	2	3	4	0	15	●	45

16. Were the last 7 days a typical week in terms of the amount of physical activity that you usually do?

- ○ Yes
- ○ No, I was *more* active in the last 7 days
- ○ No, I was *less* active in the last 7 days

○○○○○○○○○○○○○○○○○○○○○○○○ [serial]

17. Your closest friends are the friends you like to spend the most time with. How many of your closest friends are <u>physically active</u>?

- ◯ None
- ◯ 1 friend
- ◯ 2 friends
- ◯ 3 friends
- ◯ 4 friends
- ◯ 5 or more friends

18. Are you taking a physical education class at school this year?

- ◯ **Yes**, I am taking one **this term**
- ◯ **Yes,** I will be taking one or have taken one this school year, **but not this term**.
- ◯ **No**, I am not taking a physical education class at school this year

19. Do you participate in before-school, noon hour, or after-school physical activities organized by your school? *(e.g., intramurals, non-competitive clubs)*

- ◯ Yes
- ◯ No
- ◯ None offered at my school

20. Do you participate in competitive school sports teams that compete against other schools? *(e.g., junior varsity or varsity sports)*

- ◯ Yes
- ◯ No
- ◯ None offered at my school

21. Do you participate in league or team sports outside of school?

- ◯ Yes
- ◯ No
- ◯ There are none available where I live

22. On how many days in the last 7 days did you do exercises to strengthen or tone your muscles? *(e.g., push-ups, sit-ups, or weight-training)*

- ◯ 0 days
- ◯ 1 day
- ◯ 2 days
- ◯ 3 days
- ◯ 4 days
- ◯ 5 days
- ◯ 6 days
- ◯ 7 days

Healthy Eating

23. If you do not eat breakfast every day, why do you skip breakfast? *(Mark all that apply)*

- ○ I eat breakfast every day

- ○ I don't have time for breakfast
- ○ The bus comes too early
- ○ I sleep in
- ○ I'm not hungry in the morning
- ○ I feel sick when I eat breakfast
- ○ I'm trying to lose weight
- ○ There is nothing to eat at home
- ○ Other

24. In a *usual* school week *(Monday to Friday)*, on how many days do you do the following?

	None	1 day	2 days	3 days	4 days	5 days
a) Eat breakfast	○	○	○	○	○	○
b) Eat breakfast provided to you **as part of a school program**	○	○	○	○	○	○
c) Eat lunch at school - lunch packed and brought <u>from home</u>	○	○	○	○	○	○
d) Eat lunch at school - lunch <u>purchased in the cafeteria</u>	○	○	○	○	○	○
e) Eat lunch purchased at a fast food place or restaurant	○	○	○	○	○	○
f) Eat snacks purchased from a vending machine **in your school**	○	○	○	○	○	○
g) Eat snacks purchased from a vending machine, corner store, snack bar, or canteen **off school property**	○	○	○	○	○	○
h) Drink sugar-sweetened beverages (soda pop, Kool-Aid, Gatorade, etc.) <u>Do not include diet/sugar-free drinks</u>	○	○	○	○	○	○
i) Drink high-energy drinks (Red Bull, Monster, Rock Star, etc.)	○	○	○	○	○	○
j) Drink coffee or tea **with sugar** (include cappuccino, frappuccino, iced-tea, iced-coffees, etc.)	○	○	○	○	○	○
k) Drink coffee or tea **without sugar**	○	○	○	○	○	○

25. On a *usual* weekend *(Saturday and Sunday)*, on how many days do you do the following?

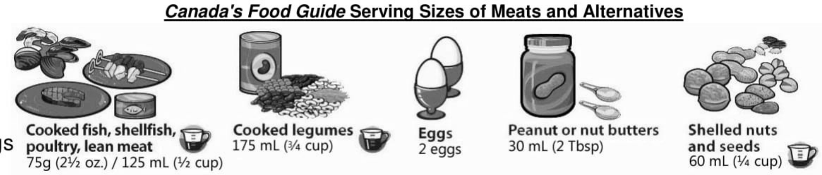
	None	1 day	2 days
a) Eat breakfast	○	○	○
b) Eat lunch	○	○	○
c) Eat foods purchased at a fast food place or restaurant	○	○	○
d) Eat snacks purchased from a vending machine, corner store, snack bar, or canteen	○	○	○
e) Drink sugar-sweetened beverages (soda pop, Kool-Aid, Gatorade, etc.) <u>Do not include diet/sugar-free drinks</u>	○	○	○
f) Drink high energy drinks (Red Bull, Monster, Rock Star, etc.)	○	○	○
g) Drink coffee or tea **with sugar** (include cappuccino, frappuccino, iced-tea, iced-coffees, etc.)	○	○	○
h) Drink coffee or tea **without sugar**	○	○	○

[serial]

26. YESTERDAY, ***from the time you woke up until the time you went to bed*****, how many <u>servings</u> of meats and alternatives did you have?** *One 'Food Guide' <u>serving</u> of meat and alternatives includes cooked fish, chicken, beef, pork, or game meat, eggs, nuts or seeds, peanut butter or nut butters, legumes (beans), and tofu.*

- ○ None
- ○ 1 serving
- ○ 2 servings
- ○ 3 servings
- ○ 4 servings
- ○ 5 or more servings

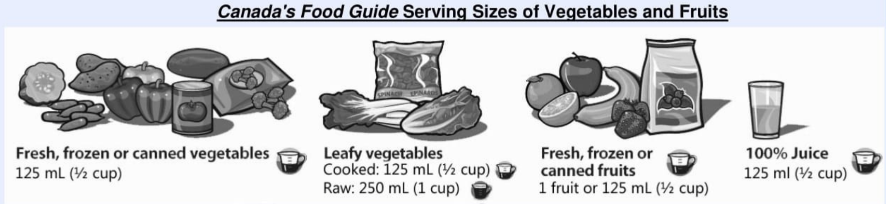
<u>Canada's Food Guide</u> **<u>Serving Sizes of Meats and Alternatives</u>**



27. YESTERDAY, ***from the time you woke up until the time you went to bed*****, how many <u>servings</u> of vegetables and fruits did you have?** *One 'Food Guide' <u>serving</u> of vegetables and fruit includes pieces of fresh vegetable or fruit, salad or raw leafy greens, cooked leafy green vegetables, dried or canned or frozen fruit, and 100% fruit or vegetable juice.*

- ○ None
- ○ 1 serving
- ○ 2 servings
- ○ 3 servings
- ○ 4 servings
- ○ 5 servings
- ○ 6 servings
- ○ 7 servings
- ○ 8 servings
- ○ 9 or more servings

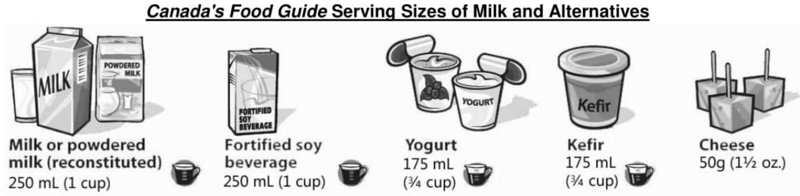
<u>Canada's Food Guide</u> **<u>Serving Sizes of Vegetables and Fruits</u>**



28. YESTERDAY, ***from the time you woke up until the time you went to bed*****, how many <u>servings</u> of milk and alternatives did you have?** *One 'Food Guide' <u>serving</u> of milk or milk alternatives includes milk, fortified soy beverage, reconstituted powdered milk, canned (evaporated) milk, yogurt or kefir (another type of cultured milk product), and cheese.*

- ○ None
- ○ 1 serving
- ○ 2 servings
- ○ 3 servings
- ○ 4 servings
- ○ 5 servings
- ○ 6 or more servings

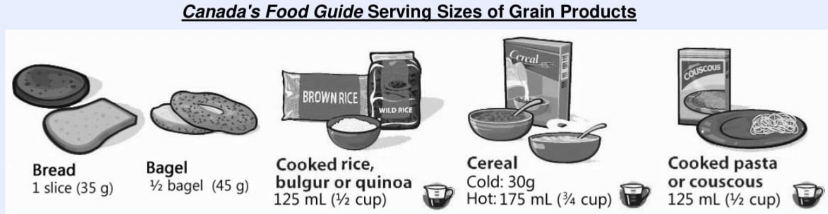
<u>Canada's Food Guide</u> **<u>Serving Sizes of Milk and Alternatives</u>**



29. YESTERDAY, ***from the time you woke up until the time you went to bed*****, how many <u>servings</u> of grain products did you have?** *One 'Food Guide' <u>serving</u> of grain products includes bread, bagels, flatbread such as tortilla, pita, cooked rice or pasta, and cold cereal.*

- ○ None
- ○ 1 serving
- ○ 2 servings
- ○ 3 servings
- ○ 4 servings
- ○ 5 servings
- ○ 6 servings
- ○ 7 servings
- ○ 8 servings
- ○ 9 or more servings

<u>Canada's Food Guide</u> **<u>Serving Sizes of Grain Products</u>**



Your Experience with Smoking

30. Have you ever tried cigarette smoking, even just a few puffs?

- ○ Yes
- ○ No

31. Do you think in the future you might try smoking cigarettes?

- ○ Definitely yes
- ○ Probably yes
- ○ Probably not
- ○ Definitely not

32. If one of your best friends were to offer you a cigarette, would you smoke it?

- ○ Definitely yes
- ○ Probably yes
- ○ Probably not
- ○ Definitely not

33. At any time during the next year do you think you will smoke a cigarette?

- ○ Definitely yes
- ○ Probably yes
- ○ Probably not
- ○ Definitely not

34. Have you ever smoked 100 or more whole cigarettes in your life?

- ○ Yes
- ○ No

35. On how many of the last 30 days did you smoke one or more cigarettes?

- ○ None
- ○ 1 day
- ○ 2 to 3 days
- ○ 4 to 5 days
- ○ 6 to 10 days
- ○ 11 to 20 days
- ○ 21 to 29 days
- ○ 30 days *(every day)*

36. Your closest friends are the friends you like to spend the most time with. How many of your closest friends smoke cigarettes?

- ○ None
- ○ 1 friend
- ○ 2 friends
- ○ 3 friends
- ○ 4 friends
- ○ 5 or more friends

37. Have you ever tried to quit smoking cigarettes?

- ○ I have never smoked
- ○ I have only smoked a few times
- ○ I have never tried to quit
- ○ I have tried to quit once
- ○ I have tried to quit 2 or 3 times
- ○ I have tried to quit 4 or 5 times
- ○ I have tried to quit 6 or more times

38. Have you ever tried an electronic cigarette, also known as an e-cigarette?

- ○ Yes
- ○ No

39. Have you used e-cigarettes for any of the following reasons? *(Mark all that apply)*

- ○ I have not used e-cigarettes
- ○ Curiosity / to try something new
- ○ I can use e-cigarettes in places where smoking is not allowed
- ○ To smoke fewer cigarettes
- ○ To help me quit smoking cigarettes
- ○ I have used e-cigarettes for some other reason

40. In the last 30 days, did you use any of the following? *(Mark all that apply)*

- ○ Pipe tobacco
- ○ Cigarillos or little cigars (*plain or flavoured*)
- ○ Cigars (not including cigarillos or little cigars, *plain or flavoured*)
- ○ Roll-your-own cigarettes (tobacco only)
- ○ Loose tobacco mixed with marijuana
- ○ E-cigarettes (electronic cigarettes that look like cigarettes/cigars, but produce vapour instead of smoke)
- ○ Smokeless tobacco (chewing tobacco, pinch, snuff, or snus)
- ○ Nicotine patches, nicotine gum, nicotine lozenges, or nicotine inhalers
- ○ Hookah (water-pipe) to smoke tobacco
- ○ Hookah (water-pipe) to smoke herbal sheesha/shisha
- ○ Blunt wraps (a sheet or tube made of tobacco used to roll cigarette tobacco)
- ○ I have not used any of these things in the last 30 days

41. On how many of the last 30 days did you use an e-cigarette?

- ○ None
- ○ 1 day
- ○ 2 to 3 days
- ○ 4 to 5 days
- ○ 6 to 10 days
- ○ 11 to 20 days
- ○ 21 to 29 days
- ○ 30 days *(every day)*

[serial]

Alcohol and Drug Use

Please remember that we will keep your answers ***completely confidential***.

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

42. In the last 12 months, how often did you have a drink of alcohol that was more than just a sip?

- ○ I have never drunk alcohol
- ○ I did not drink alcohol in the last 12 months
- ○ I have only had a sip of alcohol
- ○ Less than once a month
- ○ Once a month
- ○ 2 or 3 times a month
- ○ Once a week
- ○ 2 or 3 times a week
- ○ 4 to 6 times a week
- ○ Every day

43. How old were you when you first had a drink of alcohol that was more than just a sip?

- ○ I have never drunk alcohol
- ○ I have only had a sip of alcohol
- ○ I do not know

- ○ 8 years or younger
- ○ 9 years
- ○ 10 years
- ○ 11 years
- ○ 12 years
- ○ 13 years
- ○ 14 years
- ○ 15 years
- ○ 16 years
- ○ 17 years
- ○ 18 years or older

44. In the last 12 months, how often did you have 5 drinks of alcohol or more on one occasion?

- ○ I have never done this
- ○ I did not have 5 or more drinks on one occasion in the last 12 months
- ○ Less than once a month
- ○ Once a month
- ○ 2 to 3 times a month
- ○ Once a week
- ○ 2 to 5 times a week
- ○ Daily or almost daily

45. In the last 12 months, have you had alcohol mixed or pre-mixed with an energy drink (such as Red Bull, Rock Star, Monster, or another brand)?

- ○ I have never done this
- ○ I did not do this in the last 12 months
- ○ Yes
- ○ I do not know

46. In the <u>last 12 months</u>, how often did you use marijuana or cannabis? (a joint, pot, weed, hash)

- ○ I have never used marijuana
- ○ I have used marijuana but not in the last 12 months
- ○ Less than once a month
- ○ Once a month
- ○ 2 or 3 times a month
- ○ Once a week
- ○ 2 or 3 times a week
- ○ 4 to 6 times a week
- ○ Every day

47. If you have used marijuana or cannabis in the <u>last 12 months</u>, how did you use it? *(Mark all that apply)*

- ○ I have used it by smoking it (e.g., in a joint, a pipe, a bong)
- ○ I have used it by vaping it
- ○ I have used it by eating or drinking it (e.g., in brownies, cookies, candies, tea)
- ○ I have not used marijuana or cannabis in the last 12 months

48. How old were you when you first used marijuana or cannabis?

- ○ I have never used marijuana
- ○ I do not know

- ○ 8 years or younger
- ○ 9 years
- ○ 10 years
- ○ 11 years
- ○ 12 years
- ○ 13 years
- ○ 14 years
- ○ 15 years
- ○ 16 years
- ○ 17 years
- ○ 18 years or older

49. Do you think it would be difficult or easy for you to get marijuana if you wanted some?

- ○ Difficult
- ○ Easy
- ○ I do not know

50. Have you used or tried any of the following medications TO GET HIGH?	**No**, I have <u>never</u> done this	**Yes**, I have done this in the <u>last 12 months</u>	**Yes**, I have done this, but <u>NOT</u> in the <u>last 12 months</u>
a) Oxycodone (oxy, OC, APO, OxyContin®, percs, roxies, OxyNEO®)	○	○	○
b) Fentanyl (china white, synthetic heroin, china girl)	○	○	○
c) Other prescription pain relievers (codeine, morphine, Tylenol 3)	○	○	○

51. Do you think it would be difficult or easy to get pain relievers (Oxycodone, Fentanyl, codeine, etc.) if you wanted some?

- ○ Difficult
- ○ Easy
- ○ I do not know

○○○○○○○○○○○○○○○○○○○○○○○○ [serial]

Mental Health

52. How much do you agree or disagree with the following statements?

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a) I have a happy home life	○	○	○	○	○
b) My parents/guardians expect too much of me	○	○	○	○	○
c) I can talk about my problems with my family	○	○	○	○	○
d) I can talk about my problems with my friends	○	○	○	○	○

53. How much do you agree or disagree with the following statements?

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a) I lead a purposeful and meaningful life	○	○	○	○	○
b) My social relationships are supportive and rewarding	○	○	○	○	○
c) I am engaged and interested in my daily activities	○	○	○	○	○
d) I actively contribute to the happiness and well-being of others	○	○	○	○	○
e) I am competent and capable in the activities that are important to me	○	○	○	○	○
f) I am a good person and live a good life	○	○	○	○	○
g) I am optimistic about my future	○	○	○	○	○
h) People respect me	○	○	○	○	○
i) I generally recover from setbacks quickly	○	○	○	○	○

54. Choose the answer that best describes how you feel.

	True	Mostly true	Sometimes true, sometimes false	Mostly false	False
a) In general, I like the way I am	○	○	○	○	○
b) Overall, I have a lot to be proud of	○	○	○	○	○
c) A lot of things about me are good	○	○	○	○	○
d) When I do something, I do it well	○	○	○	○	○
e) I like the way I look	○	○	○	○	○

55. If you had concerns regarding your mental health, are there any reasons why you would not talk to an adult at school (e.g., a school social worker, child and youth worker, counsellor, psychologist, nurse, teacher, or other staff person)? *(Mark all that apply)*

- ○ I would have no problem talking to an adult at school about my mental health
- ○ Worried about what others would think of me (e.g., I'd be too embarrassed)
- ○ Lack of trust in these people - word would get out
- ○ Prefer to handle problems myself
- ○ Do not think these people would be able to help
- ○ Would not know who to approach
- ○ There is no one I feel comfortable talking to

56. Over the last 2 weeks, how often have you been bothered by the following problems?

	Not at all	Several days	Over half the days	Nearly every day
a) Feeling nervous, anxious, or on edge				
b) Not being able to stop or control worrying				
c) Worrying too much about different things				
d) Trouble relaxing				
e) Being so restless that it is hard to sit still				
f) Becoming easily annoyed or irritable				
g) Feeling afraid as if something awful might happen				

57. Please indicate how often the following statements apply to you:

	Almost never	Sometimes	About half the time	Most of the time	Almost always
a) I have difficulty making sense out of my feelings					
b) I pay attention to how I feel					
c) When I'm upset, I have difficulty concentrating					
d) When I'm upset, I believe there is nothing I can do to make myself feel better					
e) When I'm upset, I lose control over my behaviour					
f) When I'm upset, I feel ashamed for feeling that way					

58. On how many of the last 7 days did you feel the following ways?

	None or less than 1 day	1-2 days	3-4 days	5-7 days
a) I was bothered by things that usually don't bother me				
b) I had trouble keeping my mind on what I was doing				
c) I felt depressed				
d) I felt that everything I did was an effort				
e) I felt hopeful about the future				
f) I felt fearful				
g) My sleep was restless				
h) I was happy				
i) I felt lonely				
j) I could not get "going"				

59. In general, how would you rate your mental health?

- Excellent
- Very good
- Good
- Fair
- Poor

If you are a young person in Canada who needs support, you can reach out to Kids Help Phone's professional counsellors by calling 1-800-668-6868 or visiting kidshelpphone.ca. Their service is free, anonymous, confidential, and available 24/7/365.

Kids Help Phone

1-800-668-6868

[serial]

Your School and You

60. How strongly do you agree or disagree with each of the following statements?

	Strongly agree	Agree	Disagree	Strongly disagree
a) I feel close to people at my school	○	○	○	○
b) I feel I am part of my school	○	○	○	○
c) I am happy to be at my school	○	○	○	○
d) I feel the teachers at my school treat me fairly	○	○	○	○
e) I feel safe in my school	○	○	○	○
f) Getting good grades is important to me	○	○	○	○

61. In the <u>last 30 days</u>, in what ways were you bullied by other students? *(Mark all that apply)*

- ○ I have not been bullied in the last 30 days
- ○ Physical attacks (e.g., getting beaten up, pushed, or kicked)
- ○ Verbal attacks (e.g., getting teased, threatened, or having rumours spread about you)
- ○ Cyber-attacks (e.g., being sent mean text messages or having rumours spread about you on the internet)
- ○ Had someone steal from you or damage your things

62. In the <u>last 30 days</u>, how often have you been bullied by other students?

- ○ I have not been bullied by other students in the last 30 days
- ○ Less than once a week
- ○ About once a week
- ○ 2 or 3 times a week
- ○ Daily or almost daily

63. In the <u>last 30 days</u>, in what ways did you bully other students? *(Mark all that apply)*

- ○ I did not bully other students in the last 30 days
- ○ Physical attacks (e.g., beat up, pushed, or kicked them)
- ○ Verbal attacks (e.g., teased, threatened, or spread rumours about them)
- ○ Cyber-attacks (e.g., sent mean text messages or spread rumours about them on the internet)
- ○ Stole from them or damaged their things

64. In the <u>last 30 days</u>, how often have you taken part in bullying other students?

- ○ I did not bully other students in the last 30 days
- ○ Less than once a week
- ○ About once a week
- ○ 2 or 3 times a week
- ○ Daily or almost daily

65. How supportive is your school of the following?

	Very supportive	Supportive	Unsupportive	Very unsupportive
a) Making sure there are opportunities for students to be physically active	○	○	○	○
b) Making sure students have access to healthy foods and drinks	○	○	○	○
c) Making sure no one is bullied at school	○	○	○	○
d) Giving students the support they need to resist or quit tobacco	○	○	○	○
e) Giving students the support they need to resist or quit drugs and/or alcohol	○	○	○	○

66. In your current or most recent Math course, what is your approximate overall mark?
(Think about last year if you have not taken math this year)

- ○ 90% - 100%
- ○ 80% - 89%
- ○ 70% - 79%
- ○ 60% - 69%
- ○ 55% - 59%
- ○ 50% - 54%
- ○ Less than 50%

67. In your current or most recent English course, what is your approximate overall mark?
(Think about last year if you have not taken English this year)

- ○ 90% - 100%
- ○ 80% - 89%
- ○ 70% - 79%
- ○ 60% - 69%
- ○ 55% - 59%
- ○ 50% - 54%
- ○ Less than 50%

68. What is the highest level of education you would like to get? *(Choose only one)*

- ○ Some high school or less
- ○ High school diploma or graduation equivalency
- ○ College/trade/vocational certificate
- ○ University Bachelor's degree
- ○ University Master's / PhD / law school / medical school / teachers' college degree
- ○ I don't know

69. What is the highest level of education you think you will get? *(Choose only one)*

- ○ Some high school or less
- ○ High school diploma or graduation equivalency
- ○ College/trade/vocational certificate
- ○ University Bachelor's degree
- ○ University Master's / PhD / law school / medical school / teachers' college degree
- ○ I don't know

70. In the last 4 weeks, how many days of school did you miss because of your health?

- ○ 0 days
- ○ 1 or 2 days
- ○ 3 to 5 days
- ○ 6 to 10 days
- ○ 11 or more days

71. In the last 4 weeks, how many classes did you skip when you were not supposed to?

- ○ 0 classes
- ○ 1 or 2 classes
- ○ 3 to 5 classes
- ○ 6 to 10 classes
- ○ 11 to 20 classes
- ○ More than 20 classes

72. How often do you go to class without your homework complete?

- ○ Never
- ○ Seldom
- ○ Often
- ○ Usually

[serial]

Appendix B: COMPASS School Policies and Practices Questionnaire (2017-18, 2018-19) – Mental Health Module

Mental Health Questions

51. Please rank the following areas of primary concern related to your students' mental health:
(Rank items from 1 to 8where 1 =highest priority, 8 = lowest priority)

a. Attention problems ________
b. Disruptive behavioural issues ________
c. Depressed mood ________
d. Anxiety symptoms ________
e. Disordered eating ________
f. Self-harm and/or suicidality ________
g. Trauma ________
h. Substance use ________

52. During the past 12 months, how many staff have received the following training related to mental health?

		All or most	Some (e.g., 1-5)	None
a.	Mental health awareness/literacy (e.g., basic information, key warning signs)	○	○	○
b.	Providing mental health support (e.g., mental health first aid, Supporting Minds, etc.)	○	○	○
c.	Suicide prevention	○	○	○
d.	Other (please specify)	○	○	○

53. Please indicate the availability of the following mental health professionals at your school *(Select all availability options that apply)*

		On-call	On-site full-time	Regularly scheduled __ hours/month
a.	Child and Youth Worker	○	○	○
b.	Counsellor	○	○	○
c.	Social Worker	○	○	○
d.	Psychologist	○	○	○
e.	Mental Health Nurse	○	○	○
f.	Other (please list): __________________________	○	○	○

54. Are any of the following mental health services available <u>on-site</u> at your school? *(Check all that apply)*

a. Assessment for emotional or behavioural problems (including behavioural observation, psychosocial assessment and observation checklists)
b. Diagnostic assessment (comprehensive psychological evaluation)
c. Behavioural management consultation with teachers, students, or families
d. Case management, including monitoring and coordination of services
e. Referral to specialized programs or services for emotional or behavioural problems or disorders
f. Crisis intervention (e.g., response to traumatic events, including disasters, serious injury/death of a member of the school community)
g. Individual counselling/therapy
h. Group counselling/therapy
i. Substance abuse counselling
j. Family support services in school setting (e.g., child/family advocacy, counselling)

55. What are your general practices for routine <u>referral to and coordination</u> with community-based mental health organizations or providers? *(Check all that apply)*

a. Staff make passive referrals (e.g., give brochures, lists and contact information of providers or organizations)
b. Staff make active referrals (e.g., staff complete form with family, make calls or appointments, assist with transportation)
c. Staff follow-up with student/family (e.g., calls to ensure appointment kept, assess satisfaction with referral, need for follow-up)
d. Staff follow-up with provider (via phone, e-mail, mail)
e. Staff host or attend team meetings with community providers
f. Staff do not make referrals

56. During the <u>past 12 months</u>, what role did your local Public Health Unit (PHU) play when working with your school on improving <u>mental health</u> for students? *(Check all that apply)*

a. No contact with local Public Health Unit
b. Provided information/resources/programs (e.g., posters, toolkits)
c. Solved problems jointly
d. Developed/implemented program activities jointly

57. Other than classes/curriculum, does your school offer any programs to promote mental health? (e.g., stigma reduction, suicide prevention, peer support, stress management strategies, mental health literacy)

a. Yes
b. No

b) (If yes to a) Who runs these programs? *(Check all that apply)*

c. Programs run by school
d. Programs run by Public Health Unit
e. Programs run by external organization

c) (If yes to a) Are these programs new this year, or continuing from previous years?

- All programs are new this year
- All programs are continuing from past years
- We have both new and continuing programs

d) (If yes to a). Please provide additional details and indicate which programs are new or continuing:

____
____